IMPACT OF TECHNOLOGICAL INNOVATIONS ON THE INVESTMENT BEHAVIOUR OF STOCK MARKET INVESTORS

Thesis
Submitted to the University of Calicut
for the award of the degree of

Doctor of Philosophy in Commerce

AGHILESH M

Under the Supervision of

Dr. BALAKRISHNAN P
Assistant Professor
PG & Research Department of Commerce and Management Studies
St. Mary's College, Sulthan Bathery

Post Graduate and Research Department of Commerce
Government College Madappally, Kerala
(Affiliated to the University of Calicut)

September 2025

DECLARATION

I hereby declare that the work presented in the thesis entitled **"Impact of Technological Innovations on the Investment Behaviour of Stock Market Investors"** is my own original work under the guidance of **Dr. Balakrishnan P.**, Assistant Professor, PG & Research Department of Commerce and Management Studies, St. Mary's College, Sulthan Bathery (Research Supervisor, Post Graduate and Research Department of Commerce, Government College Madappally) and has not been submitted as part of any other thesis which might have been used to claim any degree in the past. The contents of the thesis are undergone plagiarism check using iThenticate software at C.H.M.K. Library, University of Calicut and the similarity index found within the acceptable limit. I also declare that the thesis does not include contents created by AI.

Aghilesh M

Dr. Balakrishnan .P

Dr. BALAKRISHNAN. P
RESEARCH GUIDE
Research Department of
Commerce and Management Studies
St. Mary's College, Sulthan Bathery

Research Department of Commerce and Management Studies ★ St. Mary's College Sulthan Bathery Pin - 673592

Madappally

Date: 06.01.2026

GOVERNMENT COLLEGE, MADAPPALLY
KOZHIKODE DISTRICT
PIN: 673 102
MADAPPALLY COLLEGE P.O.

Post Graduate and Research Department of Commerce
Government College Madappally
(Affiliated to the University of Calicut)
Madappally College P.O. PIN – 673102, Kerala, India

Dr. Balakrishnan P
Assistant Professor
St. Mary's College, Sulthan Bathery
Research Supervisor,
PG & Research Dept. of Commerce,
Govt. College Madappally

Mob No.: 9847100270
Email: balupanp@gmail.com

CERTIFICATE

This is to certify that the thesis entitled **"Impact of Technological Innovations on the Investment Behaviour of Stock Market Investors"** submitted to the University of Calicut in partial fulfilment of the requirements for the award of the Degree of Doctor of Philosophy in Commerce is a record of original work done by Sri. Aghilesh M under my supervision and guidance, and the thesis has not formed the basis for the award of any degree, diploma, associateship, fellowship, or other similar title to any candidate in any institute or university.

Both the examiners have not recommended any modifications or suggestions and therefore the original thesis is resubmitted as such. The soft copy attached is the same as that of the resubmitted copy.

Madappally

Date: 06.09.2025

Dr. Balakrishnan P

Dr. BALAKRISHNAN. P
RESEARCH GUIDE
Research Department of
Commerce and Management Studies
St. Mary's College, Sulthan Bathery

GOVERNMENT COLLEGE, MADAPPALLY
KOZHIKODE DISTRICT
PIN: 673 102
MADAPPALLY COLLEGE P.O.

Research Department of Commerce and Management Studies
St Mary's College
Sulthan Bathery
Pin - 673592

UNIVERSITY OF CALICUT

CERTIFICATE ON PLAGIARISM CHECK

1.	Name of the Research Scholar	Aghilesh M	
2.	Title of thesis / dissertation	Impact of Technological Innovations on the Investment Behaviour of Stock Market Investors	
3.	Name of the Supervisor	Dr. Balakrishnan P	
4.	Department/Institution	PG & Research Department of Commerce, Government College Madappally	
5.		Non Core	Core
		Introduction/ Theoretical overview/Review of literature/ Materials & Methods/ Methodology	**Analysis/Result/Discussion / Summary/Conclusion/ Recommendations**
	Similar content (%) identified	**4**	**3**
	Acceptable maximum limit (%)	10	10
6.	Software used	iThenticate	
7.	Date of verification	16.09.2025	

**Report on plagiarism check, specifying included/excluded items with % of similarity to be attached.*

SEEMA M.V.
Assistant Librarian
University of Calicut
Malappuram - 673 635

Checked by (with name , designation & signature) Seema

Name and signature of the Researcher Aghilesh . M

Name and signature of the Supervisor. Dr. Balakrishnan . P

The Doctoral Committee* has verified the report on plagiarism check with the contents of the thesis, as summarized above and appropriate measures have been taken to ensure originality of the Research accomplished herein.

Name & Signature of the HoD/HoI (Chairperson of the Doctoral Committee) Shinu Pattiyil Madammal

Principal
GOVERNMENT COLLEGE, MADAPPALLY
MADAPPALLY COLLEGE (P.O.
PIN: 673 102

**In case of languages like Malayalam, Tamil etc..on which no software is available for plagiarism check, a manual check shall be made by the Doctoral Committee, for which an additional certificate has to be attached.*

GOVERNMENT COLLEGE MADAPPALLY
KOZHIKODE DISTRICT
PIN 673 102

Dedicated to

All my well-wishers whose support, encouragement and blessings has been a source of strength in academic journey…

Acknowledgment

I am deeply grateful to many people for their enthusiastic support, thoughtful suggestions, and ongoing encouragement. I would like to express my sincere gratitude to all those individuals who, through direct and indirect means, have supported and encouraged the successful completion of my research work.

I would like to express my utmost gratitude to Dr. Balakrishnan P., my Research Supervisor, for his relentless guidance, valuable discussions, and constructive criticism throughout this work. Continuous supervision, timely advice, and confidence in my potential have been crucial in the timely completion of this research. I thank him beyond words for his encouragement in this work and for his inspiration that has motivated me in all my hours.

I would like to extend my sincere thanks to Mr. Shinu Padinhara Malammal, Associate Professor and Principal-in-Charge, Government College, Madappally, for his continuous support. I am also grateful to Dr. Vineethan T., Head of the Department of Commerce at Government College, Madappally, for providing a research-friendly atmosphere and for his invaluable suggestions.

I wish to extend my hearty gratitude to Dr. O K. Udayakumar (The former Principal in charge and Head of the Department of Commerce, Govt. College Madappally). I am deeply grateful to him for his unwavering support and invaluable guidance.

I hereby wish to extend my deepest gratitude to Dr. Babu P (The former Head of the Department of Commerce at Govt. College Madappally)for the insightful suggestions he provided me during the research work. I would like to express my gratitude to Dr. Preetha B, the former Principal in Charge of Government College, Madappally, for her constant support.

I extend warm gratitude to the entire faculty members of the Department of Commerce at Government College, Madappally, Dr. Praveen M V, Mrs. Jiji N, Mr. Prineesh C M, Mr. Shyju Koodayil, and Miss Remya K M for their support and sacrifice. Their abundant support and generous encouragement have played a crucial role in the successful completion of my research work.

I also extend hearty thanks and gratitude to the former faculty members of the Department of Commerce, Government College Madappally. The research work would not have been completed without the constant support and rich encouragement of Dr. Sravana K, Mr. Prasad P.J., Mr. Muhammed Salim K.C, Mr. Shajim M.S, and Mr. Mahesh P.B. I would like to thank my dear teachers, Dr. K.K. Ashokan, Dr. Abdul Assis Koroth, Dr. Venugopalan, Mr. Vinod.A, and others, who persistently encouraged me to finish my research.

I am greatly indebted to all the teaching and non-teaching staff at Government College, Madappally, for their support, particularly Mr. Pushpangadan M.G. (Senior Superintendent), Mr. Shaji Pattarachuttaparambil (Junior Superintendent), Mrs. Surya M. B., and Resma Raj K (Section Clerks). I also extend my gratitude to Mr. Kabir P and Divya (Part-time Research Scholars, GC Madapally), Mrs. Anusree Ashokan, Miss. Swathi Mohanan P K, Aswathi Ashok T V, Aswin Prakash and Nidhin Kumar K (Full-time Research Scholars GC Madappally), Dr.Shamshana V.C, Dr. Dr. Bhavana B.V, and Dr Farisa Aboobacker and other full-time and part-time research scholars in Commerce, GC Madappally.

I would like to express my heartfelt gratitude to all the respondents in my study, whose sincere responses greatly aided me in data collection, and for their patience and kind cooperation.

Finally, I would like to acknowledge my father, wife, brothers, children, father-in-law, mother-in-law, and friends who supported and sacrificed for me in the completion of my research. I extend sincere gratitude to my supportive family and friends for their love and support.

Aghilesh M

Table of Contents

Chapter 5

Factors Influencing the Adoption of Technology and Its Impact on Stock Market Investment Behaviour............ 243 – 283

Chapter 6

Summary, Findings and Conclusions.................................. 284 – 306

List of Tables

List of Figures

List of Abbreviations

AAT	-	Agency Algorithmic Traders
AI	-	Artificial Intelligence
API	-	Application Programming Interface
ATT	-	Attitude Towards Technology
AU	-	Actual Use
AVE	-	Average Variance Extracted
AVE	-	Average Variance Extracted
BI	-	Behavioural Intention
BSE	-	Bombay Stock Exchange
CP	-	Cost Perception
CvaR	-	Conditional Value-at-Risk
DFL	-	Digital financial literacy
DLT	-	Distributed ledger technology
DOI	-	Diffusion of Innovation
EUT	-	Expected Utility Theory
FC	-	Facilitating Conditions
FDI	-	Foreign Direct Investment
HFT	-	High Frequency Trading
HTMT	-	Heterotrait-Monotrait Ratio
IB	-	Investment Behaviour
IDT	-	Innovation Diffusion Theory
IPMA	-	Importance-Performance Map Analysis
IRT	-	Innovation Resistance Theory
KMO	-	Kaiser-Meyer-Olkin
LE	-	Level of Education

LSTM	-	Long Short-Term Memory
MCP	-	Multiple Country Publications
ML	-	Machine Learning
NSE	-	National Stock Exchange
PAT	-	Proprietary Algorithmic Traders
PEOU	-	Perceived Ease of Use
PLS-SEM	-	Partial Least Squares Structural Equation Modelling
PMT	-	Protection Motivation Theory
PU	-	Perceived Usefulness
RBI	-	Reserve Bank of India
RCT	-	Rational Choice Theory
RP	-	Risk Perception
SCP	-	Single Country Publications
SEBI	-	Securities and Exchange Board of India
SEC	-	Securities Exchange Commission
SOR	-	Smart Order Routing
SVAM	-	Self-efficacy-Based Value Adoption Model
TAM	-	Technology Acceptance Model
TPB	-	Theory of Planned Behaviour
TPB	-	Theory of Planned Behaviour
TPB	-	Theory of Planned Behaviour
TRA	-	Theory of Reasoned Action
TRI	-	Technology Readiness Index
TRI	-	Technology Readiness Index
UI	-	User Interface
UTAUT	-	Unified Theory of Acceptance and Use of Technology
UTAUT	-	Unified Theory of Acceptance and Use of Technology
VaR	-	Value-at-Risk
WoS	-	Web of Science

Abstract

The technology used for stock trading continues to develop rapidly, which has a significant impact on stock market participation, particularly in developing economies like India. The current study, titled "Impact of Technological Innovations on the Investment Behaviour of Stock Market Investors", explores the effects of technological innovations on the investment behaviour of retail investors. The study is both analytical and empirical in nature, relying on primary and secondary data. A structured questionnaire was used to collect primary data from 420 active stock market investors in Kerala, who were selected purposively. Descriptive statistics, Mann-Whitney U Test, Kruskal-Wallis H Test, and Partial Least Squares Structural Equation Modelling (PLS-SEM) were used in the analysis. The results indicate that the attitude of investors towards technological innovations is the most important variable determining their use of fintech tools. The attitude had a significant positive impact on the probability of investors intending to utilise such tools, and risk and cost concerns decreased after the adoption decision. These findings provide empirical evidence to support the existing theories of technology adoption, demonstrating their applicability in financial contexts. The research also indicates that technological changes transform investor behaviour to be more dynamic, enlightened and active in trading. In the context of practicality, the implications of the results to brokerage firms, regulators and policymakers are considerable. Brokerage firms are encouraged to develop user-friendly platforms that incorporate onboarding tracks tailored to various investor segments, video tutorials, and regional language support to enhance accessibility. Such insights can be utilised by regulators and policymakers to design policies that promote the responsible use of financial technologies, striking a balance between innovation and investor protection. The study contributes to the theoretical discussion of technology adoption. It lays the groundwork for future research in financial markets, particularly in the investigation of the ever-changing fintech solutions and their long-term effects on retail investment behaviour.

Keywords: Technological Innovations, Investment Behaviour, Stock Market Investors, Discount Brokers, Stock Screeners.

Dr. BALAKRISHNAN. P
RESEARCH GUIDE
Research Department of
Commerce and Management Studies
St. Mary's College, Sulthan Bathery

Research Department of Commerce and Management Studies
St. Mary's College
Sulthan Bathery
Pin - 673592

സംഗ്രഹം

ഓഹരി വിപണനത്തിന് ഉപയോഗിക്കുന്ന സാങ്കേതികവിദ്യ അതിവേഗം വികസിച്ചുകൊണ്ടിരിക്കുകയാണ് . ഇന്ത്യയെപോലെയുള്ള വികസ്വര സമ്പത്ത് വ്യവസ്ഥകളിൽ സ്റ്റോക്ക് മാർക്കറ്റ് ഇടപാടുകളിൽ ഇതിന്റെ പ്രാധാന്യം വളരെ വലുതാണ്. "സ്റ്റോക്ക് മാർക്കറ്റ് നിക്ഷേപകരുടെ നിക്ഷേപ സ്വഭാവത്തിൽ സാങ്കേതിക കണ്ടുപിടിത്തങ്ങളുടെ സ്വാധീനം" എന്ന തലക്കെട്ടിലുള്ള പഠനം, ചെറുകിട നിക്ഷേപകരുടെ നിക്ഷേപ സ്വഭാവത്തിൽ സാങ്കേതിക കണ്ടുപിടിത്തങ്ങളുടെ സ്വാധീനത്തെകുറിച്ച് വിശകലനം ചെയ്യുന്നു. പ്രാഥമികവും ദ്വിതീയവുമായ വിവരങ്ങളെ ആശ്രയിച്ച് വിശകലനപരവും അനുഭവപരവുമായ സ്വഭാവമുള്ളതാണ് പഠനം. കേരളത്തിൽ ഓഹരി വിപണിയിൽ സജീവമായി ഇടപെടുന്ന 420 ഓഹരി വിപണി നിക്ഷേപകരിൽ നിന്ന് പ്രാഥമിക വിവരങ്ങൾ ശേഖരിക്കാൻ ഒരു ഘടനാപരമായ ചോദ്യാവലി ഉപയോഗിച്ചു. വിവരണാത്മക സ്ഥിതിവിവരക്കണക്കുകൾ (Descriptive Statistics), Mann-Whitney U Test, Kruskal-Wallis H Test, Partial Least Squares Structural Equation Modelling (PLS-SEM) എന്നിവ വിശകലനത്തിന് ഉപയോഗിച്ചു. സാങ്കേതിക വിദ്യകളുടെ കണ്ടുപിടിത്തങ്ങളോടുള്ള നിക്ഷേപകരുടെ മനോഭാവമാണ് അവരുടെ സാങ്കേതിക വിദ്യ ഉപയോഗം നിർണ്ണയിക്കുന്ന ഏറ്റവും പ്രധാനപ്പെട്ട ഘടകം എന്ന് ഗവേഷണ ഫലങ്ങൾ സൂചിപ്പിക്കുന്നു. അത്തരം ഉപകരണങ്ങൾ ഉപയോഗിക്കാൻ ആഗ്രഹിക്കുന്ന നിക്ഷേപകരുടെ സാധ്യതയിൽ ഈ മനോഭാവം ഗണ്യമായ സ്വാധീനം ചെലുത്തുന്നു. ആധുനിക സാങ്കേതികവിദ്യ ഉപയോഗിക്കുന്നതിനുള്ള തീരുമാനം എടുത്തതിനുശേഷം ശേഷം നഷ്ടസാധ്യതയും ചെലവും സംബന്ധിച്ച ആശങ്കകൾ കുറഞ്ഞുവരുന്നതായി കാണുന്നു. ഈ കണ്ടെത്തലുകൾ സാങ്കേതികവിദ്യ സ്വീകരിക്കുന്നതിനുള്ള നിലവിലുള്ള സിദ്ധാന്തങ്ങളെ പിന്തുണയ്ക്കുന്നതിന് അനുഭവപരമായ തെളിവുകൾ നൽകുന്നു, സ്റ്റോക്ക് ബ്രോക്കർമാർ, റെഗുലേറ്റർമാർ, നയനിർമ്മാതാക്കൾ എന്നിവർക്ക് ഗവേഷണ ഫലങ്ങൾ പ്രായോഗികമായി വേണ്ട രീതിയിൽ ഉപയോഗിക്കാൻ പറ്റും. നിക്ഷേപകരുടെ പ്രവേശനക്ഷമത വർദ്ധിപ്പിക്കുന്നതിന് വിവിധ നിക്ഷേപ വിഭാഗങ്ങൾ, വീഡിയോ ട്യൂട്ടോറിയലുകൾ, പ്രാദേശിക ഭാഷാ പിന്തുണ എന്നിവയ്ക്ക് അനുസൃതമായി ഓൺബോർഡിംഗ് ട്രാക്കുകൾ ഉൾക്കൊള്ളുന്ന ഉപയോക്തൃ സൗഹൃദ പ്ലാറ്റ്ഫോമുകൾ വികസിപ്പിക്കാൻ ബ്രോക്കറേജ് സ്ഥാപനങ്ങളെ പ്രോത്സാഹിപ്പിക്കുന്നു. സാങ്കേതികവിദ്യകളുടെ ഉത്തരവാദിത്തപരമായ ഉപയോഗം പ്രോത്സാഹിപ്പിക്കുകയും നവീകരണവും നിക്ഷേപക സംരക്ഷണവും തമ്മിൽ സന്തുലിതാവസ്ഥ സൃഷ്ടിക്കുകയും ചെയ്യുന്ന നയങ്ങൾ രൂപകൽപ്പന ചെയ്യുന്നതിന് അത്തരം ഉൾക്കാഴ്ചകൾ റെഗുലേറ്റർമാർക്കും നയരൂപീകരണക്കാർക്കും ഉപയോഗിക്കാൻ കഴിയും. സാങ്കേതികവിദ്യ സ്വീകരിക്കുന്നതിനെക്കുറിച്ചുള്ള സൈദ്ധാന്തിക ചർച്ചയ്ക്ക് ഈ പഠനം

സംഭാവന നൽകുന്നു. സാമ്പത്തിക വിപണികളിലെ ഭാവി ഗവേഷണത്തിന്, പ്രത്യേകിച്ച് എപ്പോഴും മാറിക്കൊണ്ടിരിക്കുന്ന ഫിൻടെക് പരിഹാരങ്ങളെക്കുറിച്ചും ചില്ലറ നിക്ഷേപ സ്വഭാവത്തിൽ അവയുടെ ദീർഘകാല പ്രത്യാഘാതങ്ങളെക്കുറിച്ചും അന്വേഷിക്കുന്നതിന് ഇത് അടിത്തറയിടുന്നു.

കീവേഡുകൾ: സാങ്കേതിക കണ്ടുപിടിത്തങ്ങൾ, നിക്ഷേപ സ്വഭാവം, ഓഹരി വിപണി നിക്ഷേപകർ, ഡിസ്കൗണ്ട് ബ്രോക്കർമാർ, സ്റ്റോക്ക് സ്ക്രീനുകൾ.

Dr. BALAKRISHNAN. P
RESEARCH GUIDE
Research Department of
Commerce and Management Studies
St. Mary's College, Sulthan Bathery

Chapter 1

INTRODUCTION

1.1 Background of the Study

Technology has transformed many industries over the past few decades, with the financial sector experiencing rapid advancements in digital trading platforms, automated advisory services, and real-time data analytics (Chen & Nie, 2022). The stock market, once dominated by manual processes, now operates in a highly digital environment due to the rise of algorithmic trading, robo-advisors, and mobile trading applications (Arthur & Khindanova, 2023). These technological advancements have provided investors with new tools to manage their investments more effectively, giving them greater access to financial markets and the ability to trade at any time (Gomber et al., 2018). Traditional investment strategies have also evolved due to these technological developments. Investors now utilise artificial intelligence-based tools to predict stock movements, evaluate risk, and optimise their portfolios (Salisu, Demirer, & Gupta, 2024; Nadeem & Mazhar, 2019). Additionally, social trading platforms and financial news applications provide instant updates that influence trading decisions (Li & Wang, 2023). The accessibility of these advanced tools and real-time data has significantly shaped investor behaviour, allowing for more informed decision-making and a more dynamic investment landscape (Olanrewaju et al., 2024).

The stock market has undergone significant changes due to technological advancements (Diaz-Rainey et al., 2015). Automated trading systems execute trades in milliseconds, reducing the time required for manual execution (Huang et al., 2018). High-frequency trading has become common, affecting stock price movements and liquidity (Huang et al., 2018; Ammar et al., 2020). Blockchain technology has improved security and transparency in stock trading (Xu et al., 2021). Artificial intelligence has enabled the development of advanced predictive models, enabling investors to make data-driven decisions (Zong & Guan, 2024). Robo-advisors provide algorithm-based investment advice, making portfolio management more accessible (Kofman, 2024). Mobile trading applications have simplified trading by allowing investors to trade from their smartphones (Chong et al., 2021; Thapa et al., 2024). Digital payment systems have streamlined transactions, reducing settlement delays (Putrevu & Mertzanis, 2023). These advancements have improved efficiency, but they have also introduced new challenges. Market volatility has increased due to the rise of algorithmic trading (Arumugam et al., 2022). The reliance on artificial intelligence has raised concerns about the accuracy of decision-making (Araujo et al., 2020). Cybersecurity risks have emerged as investors rely more on digital platforms (Ng & Kwok, 2017). Despite these challenges, technological advancements continue to shape stock market investment behaviour.

Investor behaviour has changed due to technological innovations. Earlier, investors relied on traditional brokerage services and financial advisors. Now, they have access to digital platforms that provide real-time insights. Algorithmic trading has reduced human intervention, leading to faster trade execution (Lee & Schu, 2022; Arnoldi, 2015). Investors now follow social trading platforms to gain insights from other traders (Dorfleitner et al., 2018). Artificial intelligence-based models analyse historical data to provide investment recommendations (Martinez-Lopez & Casillas, 2013). Financial analytics tools help investors assess risk and optimise portfolio performance (Janabi, 2021). The availability of data has influenced trading strategies. Investors now use technical indicators and predictive models to time their trades (C. Chen et al., 2022; Chourmouziadis et al., 2020). The introduction of low-cost trading platforms has increased participation by retail investors. The democratisation of financial information has made it easier for new investors to enter the market (Block, 2013). However, the reliance on digital tools has also led to behavioural biases. Investors tend to overreact to real-time news, leading to impulsive decision-making (Tetlock, 2011). Automated trading has increased market volatility, as algorithms respond to price movements instantly (Litzenberger et al., 2012). The stock market has become more dynamic, with increased participation from both institutional and retail investors.

Existing studies have examined the role of technology in financial markets. Researchers such as Dubey et al. (2021); Hendershott et al. (2011); Boehmer et al. (2020); Seo and Chai (2013); Hendershott and Riordan (2013); Syamala and Wadhwa (2020), and Upson and Van Ness (2016) have analysed the impact of algorithmic trading on market liquidity and efficiency. The use of robo-advisors has been examined in relation to investor trust and financial decision-making (Nourallah, 2022; Tao et al., 2020). The adoption of blockchain technology in stock markets has been discussed by academic researchers, including Liu et al. (2022) and Janssen et al. (2019). The role of digital payment systems in financial markets has also been studied by Wang and Li (2024), Kazan and Damsgaard (2016), and Hofmann (2020). Researchers, including Al-Shari and Lokhande (2023) and Aggarwal et al. (2023), have explored the risks associated with fintech adoption. Studies such as Yang and Klassen (2008) and Sun and Du (2024) have emphasised the benefits of technological advancements in improving market efficiency. However, challenges such as cybersecurity risks (Tosun, 2021), algorithmic biases (Kordzadeh & Ghasemaghaei, 2021; Weller, 2017), and market manipulation (Khodabandehlou & Golpayegani, 2022; Hao et al., 2023; Golmohammadi et al., 2014) have also been identified.

Emerging studies have focused on the evolving role of financial technology in the stock market. Researchers such as Dakalbab et al. (2024) and Schrettenbrunner (2023) have analysed how artificial intelligence enhances trading strategies. Studies such as Sismanoglu et al. (2019) and Ayyappa and Kumar (2024) have explored the role of big data analytics in stock market prediction. The integration of blockchain technology in securities trading has gained attention (Liu et al., 2022; Hasan et al., 2022). The use of machine learning algorithms in risk management has been studied by Addy et al. (2024), Feng and Qu (2021) and Zhang and Chen (2021). Researchers such as Abdullah et al. (2013), Singh et al. (2024), and Kang et al. (2020) have examined investor sentiment analysis using natural language processing. The impact of mobile applications on trading frequency has been assessed by Nair et al. (2022), Kim et al. (2020) and C. Liu et al. (2024). Studies by Gan et al. (2019), Selvakumar et al. (2024) and S. X. Xu and Zhang (2009) have explored the role of social media in shaping investor sentiment. The use of deep learning models for financial forecasting has been a recent focus of research (Lin & Huang, 2020; C. Zhang et al., 2023). Researchers have examined the implications of technological innovations on regulatory frameworks. Emerging studies have provided insights into the risks and opportunities associated with digital transformation in financial markets.

The interaction between social trading platforms and investor sentiment needs further exploration. The role of financial analytics tools in shaping risk perception remains underexplored. The impact of mobile trading applications on retail investor behaviour requires more empirical investigation. Research has not fully addressed how investor psychology adapts to fintech advancements. The long-term implications of technology-driven investment strategies need further analysis. Understanding these gaps will help provide a more comprehensive perspective on the role of technology in financial markets.

This study aims to examine multiple aspects of technological innovations in stock market investments. The study will analyse changes in investment behaviour due to digital transformation. The study will examine the impact of social trading platforms and real-time news applications on trading habits. The role of financial analytics tools in investment decision-making will be assessed. The study will also examine the impact of mobile trading applications on stock trading behaviour. Finally, the study will analyse the effect of fintech adoption on investment behaviour. By addressing these objectives, the study will provide a holistic understanding of how technology shapes investment decisions.

This study introduces a novel approach by integrating multiple technological advancements. Previous research has focused on individual technologies, while this study examines their collective impact. The study is important as it explores investor behaviour in a rapidly evolving digital environment. Understanding how investors respond to technological changes will provide valuable insights. The study contributes to the field by identifying emerging trends in digital investments. The findings will help policymakers design regulations that enhance market stability. Financial institutions can utilise the results to enhance their fintech solutions. Investors will gain insights into how technology influences their decision-making process. The study will add to the academic literature by providing empirical evidence on the effects of technological innovations on investment behaviour.

1.2 Significance of the Study

This study will help investors understand how technology influences their trading behaviour. The findings will show how investor awareness of fintech developments affects decision-making. Understanding these aspects will enable investors to make informed choices while managing risk effectively. The study will provide insights into how algorithmic trading, robo-advisors, and AI-driven analytics shape investment outcomes. Policymakers can use this research to assess the risks and opportunities associated with digital trading. Financial regulators can create policies that ensure investor protection while supporting innovation. Financial institutions can utilise the study to enhance their fintech solutions and offer more effective tools for investors. Stock market platforms can enhance their services based on insights from this research. The study will investigate the impact of social trading platforms and real-time news on investor sentiment. It will assess the impact of financial analytics tools on portfolio management strategies. The findings will help identify behavioural patterns that emerge due to technological adoption. Retail investors can use this study to navigate digital trading environments more effectively. The study will also assess how mobile trading applications influence investment habits. Understanding the role of technology in shaping investment strategies will enable financial service providers to develop more effective investment solutions. The study will contribute to future research by identifying key trends in digital investing. The results will support the development of better trading models and risk management strategies.

1.3 Statement of the Problem

Investors adopt technological tools (Manrai & Gupta, 2022; Piehlmaier, 2022), but their awareness and understanding of these innovations remain uneven. Do investors make informed decisions while using AI-driven analytics, robo-advisors, and algorithmic trading? Many investors rely on social trading platforms (Wohlgemuth et al., 2016; Reith et al., 2019; Deng et al., 2023), but do they verify the accuracy of the information before making investment choices? Impulsive trading has increased with the advent of real-time news platforms, but does this lead to irrational decisions? Many investors trust mobile trading apps, but do they assess the risks associated with instant trading? The impact of digital financial analytics on decision-making is unclear. Do investors use these tools effectively, or do they blindly follow automated recommendations? The extent to which technological adoption changes investment behaviour is still not fully explored.

Irrational decision-making is a growing concern in stock market investments (Shah et al., 2017; Zahera & Bansal, 2018; Kumar & Goyal, 2016; Khare & Kapoor, 2023). Do investors evaluate risks when using algorithmic trading or follow market trends without analysis? Social trading has influenced stock selection, but do investors fact-check investment tips before acting? Many investors engage in high-frequency trading (Bershova & Rakhlin, 2012; Menkveld, 2013), but does it improve long-term returns or increase losses? Mobile trading apps provide easy market access, but do they encourage excessive trading without strategic planning? Robo-advisors offer automated portfolio management, but do investors understand their limitations? The role of technology in shaping investor psychology needs further examination. Are investors adapting to digital platforms rationally, or are they becoming overdependent on automation and market signals?

1.4 Scope of the Study

This study examined the impact of technological innovations on stock market investors by defining its scope across three key dimensions: temporal, geographical, and theoretical scope. The temporal scope focused on the current investment environment, capturing real-time fintech adoption trends among investors using data gathered from 2023 to 2024. As financial technologies continue to evolve, the study focused on the latest advancements, including mobile trading apps, robo-advisors, algorithmic trading, financial analytics tools, and social trading platforms. The research analysed investor behaviour over recent years to ensure findings remained relevant to the fast-changing digital investment environment. Since fintech adoption is dynamic, the study provided a snapshot of the present trends rather than a historical or predictive analysis.

The geographical scope of this study was limited to stock market investors in Kerala, ensuring relevance to the Indian financial system, regulatory environment, and digital trading ecosystem. India has experienced rapid growth in fintech, with increasing participation from both retail and institutional investors. The study included investors from various regions, with different trading experience levels and investment volumes, to ensure diverse representation. The theoretical scope incorporated the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), Prospect Theory, and Behavioural Finance Theory to explain how fintech adoption influenced investor behaviour. These theories helped analyse investor decision-making, risk perception, trading frequency, and fintech trust levels. The study provided a structured framework for assessing how technological advancements have reshaped stock market investments in Kerala.

1.5 Research Questions

1. How have technological advancements changed investment behaviour?
2. How do social trading platforms and real-time news influence trading habits?
3. How do technological advancements in financial analytics impact investment decision-making?
4. How do mobile trading apps affect stock trading behaviour?
5. How does the adoption of technological innovations impact investment behaviour?

1.6 Objectives

1. To analyse changes in investment behaviour due to technological advancements.
2. To evaluate the influence of social trading and real-time news platforms on trading habits.

3. To analyse the impact of technological advancements in financial analytics on investment decision-making

4. To assess the impact of mobile trading apps of discount brokers on the stock trading behaviour of investors.

5. To examine the key factors influencing the adoption of technological innovations and assess their impact on investment behaviour among stock market investors.

1.7 Hypotheses

The following are the hypotheses formulated by considering the objectives of the study.

1. H1: There is a significant difference in investment behaviour influenced by technological advancements between male and female investors.

2. H2: There is a significant difference in investment behaviour due to technological advancements among investors with different levels of education.

3. H3: There is a significant difference in investment behaviour due to technological advancements among investors with different employment statuses.

4. H4: There is a significant difference in investment behaviour due to technological advancements among investors with different age groups.

5. H5: There is a significant difference in trading habits influenced by social trading and real-time news platforms between male and female investors.

6. H6: There is a significant difference in trading habits due to social trading and real-time news platforms among investors with different levels of education.

7. H7: There is a significant difference in trading habits due to social trading and real-time news platforms among investors with different employment statuses.

8. H8: There is a significant difference in trading habits due to social trading and real-time news platforms among investors with different age groups.

9. H9: There is a significant difference in investment decision-making due to financial analytics tools between male and female investors.
10. H10: There is a significant difference in investment decision-making due to financial analytics tools among investors with different levels of education.
11. H11: There is a significant difference in investment decision-making among investors of different age groups, due to the use of financial analytics tools.
12. H12: There is a significant difference in stock trading behaviour influenced by mobile trading apps between male and female investors.
13. H13: There is a significant difference in stock trading behaviour due to mobile trading apps among investors with different levels of education.
14. H14: There is a significant difference in stock trading behaviour due to mobile trading apps among investors with different age groups.
15. H15: Perceived usefulness has a significant positive impact on attitude toward technology.
16. H16: Perceived ease of use has a significant positive impact on attitude toward technology.
17. H17: Risk perception has a significant negative impact on attitude toward technology.
18. H18: Cost perception has a significant negative impact on attitude toward technology.
19. H19: Risk perception has a significant negative impact on behavioural intention.
20. H20: Cost perception has a significant negative impact on behavioural intention.
21. H21: Risk perception has a significant negative impact on actual use.
22. H22: Cost perception has a significant negative impact on actual use.

23. H23: Facilitating conditions have a significant positive impact on attitude towards technology.

24. H24: Facilitating conditions have a significant positive impact on actual use.

25. H25: Attitude toward technology has a significant positive impact on behavioural intention.

26. H26: Behavioural intention has a significant positive impact on actual use.

27. H27: Actual use has a significant positive impact on investment behaviour.

1.8 Operational Definitions

Technological Advancements in Trading Stocks

Technological advancements in stock trading have led to the emergence of innovative technologies, including online trading platforms, algorithmic trading, automated trading, artificial intelligence, and blockchain, enabling investors to trade, access market information, and make informed decisions more effectively.

Investment Behaviour

Investor decision-making about choices of investment, timing and the selection of the investment options in the stock market. It entails risk tolerance, the frequency with which a person trades, the extent to which the individual relies on expert advice, and the preference for certain types of stocks.

Retail Investor

A non-professional investor who owns securities in his name with a view to personal, rather than the benefit of another company or organisation. In this research work, a retail investor refers to a resident of Kerala who is involved in the stock market.

Online Trading Platforms

Online platforms made available by brokers (e.g., Zerodha, Upstox, and Angel One) enable investors to purchase and sell stocks, monitor their portfolios, and view financial information online.

Mobile Trading Apps

Stockbrokers and fintech companies have created smartphone apps that enable investors to trade in real-time, monitor their portfolios, and analyse their investments on handheld devices.

Robo-Advisors

Robo advisors are automated, algorithm-based financial planning services that offer limited human intervention, providing portfolio management and investment recommendations.

Algorithmic Trading

An automated system of executing and matching trading decisions based on set criteria such as price, volume, or time, using complex algorithms and rapid computing.

Artificial intelligence in investment.

The use of machine learning, natural language processing, and predictive analytics to examine trends in the stock markets and provide insights, as well as make trading recommendations.

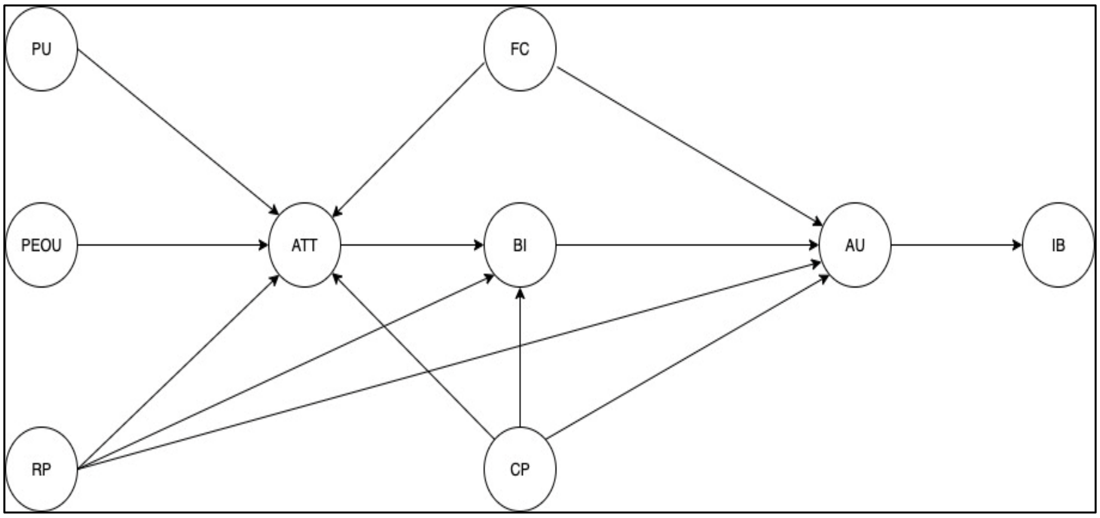
Financial Literacy

The capability of investors to comprehend the financial concepts and make educated choices about the style representing the investment alternatives, risk, and returns. It can determine the extent to which they can embrace new technologies.

1.9 Conceptual Framework

Using previous studies, a conceptual framework is developed to explain the effect of innovations on technology on investment behaviour by stock market investors. The variables and theoretical concepts employed in this study are illustrated in a diagrammatic model. It also shows the relationship between independent, intervening and dependent variables. Figure 1.1 shows the conceptual framework of the research.

Figure 1.1



PU- Perceived Usefulness

PEOU- Perceived Ease of Use

RP- Risk Perception

CP- Cost Perception

ATT- Attitude Towards Technology

FC- Facilitating Conditions

BI- Behavioural Intention

AU- Actual Use

IB- Investment Behaviour

1.10 Research Methodology

This study used an empirical analytical approach to examine how technological innovations influence investor behaviour in the stock market. This research outlines the methodology adopted to study how technological innovations influence investor behaviour in the Indian stock market. The research aimed to understand the behavioural changes among stock market investors as they adopt financial technologies such as mobile trading apps, robo-advisors, AI-powered analytics, and social trading platforms. The study also examined the acceptance and actual use of these technologies using the Extended Technology Acceptance Model (TAM), which included additional constructs like cost perception, risk perception, facilitating conditions, and investment behaviour. The methodology section presents the step-by-step process used for designing, collecting, and analysing data to test the proposed hypotheses and validate the conceptual model. The methodology was designed to suit the objectives of the research, which focused on collecting reliable and relevant responses from investors who had experience with digital financial tools. A structured research framework was applied to collect and analyse data from stock market participants. To achieve this, the study adopted a quantitative, empirical, analytical research design. It used structured questionnaires to gather primary data directly from stock market participants. The research also included secondary data from credible financial sources and regulatory institutions. Data were collected in a manner that allowed for meaningful insights into actual investment practices, rather than relying on assumptions or hypothetical scenarios. The structured format ensured consistency in responses and facilitated the application of statistical tests to measure the relationships between different variables. The research covered multiple levels of analysis, including gender-wise, education-level-based, employment status-wise, and age-wise comparisons, to reflect the diverse investment landscape in Kerala. The data collection process was planned in alignment with the statistical requirements of the tests applied later, including non-parametric techniques and PLS-SEM. The approach used in this study provided a suitable foundation to understand how investors react to financial technologies and how those reactions influence their trading decisions. The methodology encompassed a research design, data collection, and statistical analysis to evaluate the impact of fintech adoption on trading habits and investment decisions.

1.10.1 Research Design

This study used an empirical analytical research design to examine how technological innovations influenced investor behaviour in the stock market. The research relied on quantifiable data collected from stock market investors to measure their awareness, trading patterns, and decision-making influenced by fintech tools. Empirical evidence was gathered through structured surveys, ensuring that findings were based on real investment experiences rather than assumptions.

The analytical approach was used to process and interpret the collected data. Statistical models were applied to test hypotheses and examine relationships between technology adoption and investment behaviour. The study analysed measurable factors such as the use of mobile trading apps, reliance on financial analytics, and the influence of social trading platforms on trading decisions. This structured design ensured objective, data-driven insights, allowing the research to identify patterns, test significance, and explain the role of fintech in shaping investor behaviour.

The design helped to understand how actual investors responded to changes introduced by financial technology tools. It focused on real-time decision-making, trading habits, and investor reactions to mobile apps, AI tools, robo-advisors, and other fintech platforms. The study used structured quantitative methods to collect information from participants who were directly involved in stock market trading. Their experiences, preferences, and behaviour patterns were recorded using a pre-tested and validated questionnaire. The design ensured that the results were based on direct responses and not assumptions. This approach helped collect reliable data from investors who used digital financial tools in real-life situations.

The research design included a clear plan to collect and interpret data based on measurable and observed variables. The design focused on testing specific relationships, such as how the ease of using a mobile app affected an investor's willingness to trade or how risk perception changed decision-making. The design's structure enabled the researcher to apply statistical models and test various hypotheses using standard methods. These included descriptive statistics, group comparison tests, and structural modelling techniques. The design made it possible to examine each aspect of investor behaviour, including the number of trades, choice of platform, type of decisions taken, and the influence of digital tools. It also helped to understand which factors increased trust and frequency of trading, and which ones raised concern or hesitation.

The empirical part of the design required factual and experience-based input. Therefore, the study used a cross-sectional data collection method through surveys. These surveys targeted investors with varying levels of experience and backgrounds in education and profession. The survey questions captured how each participant used mobile trading apps, algorithmic tools, real-time alerts, robo-advisors, and social trading forums. The design also included demographic segmentation to observe patterns based on gender, education levels, employment status and age-wise. The analytical part of the design employed non-parametric and structural equation techniques, which worked well with the type of data collected.

1.10.2 Data

This study utilised both primary and secondary data sources to investigate the impact of technological innovations on investor behaviour in the stock market. Primary data were gathered directly from individual investors through a structured questionnaire. The participants were active traders or investors who had exposure to mobile apps, algorithmic systems, robo-advisors, and real-time analytics tools. The questionnaire included questions related to their trading experience, technology adoption level, platform preference, and the influence of digital tools on their investment choices. These questions aimed to capture behaviour related to stock analysis, transaction patterns, risk perception, and decision-making processes. Each response was measured using a five-point Likert scale. The primary data offered direct insights into how investors perceived and used financial technologies in their routine investment activities.

Secondary data were used to support the design and interpretation of the study. This included reports and statistics collected from government sources, such as the Securities and Exchange Board of India (SEBI) and the Reserve Bank of India (RBI). Additional data were collected from platforms such as Statista, which provided detailed metrics on user penetration, growth of digital trading services, and patterns in fintech adoption in India. These external data helped to support the study’s context and align the research questions with current industry trends. Peer-reviewed journals and academic databases were also referred to during model development and literature justification. These sources were used to understand theoretical models, particularly the Technology Acceptance Model and its extended frameworks, which helped build the survey items and structural paths in the conceptual model.

The data collected from multiple sources gave a broad and accurate view of how digital tools are affecting investor decisions. The financial reports from regulatory bodies provided context on how trading volumes and investor participation have changed over time. The academic literature offered tested constructs and validated models that supported the analytical structure of this research. Industry whitepapers and fintech publications were utilised to track changes in investor preferences, cost perceptions, and the rise of mobile-based trading. This combination of field data and secondary documentation enabled the study to compare personal responses with market-level trends and develop a robust explanation for how technology adoption influenced investment behaviour.

1.10.3 Population

The population of this study included stock market investors in Kerala. These investors actively participated in trading through various platforms, including mobile trading apps and online brokerage services. The study considered investors from different backgrounds, including retail investors, institutional investors, and high-frequency traders, ensuring representation from all major market participants. Stock market investors in India utilise a range of fintech tools, including robo-advisors, social trading platforms, and real-time financial analytics, to inform their investment decisions. The population included individuals with varying levels of experience, investment volumes, and trading frequencies. Some investors engaged in long-term investing, while others relied on short-term and high-frequency trading strategies. This diverse population allowed the study to analyse how technology adoption influenced different investor groups and how digital trading tools shaped their investment behaviour. The focus on Indian stock market investors ensured relevant findings applicable to the country's fintech and investment ecosystem.

1.10.4 Sample Size Calculation

The sample size for this study was determined using Cochran's formula, a widely used method for calculating the required sample size in quantitative research (Woolson et al., 1986; Sugden & Jones, 2000). The formula ensures that the selected sample represents the larger population of Indian stock market investors with an acceptable margin of error. Since the exact population size of stock market investors is large, the formula for an unknown or large population was applied.

1.10.4.1 Cochran's Formula:

$$n_0 = \frac{Z^2 p(1-p)}{e^2}$$

Where:

- n_0 = Required sample size
- $Z = Z$-score (standard normal deviation at a confidence level of $95\% = 1.96$)
- $p =$ Estimated proportion of the population with the characteristic (assumed 50% or 0.5 for maximum variability)
- $e =$ Margin of error (set at 5% or 0.05)

1.10.4.2 Explanation of the Equation

Cochran's formula is used when the total population size is large or unknown. The Z-score represents the confidence level, ensuring the results are statistically reliable. The proportion (p) is set at 0.5, as this assumption gives the maximum possible sample size, making it the safest choice when no prior data is available. The margin of error (e) is set at 5%, which is commonly accepted in financial studies.

Sample Size Calculation

$$n_0 = \frac{(1.96)^2 \times 0.5 \times (1-0.5)}{(0.05)^2}$$

$$n_0 = \frac{3.8416 \times 0.25}{0.0025}$$

$$n_0 = \frac{0.9604}{0.0025} = 384.16$$

Since the sample size must be a whole number, it was rounded up to 385 respondents. The minimum required sample size for this study was 385 stock market investors in Kerala. A total of 600 questionnaires were distributed, out of which 481 responses were collected. After removing responses with missing values and unengaged answers, the final usable sample size was 420. This ensured sufficient representation and statistical accuracy in analysing the impact of technological innovations on investment behaviour.

1.10.4.3 Sampling Technique

This study used purposive sampling to select stock market investors in Kerala who met specific criteria relevant to the research objectives. Purposive sampling is a non-probability sampling method used when the study requires participants with specific characteristics or experiences. The approach ensured that only investors with relevant exposure to technological innovations in stock trading were included in the study.

Two criteria were used to select participants:

1. **Investment Experience** – Investors must have actively participated in the stock market for more than one year. This criterion ensured that participants had sufficient market exposure and could provide meaningful insights into how technological advancements influenced their trading behaviour. Investors with limited experience might not have fully adapted to digital investment tools, which could affect the accuracy of responses.

2. **Familiarity with Technological Innovations** – Investors must have used or have familiarity with mobile trading apps, robo-advisors, algorithmic trading, financial analytics tools, or social trading platforms. This ensured that participants had direct experience with fintech solutions and could provide insights into how these technologies shaped their investment decisions. Investors unfamiliar with digital trading tools would not be able to contribute effectively to the study's objectives.

This sampling method allowed the study to focus on a targeted group of investors who could provide valuable responses regarding the adoption, impact, and behavioural changes resulting from fintech innovations.

1.10.5 Methods

This study used descriptive statistics to summarise and analyse the collected data. The descriptive analysis included mean, median, standard deviation, minimum, and maximum values for each variable. These measures helped assess investor awareness, trading behaviour, and the extent of fintech adoption among stock market investors. The mean provided an average response for key variables, while the median indicated the central tendency, reducing the influence of extreme values. The standard deviation measures the variability of responses, and the minimum and maximum values help to understand the range of responses. These statistical measures ensured a clear representation of investor behaviour before further analysis.

A normality test was conducted to check whether the data followed a normal distribution. The Kolmogorov-Smirnov (K-S) test and Shapiro-Wilk test were applied to determine normality. Skewness and kurtosis values were examined to assess data distribution. The results indicated that the data were not normally distributed, suggesting deviations from parametric assumptions. Since normality is a requirement for many inferential statistical techniques, alternative approaches were necessary for accurate data analysis.

Due to non-normal data distribution, non-parametric and distribution-free tests were used. The Mann-Whitney U test and Kruskal-Wallis test were applied to compare groups. Partial Least Squares Structural Equation Modelling (PLS-SEM) was used to examine the impact of technological innovations on investor behaviour. PLS-SEM is suitable for non-normal data and complex models, making it ideal for assessing fintech adoption, investor awareness, and behavioural changes. These methods ensured robust analysis without violating statistical assumptions.

1.10.6 Pilot study

The pilot study was conducted to evaluate the effectiveness of a meticulously designed questionnaire, involving a total of 50 investors. The primary objective of this preliminary study was to pretest the questionnaire and gather critical insights required to determine an appropriate sample size for the primary data collection phase.

Additionally, the feedback obtained from respondents was carefully analysed to identify areas requiring refinement. Based on these insights, necessary modifications were incorporated to enhance the clarity, relevance, and comprehensiveness of the questionnaire, ensuring its suitability for capturing accurate and meaningful data during the full-scale study.

1.10 .7 Normality Test

This study used the Shapiro-Wilk test and the Kolmogorov-Smirnov test to check the assumption of normality in the collected data (Lilliefors, 1967; Yap & Sim, 2011). Normality testing is a required step in quantitative analysis because it determines whether the data meet the assumptions for parametric statistical methods. When data do not follow a normal distribution, non-parametric statistical techniques are more suitable for analysis. The application of these tests in this study ensured that the subsequent statistical procedures matched the characteristics of the data.

The Shapiro-Wilk test was used in this study as one of the primary tests to evaluate the normality of each variable. This test was selected because it is well-suited for small and medium-sized samples and is regarded as more accurate than other normality tests for such datasets (Shapiro et al., 1968; Yap & Sim, 2011). The test evaluates whether the sample distribution significantly deviates from a normal distribution. In this method, the null hypothesis states that the data is normally distributed. A significant value (typically $p < 0.05$) indicates a departure from normality. The study used this test across all key constructs to determine if the dataset adhered to the assumptions of normality required for parametric tests.

In addition to the Shapiro-Wilk test, this study also employed the Kolmogorov-Smirnov (K-S) test to corroborate the normality assessment. The K-S test measures the maximum distance between the observed cumulative distribution and the expected cumulative distribution under normality. It tests the same null hypothesis as the Shapiro-Wilk test, that the sample data come from a normally distributed population. Using both tests together provided a robust check on the distribution shape and ensured the analysis followed an appropriate statistical path.

1.10.8 Reliability Test

This study used Cronbach's Alpha to measure the internal consistency and reliability of the items within each construct (Vaske et al., 2016). Reliability testing ensures that a scale consistently measures a given concept. The application of Cronbach's Alpha in this study confirmed whether items related to investment behaviour, perceived ease of use, perceived usefulness, risk perception, cost perception, and other related constructs were internally stable and coherent. The test was applied to each set of items representing individual constructs used in the questionnaire.

Cronbach's Alpha is widely accepted in social science and behavioural finance research. It evaluates the degree to which items within a construct are positively correlated and yields consistent results. According to the benchmark provided by Hair et al. (2019), a Cronbach's Alpha value of 0.70 or higher is considered acceptable for exploratory research, and values above 0.80 are considered good. In this study, Cronbach's Alpha values were computed for all constructs, which helped ensure the reliability of the data before proceeding to further analysis. This reliability testing step allowed the study to identify any constructs with weak internal consistency. If any Cronbach's Alpha value were below the threshold, revision of the corresponding scale items would have been necessary before proceeding.

1.10.9 Validity Tests

The study assessed validity using two important statistical tests: Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity (Ibikunle et al., 2021). Both these tests were used before analysis to confirm whether the dataset was suitable for such procedures. Establishing validity is crucial to ensure that the constructs truly reflect what they are intended to measure. The KMO test was used to check the sampling adequacy. It determines whether the correlations among variables are sufficient to conduct factor analysis. The test produces values between 0 and 1. Values above 0.6 indicate a reasonable degree of sampling adequacy, with values above 0.8 considered very good (Hair et al., 2017). In this study, the KMO value was calculated across all items included. This helped confirm that the correlations among the items were compact and suitable for structure detection. The Bartlett's Test of

Sphericity checks whether the correlation matrix is significantly different from an identity matrix. In other words, it determines whether the variables are sufficiently correlated to justify the use of factor analysis. The null hypothesis for this test states that the correlation matrix is an identity matrix, implying that the variables are unrelated and therefore unsuitable for factor analysis. A significant result ($p < 0.05$) supports the rejection of the null hypothesis, confirming that the items are indeed interrelated.

1.10.10 Selection of Parametric and Non-Parametric Tests

This study selected statistical tests based on the distribution pattern of the collected data (Harwell, 1988). The assessment of normality was done using the Shapiro-Wilk and Kolmogorov-Smirnov tests, both of which are standard tools for detecting deviations from normal distribution (Mohammadi & Amri, 2007). The results from both tests indicated significant departures from normality, as the p-values were less than 0.001. This confirmed that the dataset did not meet the assumption of normality, which is a prerequisite for applying parametric tests. As a result, the study used non-parametric methods that are distribution-free and do not require normally distributed data.

To compare groups within the sample, the study used the Mann-Whitney U test for analysing differences between two independent groups and the Kruskal-Wallis H test for more than two groups. These tests are widely accepted for ordinal and non-normally distributed interval data. They are also considered reliable when dealing with skewed data or small sample sizes. For multivariate analysis and hypothesis testing in the conceptual model, the study employed Partial Least Squares Structural Equation Modelling (PLS-SEM). This method is recognised for its ability to handle non-normal data, small to medium sample sizes, and complex models that involve latent constructs and multiple indicators. PLS-SEM is also preferred when the primary focus is on prediction and theory development rather than model fit (Hair et al., 2017).

1.10.10.1 Mann-Whitney U Test

This study employed the Mann-Whitney U test to compare the responses of two independent groups, where the assumption of normality was not met (Rochon et al., 2012). The results of the Shapiro-Wilk and Kolmogorov-Smirnov tests confirmed that the data did not follow a normal distribution. Because of this, the study selected the Mann-Whitney U test as a suitable non-parametric alternative to the independent samples t-test. The Mann-Whitney U test does not require normality and is suitable for ordinal or non-normally distributed continuous data. The primary purpose of using this test in the study was to examine whether there was a statistically significant difference between male and female investors in their responses to various aspects of technological innovation in investment behaviour. The test procedure involved ranking all the scores from both groups together. Then, the sum of ranks for each group was calculated. The U value helped determine whether one group had consistently higher or lower scores than the other. For this study, the U statistic, its corresponding Z score, and p-value were calculated for each variable measuring technological aspects, including mobile trading apps, robo-advisors, algorithmic tools, and financial analytics. The analysis focused on identifying whether male and female respondents differed significantly in their perception and adoption of these tools. The study also calculated the effect size using the formula $r = Z / \sqrt{N}$, where Z represents the standard score and N is the total number of observations. This provided a way to report the strength of the observed differences.

The Mann-Whitney U test was appropriate for the type of responses received in the survey. The test allowed the study to detect group differences without being affected by the skewness or outliers often found in behavioural data. The method followed recommendations from Nachar (2008), who suggests the Mann-Whitney U test for non-parametric group comparisons in social science and behavioural research. This approach supported the objective of identifying gender-based patterns in the adoption and impact of financial technologies in the stock market.

1.10.10.2 Kruskal-Wallis H Test

This study used the Kruskal-Wallis H test to compare more than two independent groups when the assumption of normality was not met (Feir-Walsh & Toothaker, 1974). The dataset violated the assumption of normal distribution. Since this assumption is necessary for conducting parametric tests, such as one-way ANOVA, the Kruskal-Wallis H test serves as a non-parametric alternative. This test helped in analysing whether investors from different education levels reported significantly different perceptions or behaviours toward technology adoption in stock trading.

The Kruskal-Wallis H test operates by ranking all the data from all groups together. Each observation is assigned a rank, and the test calculates whether the mean rank of each group differs significantly. The null hypothesis states that all groups have the same distribution, and a significant p-value indicates that at least one group differs significantly from the others. In this study, the test was applied across categories such as education level, Employment status, and age, covering variables related to mobile trading apps, robo-advisory services, real-time alerts, financial analytics tools, and social trading platforms. This made it possible to understand whether educational background, employment status, and age influenced the adoption of technological innovations among stock market investors.

The statistical output of the test included the H-statistic, degrees of freedom, and the associated p-value. Additionally, the study calculated the effect size using η^2 (eta squared), which helped estimate the proportion of variance accounted for by group differences. According to Panoutsakopoulos et al. (2021), η^2 values of 0.01, 0.06, and 0.14 correspond to small, moderate, and substantial effects, respectively. The Kruskal-Wallis H test was used to assess education, employment, and age differences, utilising fintech tools. This was crucial in determining whether the impact of technology varied significantly among individuals with different academic qualifications, employment status, and age.

1.10.10.3 Partial Least Squares Structural Equation Modelling (PLS-SEM) and Importance-Performance Map Analysis (IPMA)

This study employed Partial Least Squares Structural Equation Modelling (PLS-SEM) to examine the intricate relationships among latent constructs within the extended Technology Acceptance Model (TAM) framework. PLS-SEM was selected because the data did not meet normality assumptions, as confirmed through both the Shapiro-Wilk and Kolmogorov-Smirnov tests. According to Hair et al. (2017), PLS-SEM is particularly suitable when the data are non-normal, the models are complex, and the research focuses on prediction and theory development. The model in this study included several interconnected constructs such as perceived usefulness, ease of use, cost perception, risk perception, attitude, behavioural intention, facilitating conditions, actual use, and investment behaviour.

PLS-SEM allowed the study to assess both the measurement model (outer model) and the structural model (inner model). In the measurement model, internal consistency reliability was evaluated using Cronbach's alpha and composite reliability. At the same time, convergent validity was assessed using Average Variance Extracted (AVE), following the recommended thresholds by Hair et al. (2017): Cronbach's alpha and composite reliability > 0.7, AVE > 0.5. Discriminant validity was assessed using the Fornell-Larcker criterion and the Heterotrait-Monotrait Ratio (HTMT), ensuring that the constructs were statistically distinct. The structural model was then evaluated using path coefficients, t-values, and R^2 values to determine the significance and explanatory power of the hypothesised relationships. Bootstrapping with 5,000 subsamples was performed to test the significance of each path. The predictive relevance (Q^2) of endogenous constructs was also checked using blindfolding procedures.

In addition to the fundamental PLS-SEM analysis, the study used Importance-Performance Map Analysis (IPMA) to identify constructs that offered the most valuable targets for practical improvement. The IPMA is an extension of PLS-SEM that not only considers the importance (total effect) of a construct on a target construct (such as investment behaviour), but also its performance (average latent variable score). This dual perspective helped the study prioritise which constructs were both highly influential and underperforming, so that future interventions could focus efforts on areas that would yield the most meaningful outcomes. For instance, even if a construct like perceived usefulness had high importance in predicting behavioural intention or actual use, a low performance score would signal the need for managerial or policy-level improvements.

1.11 Limitations of the Study

The study has the following limitations:

1. It relied on cross-sectional survey data, which restricts the ability to infer causal relationships between technology use and behaviour change.
2. Self-reported responses may contain bias, as investors might overstate their comfort with digital tools or recall their usage inaccurately.
3. The sample drew only active retail investors in Kerala, so findings may not generalise to institutional traders or investors in other states with different market infrastructures.
4. The analysis focused on descriptive statistics, Mann–Whitney U, Kruskal–Wallis, and PLS-SEM techniques, but it did not include longitudinal tracking or experimental manipulation to observe behaviour over time or under controlled conditions.
5. The study also measured broad categories of tools but did not capture usage frequency or intensity for specific platform features, which could mask nuanced adoption patterns.
6. Demographic factors such as income and regional connectivity received limited attention, even though they may shape technology adoption.
7. Finally, emerging tools like blockchain, AI forecasting, and sentiment analysis received mixed responses, but the study did not probe underlying reasons through qualitative methods. Addressing these constraints in future research would strengthen the validity and applicability of the findings.

1.12 Chapterisation

The research report consists of seven separate chapters.

Chapter 1: Introduction

This chapter introduces the topic of the thesis. It provides a historical and relevant context for the topic, explains the research problem, and outlines the study's objectives. In addition, it presents the proposed hypotheses, the techniques used in the research, and the study's limitations.

Chapter 2: Review of Literature

This chapter reviews the research on technological advances in the stock market and the behaviour of people who invest in stocks. The reviewed research is organised and explained according to the underlying themes. The chapter also highlights and discusses the gaps in existing research as identified in the literature. The chapter examines how the intersection of technology and investors' actions has evolved by applying bibliometric analysis and using a review method.

Chapter 3: Theoretical Framework

This chapter discusses the main theories and frameworks that guide the study. It explains the essential theories about technology and its impact on stock investment decisions. The chapter describes key theories of behavioural finance, models of innovation adoption, and frameworks used in decision-making, supporting the research. With these approaches, the chapter outlines a solid structure for understanding how technological progress affects investor beliefs, attitudes and actions in the stock market.

Chapter 4: Factors Influencing the Adoption of Technology and Its Impact on Stock Market Investment Behaviour

This chapter examines the impact of technological advancements, including algorithm funding, robo-advisory services, and real-time capital market analytics, on the investment business. It examines the impact of technological innovations on investment behaviour, as well as the influence of social trading platforms and real-time news on trading behaviour. It also focuses on the effects of technological development in financial analytics and the role of mobile trading applications on the trading behaviour of investors. It also displays the consequences of the investment behaviour of technology on the market efficiency as well as its direct participation in retail investors.

Chapter 5: Analysis of Factors Influencing the Adoption of Technology and Its Impact on Stock Market Investment Behaviour

This chapter thoroughly examines the data and explains its significance to the study. It examines the relationships among key factors in the conceptual model by evaluating hypotheses based on the extended Technology Acceptance Model (TAM). This part of the work employs statistical techniques to examine the model and measure the impact of technological influences on investment decisions made by stock market participants. Moreover, it looks at how demographic and behavioural variables influence the findings. The findings are explained using theories and past research to demonstrate how technology is currently utilised in selecting investments on the stock market.

Chapter 6: Summary of Findings and Conclusions,

This chapter summarises the entire study and highlights the most significant results obtained from analysing the data. Research work returns to the stated objectives and checks if they have been accomplished. The findings are evaluated in light of the theory and other literature, which leads to relevant conclusions. It explains the study's main consequences, including theoretical, practical, policy, and research outcomes, which contribute to both learning and practical use. The chapter further introduces useful recommendations that are supported by the findings and insights. Finally, it points out what the study did not cover and recommends areas for future research, which can help advance the understanding of technological adoption and investment choices.

Chapter 7: Recommendations

This chapter offers practical policy recommendations to policymakers, regulators, and market intermediaries, aiming to enhance investor awareness and trust in the adoption of technology innovations in stock trading. These results are significant in enriching financial literacy, enhancing digital infrastructure, and protecting investors in the transforming Kerala-based stock market. This chapter also suggests that further studies on investor reactions to changes in technology are warranted.

References

Abdullah, S. S., Rahaman, M. S., & Rahman, M. S. (2013). Analysis of stock market using text mining and natural language processing. *2013 International Conference on Informatics, Electronics and Vision (ICIEV)*. https://doi.org/10.1109/iciev.2013.6572673

Addy, N. W. A., Ajayi-Nifise, N. a. O., Bello, N. B. G., Tula, N. S. T., Odeyemi, N. O., & Falaiye, N. T. (2024). Machine learning in financial markets: A critical review of algorithmic trading and risk management. *International Journal of Science and Research Archive*, *11*(1), 1853–1862. https://doi.org/10.30574/ijsra.2024.11.1.0292

Aggarwal, M., Nayak, K. M., & Bhatt, V. (2023). Examining the factors influencing fintech adoption behaviour of gen Y in India. *Cogent Economics & Finance*, *11*(1). https://doi.org/10.1080/23322039.2023.2197699

Al-Shari, H. A., & Lokhande, M. A. (2023). The relationship between the risks of adopting FinTech in banks and their impact on the performance. *Cogent Business & Management*, *10*(1). https://doi.org/10.1080/23311975.2023.2174242

Ammar, I. B., Hellara, S., & Ghadhab, I. (2020). High-frequency trading and stock liquidity: An intraday analysis. *Research in International Business and Finance*, *53*, 101235. https://doi.org/10.1016/j.ribaf.2020.101235

Araujo, T., Helberger, N., Kruikemeier, S., & De Vreese, C. H. (2020). In AI we trust? Perceptions about automated decision-making by artificial intelligence. *AI & Society*, *35*(3), 611–623. https://doi.org/10.1007/s00146-019-00931-w

Arnoldi, J. (2015). Computer algorithms, market manipulation and the institutionalization of high frequency trading. *Theory Culture & Society*, *33*(1), 29–52. https://doi.org/10.1177/0263276414566642

Arthur, C., & Khindanova, I. (2023). Technological acquisitions: The impact of innovation on stock performance. *Journal of Applied Business and Economics*, *25*(4). https://doi.org/10.33423/jabe.v25i4.6351

Arumugam, D., Prasanna, P. K., & Marathe, R. R. (2022). Do algorithmic traders exploit volatility? *Journal of Behavioral and Experimental Finance*, *37*, 100778. https://doi.org/10.1016/j.jbef.2022.100778

Ayyappa, Y., & Kumar, A. P. S. (2024). Stock market prediction with political data Analysis (SP-PDA) model for handling big data. *Multimedia Tools and Applications*, *83*(34), 80583–80611. https://doi.org/10.1007/s11042-024-18610-4

Bershova, N., & Rakhlin, D. (2012). High Frequency Trading and Long-Term Investors: A View from the Buy-Side. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2066884

Block, F. (2013). Democratizing finance. *Politics & Society*, *42*(1), 3–28. https://doi.org/10.1177/0032329213512976

Boehmer, E., Fong, K., & Wu, J. (2020). Algorithmic trading and market quality: international evidence. *Journal of Financial and Quantitative Analysis*, *56*(8), 2659–2688. https://doi.org/10.1017/s0022109020000782

Chen, C., Gong, Y., & Wu, J. M. (2022). Impact of technical indicators and leading indicators on stock trends on the internet of things. *Wireless Communications and Mobile Computing*, *2022*, 1–15. https://doi.org/10.1155/2022/9916310

Chen, T., & Nie, C. (2022). The impact of stock market development and credit market development on technological innovation: an empirical study based on Cross-Country panel data. *Asian Economic and Financial Review*, *12*(5), 329–340. https://doi.org/10.55493/5002.v12i5.4488

Chong, L., Ong, H., & Tan, S. (2021). Acceptability of mobile stock trading application: A study of young investors in Malaysia. *Technology in Society*, *64*, 101497. https://doi.org/10.1016/j.techsoc.2020.101497

Chourmouziadis, K., Chourmouziadou, D. K., & Chatzoglou, P. D. (2020). Embedding four Medium-Term Technical Indicators to an intelligent stock trading fuzzy system for predicting: a portfolio management approach. *Computational Economics*, *57*(4), 1183–1216. https://doi.org/10.1007/s10614-020-10016-2

Dakalbab, F., Talib, M. A., Nasir, Q., & Saroufil, T. (2024). Artificial intelligence techniques in financial trading: A systematic literature review. *Journal of King Saud University - Computer and Information Sciences*, *36*(3), 102015. https://doi.org/10.1016/j.jksuci.2024.102015

Deng, J., Yang, M., Pelster, M., & Tan, Y. (2023). Social trading, communication, and networks. *Information Systems Research*, *35*(4), 1546–1564. https://doi.org/10.1287/isre.2021.0143

Diaz-Rainey, I., Ibikunle, G., & Mention, A. (2015). The technological transformation of capital markets. *Technological Forecasting and Social Change*, *99*, 277–284. https://doi.org/10.1016/j.techfore.2015.08.006

Dorfleitner, G., Fischer, L., Lung, C., Willmertinger, P., Stang, N., & Dietrich, N. (2018). To follow or not to follow – An empirical analysis of the returns of actors on social trading platforms. *The Quarterly Review of Economics and Finance*, *70*, 160–171. https://doi.org/10.1016/j.qref.2018.04.009

Dubey, R. K. (2022). Algorithmic Trading: The intelligent trading systems and its impact on trade size. *Expert Systems With Applications*, *202*, 117279. https://doi.org/10.1016/j.eswa.2022.117279

Dubey, R. K., Babu, A. S., Jha, R. R., & Varma, U. (2021). Algorithmic Trading Efficiency and its Impact on Market-Quality. *Asia-Pacific Financial Markets*, *29*(3), 381–409. https://doi.org/10.1007/s10690-021-09353-5

Feir-Walsh, B. J., & Toothaker, L. E. (1974). An empirical comparison of the Anova F-Test, Normal Scores Test and Kruskal-Wallis Test under violation of assumptions. *Educational and Psychological Measurement*, *34*(4), 789–799. https://doi.org/10.1177/001316447403400406

Feng, R., & Qu, X. (2021). Analyzing the Internet financial market risk management using data mining and deep learning methods. *Journal of Enterprise Information Management*, *35*(4/5), 1129–1147. https://doi.org/10.1108/jeim-03-2021-0155

Gan, B., Alexeev, V., Bird, R., & Yeung, D. (2019). Sensitivity to sentiment: News vs social media. *International Review of Financial Analysis*, *67*, 101390. https://doi.org/10.1016/j.irfa.2019.101390

Golmohammadi, K., Zaiane, O. R., & Diaz, D. (2014). Detecting stock market manipulation using supervised learning algorithms. In *2014 International Conference on Data Science and Advanced Analytics (DSAA)*. https://doi.org/10.1109/dsaa.2014.7058109

Gomber, P., Kauffman, R. J., Parker, C., & Weber, B. W. (2018). On the Fintech Revolution: Interpreting the Forces of Innovation, Disruption, and Transformation in Financial Services. *Journal of Management Information Systems*, *35*(1), 220–265. https://doi.org/10.1080/07421222.2018.1440766

Gunjan, A., & Bhattacharyya, S. (2022). A brief review of portfolio optimization techniques. *Artificial Intelligence Review*, *56*(5), 3847–3886. https://doi.org/10.1007/s10462-022-10273-7

Hao, Y., Vand, B., Delgado, B. M., & Baldi, S. (2023). Market Manipulation in Stock and Power Markets: A Study of Indicator-Based Monitoring and Regulatory Challenges. *Energies*, *16*(4), 1894. https://doi.org/10.3390/en16041894

Hasan, M. K., Alkhalifah, A., Islam, S., Babiker, N. B. M., Habib, A. K. M. A., Aman, A. H. M., & Hossain, M. A. (2022). Blockchain technology on smart grid, energy trading, and big data: security issues, challenges, and recommendations. *Wireless Communications and Mobile Computing*, *2022*, 1–26. https://doi.org/10.1155/2022/9065768

Hendershott, T., & Riordan, R. (2013). Algorithmic trading and the market for liquidity. *Journal of Financial and Quantitative Analysis*, *48*(4), 1001–1024. https://doi.org/10.1017/s0022109013000471

Hendershott, T., Jones, C. M., & Menkveld, A. J. (2011). Does algorithmic trading improve liquidity? *The Journal of Finance*, *66*(1), 1–33. https://doi.org/10.1111/j.1540-6261.2010.01624.x

Hofmann, C. (2020). The changing concept of money: a threat to the monetary system or an opportunity for the financial sector? *European Business Organization Law Review*, *21*(1), 37–68. https://doi.org/10.1007/s40804-020-00182-z

Huang, B., Huan, Y., Da Xu, L., Zheng, L., & Zou, Z. (2018). Automated trading systems, statistical and machine learning methods, and hardware implementation: a survey. *Enterprise Information Systems*, *13*(1), 132–144. https://doi.org/10.1080/17517575.2018.1493145

Janabi, M. a. A. (2021). Optimization algorithms and investment portfolio analytics with machine learning techniques under time-varying liquidity constraints. *Journal of Modelling in Management*, *17*(3), 864–895. https://doi.org/10.1108/jm2-10-2020-0259

Janssen, M., Weerakkody, V., Ismagilova, E., Sivarajah, U., & Irani, Z. (2019). A framework for analysing blockchain technology adoption: Integrating institutional, market and technical factors. *International Journal of Information Management*, *50*, 302–309. https://doi.org/10.1016/j.ijinfomgt.2019.08.012

Kang, Y., Cai, Z., Tan, C., Huang, Q., & Liu, H. (2020). Natural language processing (NLP) in management research: A literature review. *Journal of Management Analytics*, *7*(2), 139–172. https://doi.org/10.1080/23270012.2020.1756939

Kazan, E., & Damsgaard, J. (2016). Towards a new market entry framework for digital payment platforms. *Communications of the Association for Information Systems*, *38*, 761–783. https://doi.org/10.17705/1cais.03837

Khare, T., & Kapoor, S. (2023). Behavioral biases and the rational decision-making process of financial professionals: significant factors that determine the future of the financial market. *Journal of Advances in Management Research*, *21*(1), 44–65. https://doi.org/10.1108/jamr-03-2023-0086

Khodabandehlou, S., & Golpayegani, S. a. H. (2022). Market manipulation detection: A systematic literature review. *Expert Systems With Applications*, *210*, 118330. https://doi.org/10.1016/j.eswa.2022.118330

Kim, D., Park, K., Lee, D., & Ahn, Y. (2020). Predicting mobile trading system discontinuance: The role of attention. *Electronic Commerce Research and Applications*, *44*, 101008. https://doi.org/10.1016/j.elerap.2020.101008

Kofman, P. (2024). Scoring The Ethics of AI Robo-Advice: Why we need gateways and ratings. *Journal of Business Ethics*. https://doi.org/10.1007/s10551-024-05753-5

Kordzadeh, N., & Ghasemaghaei, M. (2021). Algorithmic bias: review, synthesis, and future research directions. *European Journal of Information Systems*, *31*(3), 388–409. https://doi.org/10.1080/0960085x.2021.1927212

Kumar, S., & Goyal, N. (2016). Evidence on rationality and behavioural biases in investment decision making. *Qualitative Research in Financial Markets*, *8*(4), 270–287. https://doi.org/10.1108/qrfm-05-2016-0016

Lee, J., & Schu, L. (2022). Regulation of algorithmic trading: frameworks or human supervision and direct market interventions. *European Business Law Review*, *33*(Issue 2), 193–226. https://doi.org/10.54648/eulr2022006

Li, Y., & Wang, F. (2023). Impact of capital market openness on corporate green technology innovation: evidence from the Shanghai-Hong Kong Stock Connect program. *Economic Research-Ekonomska Istraživanja*, *36*(3). https://doi.org/10.1080/1331677x.2023.2190798

Lin, S., & Huang, H. (2020). Improving deep learning for forecasting accuracy in financial data. *Discrete Dynamics in Nature and Society*, *2020*, 1–12. https://doi.org/10.1155/2020/5803407

Litzenberger, R. H., Castura, J., & Gorelick, R. (2012). The impacts of automation and high frequency trading on market quality. *Annual Review of Financial Economics*, *4*(1), 59–98. https://doi.org/10.1146/annurev-financial-110311-101744

Liu, C., Mithas, S., Pan, Y., & Hsieh, J. J. P. (2024). Mobile Apps, Trading Behaviours, and Portfolio Performance: Evidence from a Quasi-Experiment in China. *Information Systems Research*. https://doi.org/10.1287/isre.2020.0616

Liu, W., Wang, J., Jia, F., & Choi, T. (2022). Blockchain announcements and stock value: a technology management perspective. *International Journal of Operations & Production Management*, *42*(5), 713–742. https://doi.org/10.1108/ijopm-08-2021-0534

Manrai, R., & Gupta, K. P. (2022). Investor's perceptions on artificial intelligence (AI) technology adoption in investment services in India. *Journal of Financial Services Marketing*, *28*(1), 1–14. https://doi.org/10.1057/s41264-021-00134-9

Martínez-López, F. J., & Casillas, J. (2013). Artificial intelligence-based systems applied in industrial marketing: An historical overview, current and future insights. *Industrial Marketing Management*, *42*(4), 489–495. https://doi.org/10.1016/j.indmarman.2013.03.001

Menkveld, A. J. (2013). High frequency trading and the new market makers. *Journal of Financial Markets*, *16*(4), 712–740. https://doi.org/10.1016/j.finmar.2013.06.006

Nadeem, F., & Mazhar, S. S. (2019). Innovations in Investment Products and its Impact on Financial Services Sector. *International Journal of Management Studies*, *VI*(1(4)), 53. https://doi.org/10.18843/ijms/v6i1(4)/06

Nair, P. S., Shiva, A., Yadav, N., & Tandon, P. (2022). Determinants of mobile apps adoption by retail investors for online trading in emerging financial markets. *Benchmarking an International Journal*, *30*(5), 1623–1648. https://doi.org/10.1108/bij-01-2022-0019

Ng, A. W., & Kwok, B. K. (2017). Emergence of Fintech and cybersecurity in a global financial centre. *Journal of Financial Regulation and Compliance*, *25*(4), 422–434. https://doi.org/10.1108/jfrc-01-2017-0013

Nourallah, M. (2022). One size does not fit all: Young retail investors' initial trust in financial robo-advisors. *Journal of Business Research*, *156*, 113470. https://doi.org/10.1016/j.jbusres.2022.113470

Olanrewaju, N. O. I. K., Daramola, N. G. O., & Ekechukwu, N. D. E. (2024). Strategic financial decision-making in sustainable energy investments: Leveraging big data for maximum impact. *World Journal of Advanced Research and Reviews*, *22*(3), 564–573. https://doi.org/10.30574/wjarr.2024.22.3.1758

Piehlmaier, D. M. (2022). Overconfidence and the adoption of robo-advice: why overconfident investors drive the expansion of automated financial advice. *Financial Innovation*, *8*(1). https://doi.org/10.1186/s40854-021-00324-3

Putrevu, J., & Mertzanis, C. (2023). The adoption of digital payments in emerging economies: challenges and policy responses. *Digital Policy Regulation and Governance*, *26*(5), 476–500. https://doi.org/10.1108/dprg-06-2023-0077

Reith, R., Fischer, M., & Lis, B. (2019). Explaining the intention to use social trading platforms: an empirical investigation. *Journal of Business Economics*, *90*(3), 427–460. https://doi.org/10.1007/s11573-019-00961-2

Salisu, A. A., Demirer, R., & Gupta, R. (2024). Technological shocks and stock market volatility over a century. *Journal of Empirical Finance*, 101561. https://doi.org/10.1016/j.jempfin.2024.101561

Schrettenbrunner, M. B. (2023). Artificial-Intelligence-Driven management: Autonomous Real-Time trading and testing of portfolio or inventory strategies. *IEEE Engineering Management Review*, *51*(3), 65–76. https://doi.org/10.1109/emr.2023.3288609

Selvakumar, P., Mishra, R. K., Budhiraja, A., Dahake, P. S., Chandel, P. S., & Vats, C. (2024). Social media influence on market sentiment. In *Advances in business strategy and competitive advantage book series* (pp. 225–250). https://doi.org/10.4018/979-8-3693-9380-2.ch009

Seo, J., & Chai, S. (2013). The role of algorithmic trading systems on stock market efficiency. *Information Systems Frontiers*, *15*(5), 873–888. https://doi.org/10.1007/s10796-013-9442-9

Shah, S. Z. A., Ahmad, M., & Mahmood, F. (2017). Heuristic biases in investment decision-making and perceived market efficiency. *Qualitative Research in Financial Markets*, *10*(1), 85–110. https://doi.org/10.1108/qrfm-04-2017-0033

Singh, B., Abilasha, N., & Swarna, C. (2024). Real-Time Market Sentiment Analysis Using Natural Language Processing and ML. *2024 IEEE International Conference on Computing, Power and Communication Technologies (IC2PCT)*, 1585–1588. https://doi.org/10.1109/ic2pct60090.2024.10486228

Sismanoglu, G., Onde, M. A., Kocer, F., & Sahingoz, O. K. (2019). Deep Learning Based Forecasting in Stock Market with Big Data Analytics. *2019 Scientific Meeting on Electrical-Electronics & Biomedical Engineering and Computer Science (EBBT)*, 1–4. https://doi.org/10.1109/ebbt.2019.8741818

Sugden, R. A., & Jones, T. M. F. S. a. R. P. (2000). Cochran's rule for simple random sampling. *Journal of the Royal Statistical Society. Series B*, *62*(4), 787–793. https://www.jstor.org/stable/2680621

Sun, X., & Du, Z. (2024). Enhancing capital market efficiency: The role of data assets disclosure in reducing stock price synchronicity. *International Review of Economics & Finance*, *94*, 103351. https://doi.org/10.1016/j.iref.2024.05.030

Syamala, S. R., & Wadhwa, K. (2020). Trading performance and market efficiency: Evidence from algorithmic trading. *Research in International Business and Finance*, *54*, 101283. https://doi.org/10.1016/j.ribaf.2020.101283

Tao, R., Su, C., Xiao, Y., Dai, K., & Khalid, F. (2020). Robo advisors, algorithmic trading and investment management: Wonders of fourth industrial revolution in financial markets. *Technological Forecasting and Social Change*, *163*, 120421. https://doi.org/10.1016/j.techfore.2020.120421

Tetlock, P. C. (2011). All the News That's Fit to Reprint: Do Investors React to Stale Information? *Review of Financial Studies*, *24*(5), 1481–1512. https://doi.org/10.1093/rfs/hhq141

Thapa, S., Panda, S., Ghimire, A., & Kim, D. J. (2024). From engagement to retention: Unveiling factors driving user engagement and continued usage of mobile trading apps. *Decision Support Systems*, *183*, 114265. https://doi.org/10.1016/j.dss.2024.114265

Tosun, O. K. (2021). Cyber-attacks and stock market activity. *International Review of Financial Analysis*, *76*, 101795. https://doi.org/10.1016/j.irfa.2021.101795

Upson, J., & Van Ness, R. A. (2016). Multiple markets, algorithmic trading, and market liquidity. *Journal of Financial Markets*, *32*, 49–68. https://doi.org/10.1016/j.finmar.2016.05.004

Wang, W., & Li, L. (2024). Digital payment, money market fund and investment behavior. *Pacific-Basin Finance Journal*, *85*, 102348. https://doi.org/10.1016/j.pacfin.2024.102348

Weller, B. M. (2017). Does algorithmic trading reduce information acquisition? *Review of Financial Studies*, *31*(6), 2184–2226. https://doi.org/10.1093/rfs/hhx137

Wohlgemuth, V., Berger, E. S., & Wenzel, M. (2016). More than just financial performance: Trusting investors in social trading. *Journal of Business Research*, *69*(11), 4970–4974. https://doi.org/10.1016/j.jbusres.2016.04.061

Woolson, R. F., Bean, J. A., & Rojas, P. B. (1986). Sample size for Case-Control studies using Cochran's statistic. *Biometrics*, *42*(4), 927. https://doi.org/10.2307/2530706

Xu, P., Lee, J., Barth, J. R., & Richey, R. G. (2021). Blockchain as supply chain technology: considering transparency and security. *International Journal of Physical Distribution & Logistics Management*, *51*(3), 305–324. https://doi.org/10.1108/ijpdlm-08-2019-0234

Xu, S. X., & Zhang, X. (2009). *How do social media shape the information environment in the financial market?* AIS Electronic Library (AISeL). https://aisel.aisnet.org/icis2009/56

Yang, J., & Klassen, K. J. (2008). How financial markets reflect the benefits of self-service technologies. *Journal of Enterprise Information Management*, *21*(5), 448–467. https://doi.org/10.1108/17410390810904238

Zahera, S. A., & Bansal, R. (2018). Do investors exhibit behavioral biases in investment decision making? A systematic review. *Qualitative Research in Financial Markets*, *10*(2), 210–251. https://doi.org/10.1108/qrfm-04-2017-0028

Zhang, C., Sjarif, N. N. A., & Ibrahim, R. (2023). Deep learning models for price forecasting of financial time series: A review of recent advancements: 2020–2022. *Wiley Interdisciplinary Reviews Data Mining and Knowledge Discovery*, *14*(1). https://doi.org/10.1002/widm.1519

Zhang, Z., & Chen, Y. (2021). Tail risk early warning system for capital markets based on machine learning algorithms. *Computational Economics*, *60*(3), 901–923. https://doi.org/10.1007/s10614-021-10171-0

Zong, Z., & Guan, Y. (2024). AI-Driven intelligent data Analytics and predictive Analysis in Industry 4.0: Transforming knowledge, innovation, and efficiency. *Journal of the Knowledge Economy*. https://doi.org/10.1007/s13132-024-02001-z

Chapter 2

REVIEW OF LITERATURE: BIBLIOMETRIC ANALYSIS OF FINANCIAL TECHNOLOGY AND INVESTMENT BEHAVIOUR

2.1 Introduction

This chapter presents an in-depth exploration of the evolving intersection between technological innovations and investment behaviour, combining bibliometric analysis with a structured literature review. The objective is to map the intellectual trajectory of research in this domain, examine the impact of fintech advancements on investor decision-making, and identify critical gaps that warrant further exploration. With the increasing reliance on AI-driven trading algorithms, robo-advisors, blockchain technology, and mobile trading applications, understanding how these innovations influence investor psychology, market efficiency, and financial risk is crucial.

The first section of this chapter utilises bibliometric analysis to uncover dominant research themes, key contributors, and emerging trends shaping the discourse on fintech adoption and investment strategies. It highlights the concentration of high-impact studies, the evolution of thematic clusters, and the geographic distribution of research efforts. The second section systematically reviews existing literature, categorising findings into core themes such as investor awareness, behavioural biases in technology-assisted investing, the influence of social trading and real-time financial news, and the regulatory challenges surrounding fintech adoption. By integrating quantitative insights from bibliometric analysis with qualitative assessments from prior studies, this chapter establishes a comprehensive foundation for understanding the disruptive role of financial technologies in modern investing. It also identifies underexplored areas, emphasising the need for further empirical research on decision-making biases in AI-driven finance, risk assessment in algorithmic trading, and the long-term implications of fintech integration in global markets.

2.2 BIBLIOMETRIC ANALYSIS

The rise of financial technologies such as artificial intelligence, blockchain, and algorithmic trading has transformed investment behaviour, improved market efficiency, and introduced new risks. Automated trading systems now dominate global markets, while decentralised finance offers alternatives to traditional banking. Mobile trading apps and social media have increased investor participation, particularly in emerging economies, but also heightened behavioural biases, market volatility, and regulatory concerns. Despite extensive research on fintech adoption, studies remain fragmented, often focusing on specific technologies or market events rather than providing a comprehensive perspective.

This study employs bibliometric analysis to map key research trends, identify dominant themes, and highlight gaps in understanding the impact of fintech on investor decision-making. It examines publication trends, citation patterns, research collaborations, and emerging topics, including ethical AI, quantum computing, and regulatory challenges. A significant gap exists in understanding how financial technology influences investor psychology. By integrating insights from behavioural finance and technological advancements, this study provides a structured framework for future research on the evolving relationship between fintech and investment behaviour.

2.3 Data Collection

Data were extracted from the Web of Science (WoS) Core Collection, a premier database for high-impact scientific literature, to ensure access to rigorously peer-reviewed studies. WoS was selected for its comprehensive coverage of finance, technology, and management journals (e.g., Journal of Financial Markets, Technological Forecasting and Social Change) and its compatibility with bibliometric tools.

2.4 Search Strategy

A systematic search was conducted using the following Boolean query to balance precision and recall:

(("Technological Innovation" OR "FinTech" OR "Algorithmic Trading" OR "Robo-Advisory" OR "Blockchain Trading" OR "AI in Trading")

AND

("Investment Behaviour" OR "Investor Behaviour" OR "Stock Market Investment" OR "Trading Behaviour")

AND

("Structural Equation Modelling" OR "PLS-SEM" OR "Causal Relationship")

AND

("stock markets" OR "capital markets"))

2.4.1 Data Characteristics

The bibliometric analysis reveals a dataset spanning 2020-2025, comprising 1,711 articles from 256 sources. The annual growth rate of -24.4% indicates a decline in publication output, which is unusual for a rapidly evolving field like fintech and technological innovations. This negative trend may stem from database indexing delays, the consolidation of research into fewer high-impact journals, or a potential decline in interest after 2020. However, given the dynamic nature of the field, the latter seems unlikely. It is recommended to verify this trend by cross-checking it with alternative databases, such as Scopus or Dimensions, to ensure data completeness. The average document age of 2.66 years highlights the recency of the literature, reflecting the fast-paced advancements in AI, blockchain, and algorithmic trading. This suggests that older studies may quickly become obsolete, a common characteristic of technology-driven research domains.

The dataset demonstrates a high scholarly impact, with an average of 18.08 citations per document. This indicates that the field is producing influential research, likely driven by seminal works on topics such as AI-driven trading, blockchain transparency, and robo-advisory systems. The extensive referencing, with 97,049 references across the dataset, underscores the interdisciplinary nature of the field, drawing from finance, computer science, and behavioural economics. The high citation impact contrasts with the negative growth rate, suggesting that while publication numbers may be declining, the quality and influence of the research remain strong. This could imply a consolidation of research around key themes and influential papers rather than a stagnation in the field.

Keyword analysis reveals a significant disparity between Author's Keywords (5,719) and Keywords Plus (3,316). Author keywords are 1.7 times more frequent, indicating that researchers are using specific, niche terminology such as "DeFi governance" or "quantum trading," while automated systems generalise terms like "blockchain" or "AI." This suggests a highly specialised and fragmented field, with researchers focusing on emerging sub-themes. Such fragmentation highlights the need for a thematic analysis to identify core and niche areas, which can guide future research directions.

Collaboration patterns reveal a highly collaborative field, with only 2.9% of documents being single-authored. The average of 3.36 co-authors per document is slightly above the global average, reflecting the interdisciplinary nature of the research, which often requires expertise from multiple domains. International co-authorships account for 51.49% of the documents, emphasising the global nature of fintech and investment behaviour research. Partnerships between institutions in major tech hubs such as the U.S., the EU, and India likely drive this high level of international collaboration. Mapping these collaborations can provide valuable insights into the geographic and institutional hotspots that drive innovation in the field.

All documents in the dataset are articles, excluding books, conference papers, and reviews. This indicates a strong focus on journal-based, empirical research, which is typical for fields that prioritise cutting-edge advancements and practical applications. The absence of other document types may also reflect the database's focus on high-impact, peer-reviewed journals.

Table 2.1

Descriptive Statistics of the Data

Description	Results
Main Information About Data	
Timespan	2020:2025
Sources (Journals, Books, etc)	256
Documents	1711
Annual Growth Rate %	-24.4
Document Average Age	2.66
Average citations per doc	18.08
References	97049
Document Contents	
Keywords Plus (ID)	3316
Author's Keywords (DE)	5719
Authors	
Authors	4737
Authors of single-authored docs	138
Authors Collaboration	
Single-authored docs	140
Co-Authors per Doc	3.36
International co-authorships %	51.49
Document Types	
Articles	1711

Note: The table presents key bibliometric statistics, including publication trends, authorship patterns, and citation impact for the dataset spanning 2020–2025.

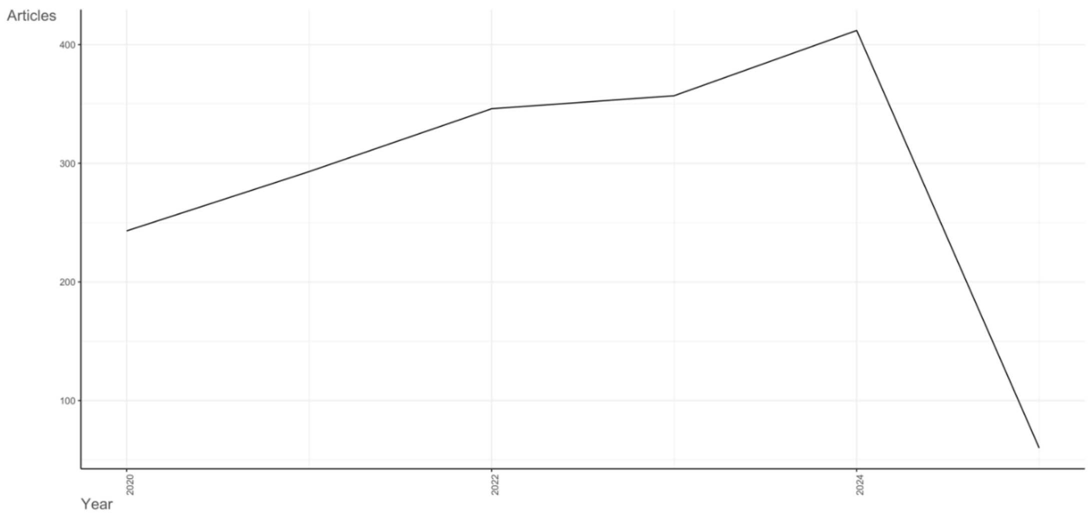
2.4.2 Scientific Production and Emerging Trends

The Annual Scientific Production chart (Figure 2.1) highlights the growth in research related to technological innovations and investment behaviour from 2020 to 2025, driven by fintech advancements such as AI-driven trading, blockchain applications, and robo-advisory systems. This increase aligned with the accelerated digital transformation during the COVID-19 period, leading to a surge in scholarly attention.

However, the decline in publications from 2023 onwards suggests potential indexing delays, research consolidation around high-impact studies, or a shift in focus toward emerging areas, such as quantum computing and decentralised finance. This trend requires further examination to determine whether it reflects actual changes in research priorities or limitations in data availability.

Figure 2. 1

Annual Scientific Production



2.4.3 Core Research Sources and Thematic Concentration

The distribution of research across academic sources follows Bradford's Law, highlighting a small number of highly productive journals that dominate scholarly contributions to technological innovations and investment behaviour. As shown in Figure 2.2, the core sources include high-impact journals such as Journal of Business Research, Finance Research Letters, and Technological Forecasting and Social Change, which publish a significant share of articles in this domain. The rapid decline in article count beyond the core sources reflects the concentrated nature of knowledge production, a pattern typical in well-established research fields. The middle-tier journals contribute a moderate number of publications, while the most extensive set of sources consists of low-productivity journals with only a few articles each. This structure confirms that research in fintech and investment behaviour is primarily shaped by a few leading outlets, making it essential for scholars to focus on these key sources when conducting literature reviews or publishing high-impact studies.

Figure 2.3 further refines this analysis by showcasing the most locally cited sources within the dataset, emphasising the journals that have had the highest impact within this specific research collection. The Journal of Finance, Journal of Financial Economics, and Review of Financial Studies are the most frequently cited, reinforcing their centrality in financial technology research. The presence of interdisciplinary journals such as Research Policy and Journal of Cleaner Production indicates a growing intersection between financial technology, sustainability, and policy implications. The high citation concentration in select sources highlights the field's reliance on a limited set of influential studies, which shape theoretical and empirical advancements. Collectively, these findings highlight the importance of these core journals in setting the research agenda and guiding future scholarly exploration in fintech and investment behaviour.

Figure 2.2

Bradfords Law

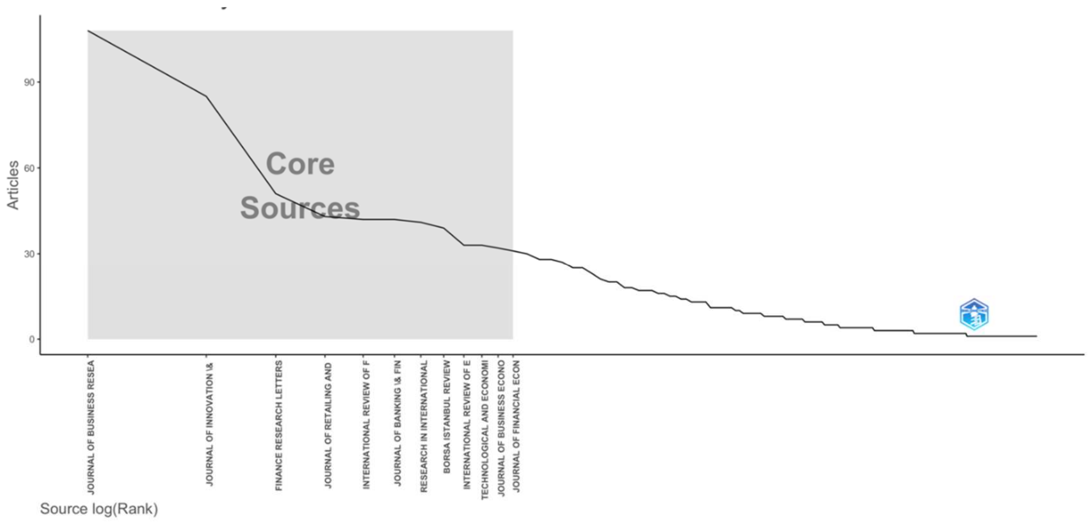
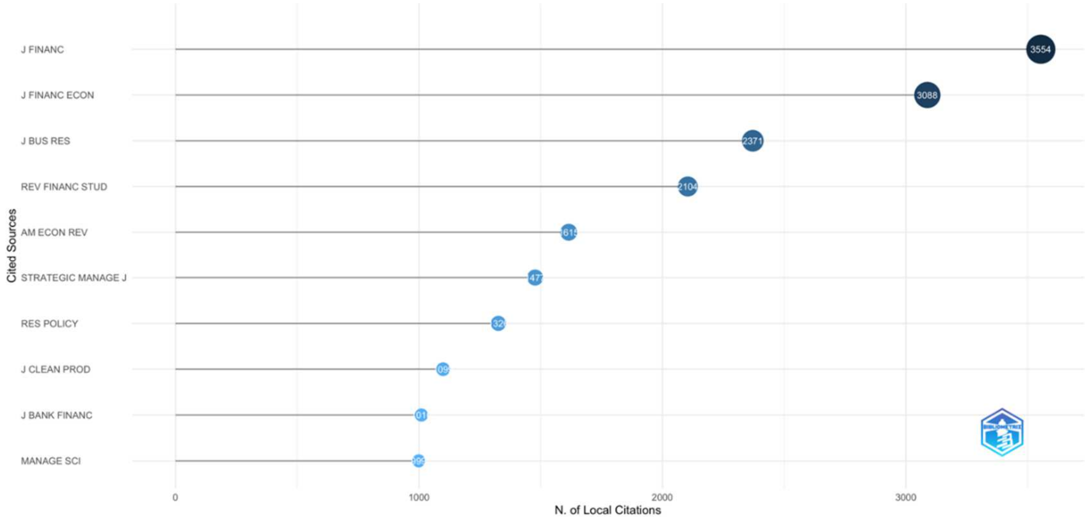


Figure 2.3

Most Local Cited Sources

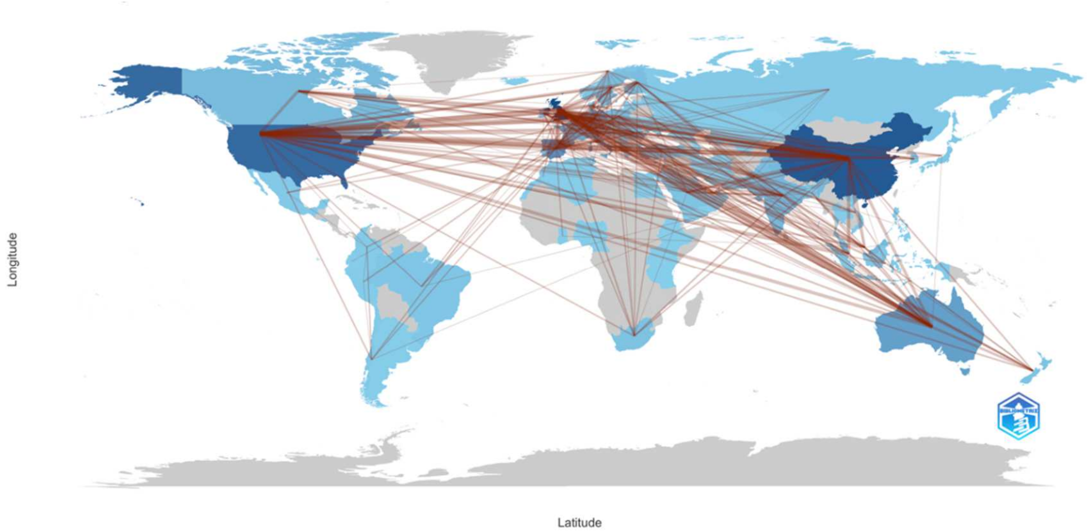


2.4.4 Geographic Research Trends and Collaboration Patterns

The Country Collaboration Map illustrates global research collaborations in technological innovations and investment behaviour. It highlights how leading research hubs, including the United States, China, India, and major European nations, form strong networks of academic partnerships. The dense interconnections indicate high international cooperation, particularly between developed economies and emerging markets. Collaborations between the U.S. and India may focus on AI-driven trading, whereas partnerships within Europe and China are likely to explore blockchain applications. The presence of emerging contributors, such as Southeast Asian and African nations, signals a growing diversification in fintech research. Identifying these collaboration networks is crucial for understanding knowledge exchange, institutional linkages, and potential areas for future research partnerships (Figure 2.4).

Figure 2.4

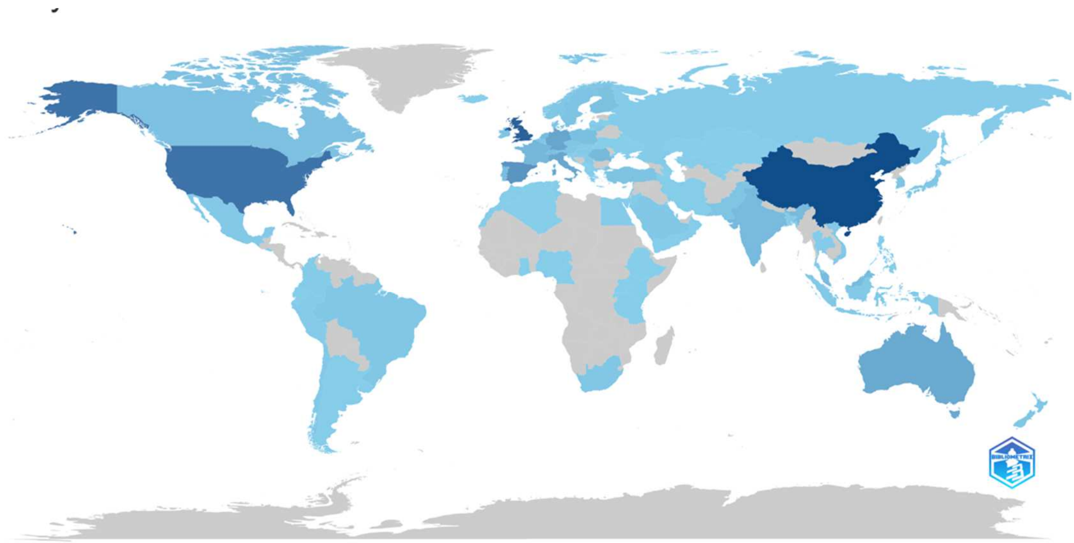
Country Collaboration Map



The Country Scientific Production chart visually represents research output by country, highlighting the dominance of regions such as China, the United States, and the United Kingdom in fintech and investment behaviour studies. These nations lead due to their strong academic ecosystems, robust regulatory frameworks, and advanced technological advancements. European countries, including Germany, Spain, and the Netherlands, also contribute significantly, reflecting their engagement in fintech policy, behavioural finance, and financial market innovations. The chart highlights research clusters and gaps, providing insights into which regions are driving global fintech discourse and where emerging research opportunities exist (Figure 2.5).

Figure 2.5

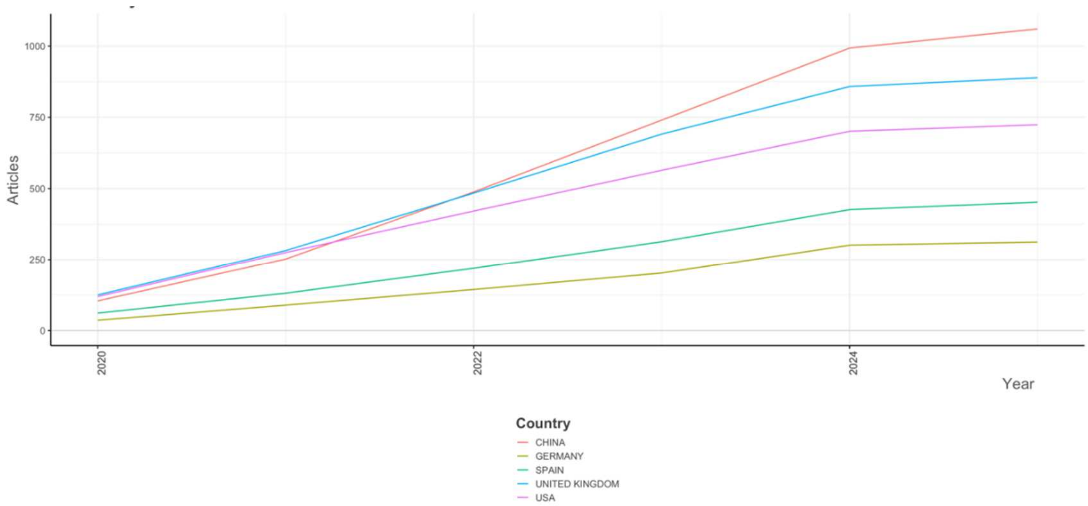
Country Scientific Production



The Country Production Over Time chart provides a temporal perspective on research growth across different nations. The upward trend in research output, particularly in China, the U.S., and India, indicates a rising focus on fintech-driven financial markets and behavioural analysis. China exhibits the highest growth trajectory, aligning with its aggressive adoption of blockchain and AI in the financial sector. The U.S. and the U.K. continue to make steady contributions, reinforcing their roles as pioneers in fintech research. Meanwhile, countries such as Germany and Spain exhibit gradual increases, reflecting growing academic interest in the regulatory and technological aspects of investment behaviour (Figure 2.6).

Figure 2.6

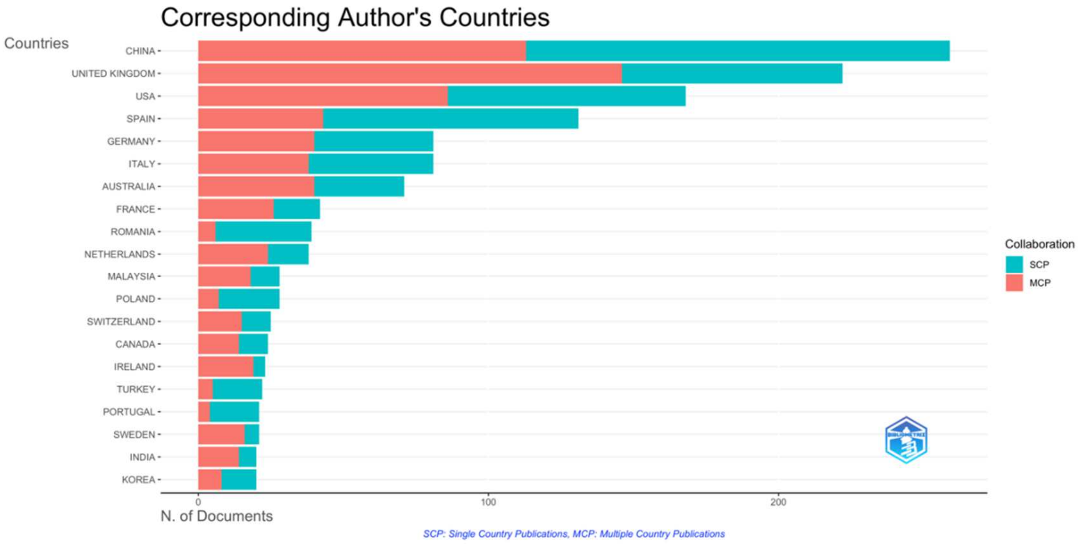
Country Production Over Time



The Corresponding Author's Countries chart identifies the primary contributing nations based on the country affiliations of corresponding authors. China, the U.K., and the U.S. emerge as leading contributors, reinforcing their dominance in fintech and investment behaviour research. The data reveal a blend of single-country publications (SCP) and multiple-country publications (MCP), indicating both national and international research efforts. Countries such as Australia, Germany, and France also feature prominently, indicating their involvement in collaborative fintech studies. This visualisation underscores the importance of geographic diversity in shaping global fintech research trends and highlights potential areas for expanding interdisciplinary and cross-border studies (Figure 2.7).

Figure 2.7

Corresponding Author's Countries

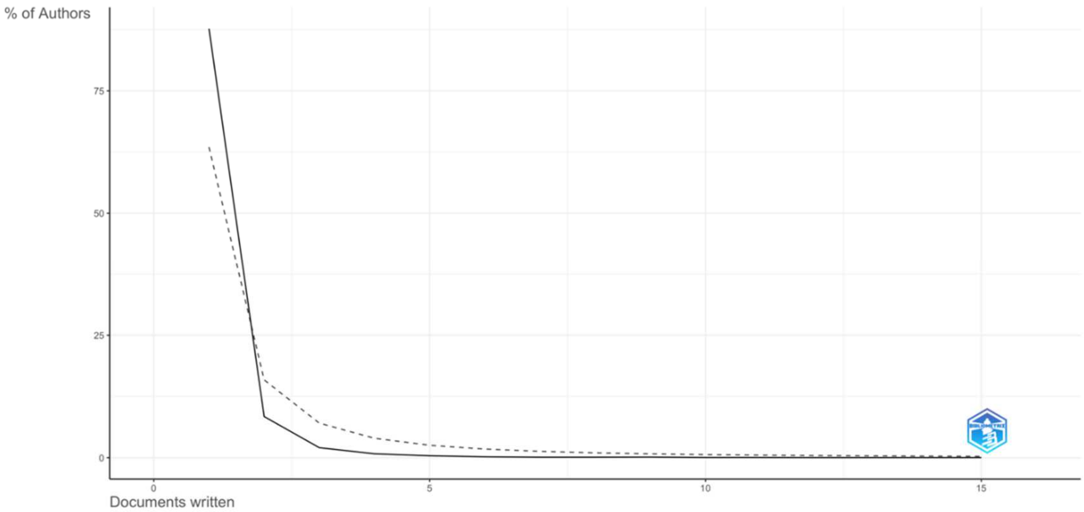


2.4.5 Author Productivity and Citation Networks

The productivity and influence of researchers in the field of technological innovations and investment behaviour are critical in understanding the development of scholarly contributions. The analysis of author productivity follows Lotka's Law, which suggests that a small percentage of authors account for a significant portion of published research. Figure 2.8 illustrates the distribution of authors based on the number of documents they have written. The chart indicates that the majority of authors (approximately 75%) have contributed only one or two papers, while a small fraction have produced five or more publications. This pattern is typical in academic research, where a handful of prolific scholars drive the field's intellectual development. Identifying these high-productivity authors provides insight into key contributors shaping discussions around fintech adoption, AI-driven investment decisions, and blockchain-based financial systems (Figure 2.8).

Figure 2.8

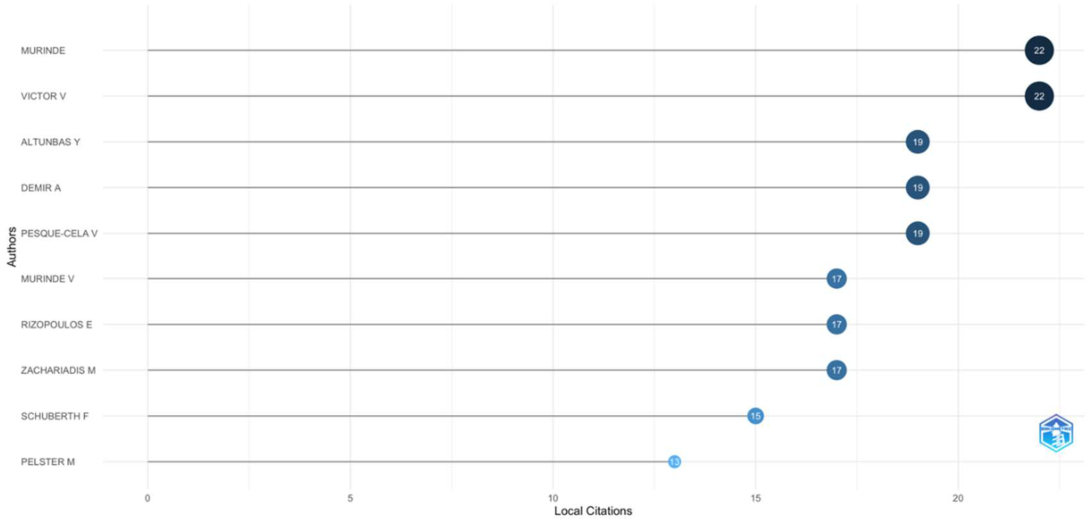
Lotkas Law



Another aspect of influence is the local citation impact, which reflects the frequency with which specific authors are cited within the analysed dataset. The most locally cited authors are shown in Figure 2.9. The chart highlights Victor Murinde, among others, as one of the most frequently cited scholars in the domain. His research, along with that of Altunbas Y, Demir A, Pesque-Cela V, Rizopoulos E, Zachariadis M, Schuberth F, and Pelster M, has significantly shaped the understanding of fintech integration, algorithmic trading, and behavioural influences on investment behaviour. These authors have contributed to pivotal studies that define the current discourse, particularly in areas of decentralised finance, AI-driven investment strategies, and market regulation. Recognising their work is essential for understanding the theoretical and empirical foundations driving the field (Figure 2.9).

Figure 2.9

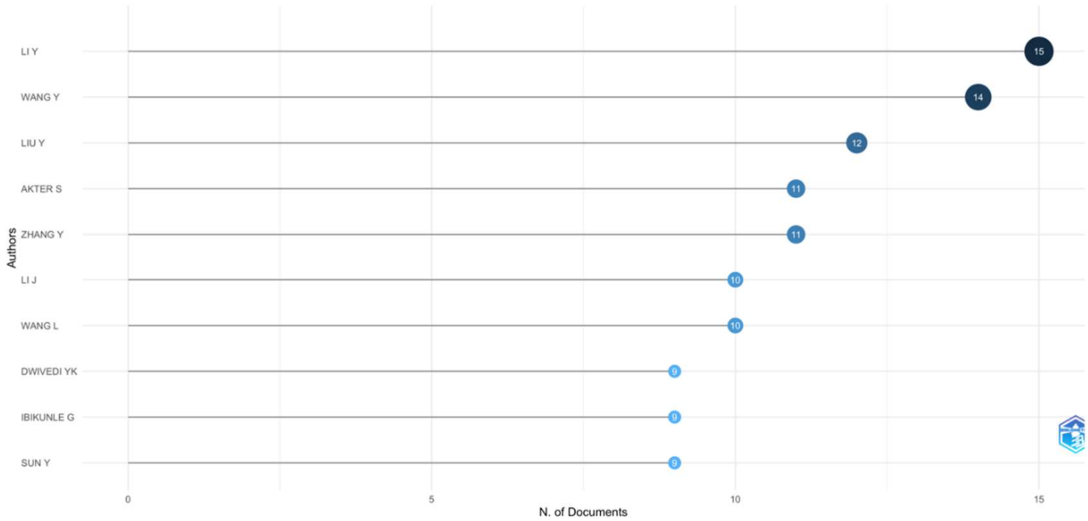
Most locally cited authors



In terms of research volume, Figure 2.10 presents the most relevant authors based on the number of published documents. Scholars such as Wang Y, Liu Y, Akter S, Zhang Y, and Li J have contributed multiple high-impact papers, indicating their substantial role in shaping the discussion on fintech-driven transformations in investment behaviour. The presence of Wang L, Dwi/Edi YK, Ibikunle G, and Sun Y further highlights contributions from diverse research backgrounds, including machine learning applications in finance, decentralised financial systems, and quantum computing in trading algorithms. The dominance of these researchers underscores their active engagement in fintech research and their impact on emerging themes in digital finance and behavioural investment trends (Figure 2.10).

Figure 2.10

Most Relevant Authors



Together, these analyses provide a structured understanding of author contributions, showing that a concentrated group of scholars plays a dominant role in advancing research in technological innovations and investment behaviour. The insights from these visualisations guide future research by identifying key contributors and emerging themes that are shaping the evolving financial landscape.

2.4.6 Influential Documents and Citation Analysis

The most locally cited documents chart presents key research studies that have received the highest citations within the specific dataset used for this bibliometric analysis. These references are crucial for shaping ongoing academic discussions in fintech adoption, AI-driven market behaviour, and blockchain-based financial innovations.

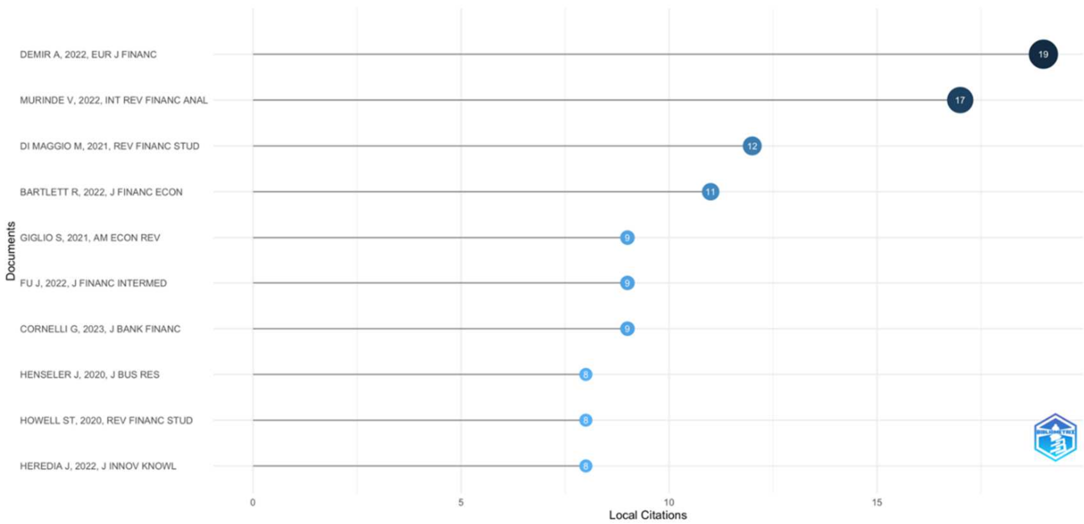
Among the most locally cited papers, Demir et al. (2020) appears prominently, indicating its significance in AI-driven trading and financial analytics. Similarly, Murinde et al. (2022), Di Maggio and Yao (2020), and Bartlett et al. (2021) contribute essential insights into financial technology and behavioural finance, particularly regarding investor sentiment and the integration of AI into decision-making.

Other influential studies include Giglio et al. (2021), Fu and Mishra (2021), and Cornelli et al. (2022), which focus on the economic implications of fintech and algorithmic trading. Additionally, Henseler and Schuberth (2020), Howell et al. (2019), and Heredia et al. (2022) explore innovation management, financial risk modelling, and the impact of fintech on investment strategies.

These highly cited works within the dataset highlight the dominant research themes and theoretical frameworks that have shaped the discourse on fintech-driven investment behaviour, providing a reference point for identifying underexplored research areas (Figure 2.11).

Figure 2.11

Most Locally Cited Documents



The reference publication year spectroscopy chart provides a temporal analysis of how citation patterns have evolved in the field of technological innovations and investment behaviour. This visualisation helps in identifying historical research milestones and the emergence of new scholarly interests.

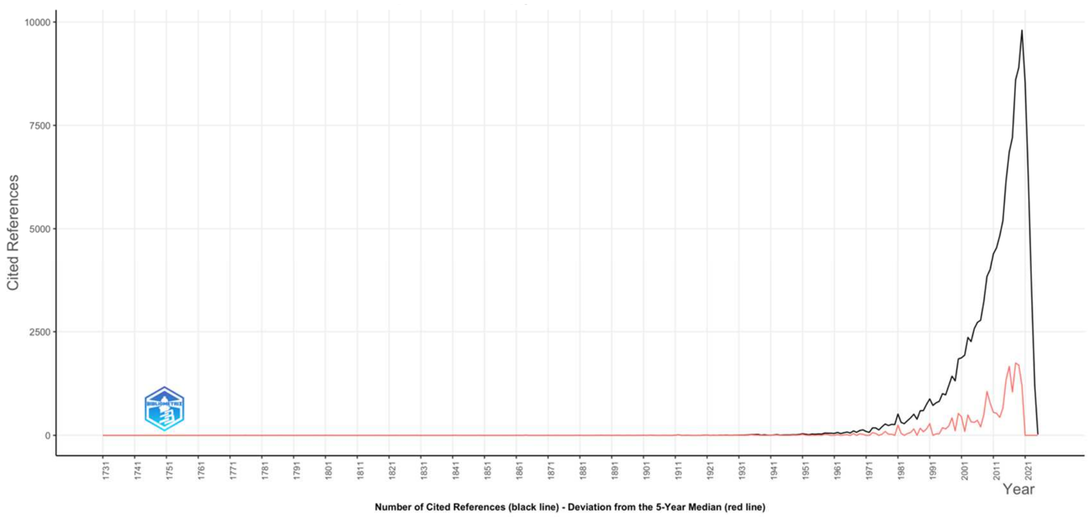
The black line in the chart represents the number of cited references by year, with noticeable peaks indicating periods of heightened research output. The peaks around 2010 - 2015 coincide with the increasing use of AI in trading and blockchain-driven financial models. A significant surge in citations between 2020 and 2021 aligns with the rapid acceleration of fintech innovations during the COVID-19 pandemic, highlighting areas such as decentralised finance, robo-advisory systems, and digital trading platforms.

The red line tracks deviations from the five-year median, showing shifts in research priorities over time. The increasing deviations in recent years suggest emerging trends in quantum computing, ethical AI in finance, and algorithmic risk assessment, which have yet to be extensively explored in empirical studies. These deviations indicate new research directions that could reshape fintech applications and investment behaviour analysis.

This chart provides a historical context for understanding how financial technology research has evolved and suggests potential research gaps, particularly in the integration of AI-driven financial analytics, blockchain transparency, and the long-term behavioural effects of algorithmic decision-making (Figure 2.12).

Figure 2.12

Reference Spectroscopy



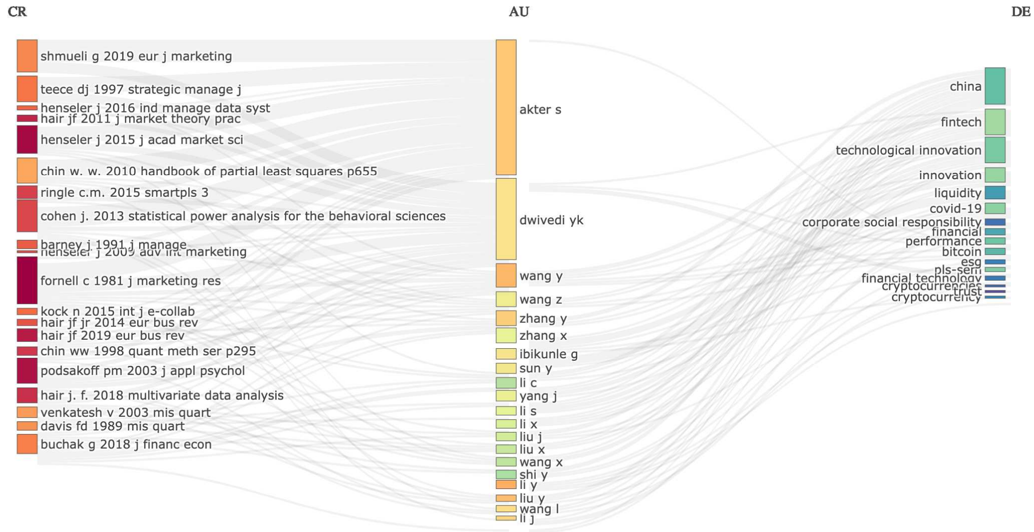
2.4.7 Thematic Mapping and Keyword Network Analysis

The three-field plot provides a comprehensive visualisation of the interconnections between key authors, keywords, and cited references within the research domain of technological innovations and investment behaviour. This analysis helps in identifying influential works, thematic trends, and research trajectories. The left section of the plot highlights foundational studies that have shaped the discourse in this field. Key references include contributions from scholars such as Fassott et al. (2016) on industrial management, Hair et al. (2011) on marketing theory, and Chin (2009) on partial least squares structural equation modelling (PLS-SEM). These works establish the theoretical and methodological underpinnings of fintech research. Additionally, studies by Venkatesh et al. (2003) on technology adoption and Davis (1989) on user acceptance of information systems provide behavioural frameworks relevant to the adoption of financial technologies.

The central portion of the plot maps keywords representing dominant themes in the literature. Concepts such as fintech, technological innovation, liquidity, and cryptocurrency dominate the discourse, reflecting the increasing role of emerging technologies in financial markets. The inclusion of covid-19 highlights its impact on accelerating digital economic transformation. Additionally, keywords related to corporate social responsibility and financial performance suggest a growing intersection between sustainable finance and fintech adoption. The right section of the plot presents a list of authors who have made significant contributions to the field. Scholars such as Akter, Wang, Zhang, and Liu are identified as leading researchers, particularly in areas related to AI-driven trading and blockchain applications. The presence of researchers like Dwivedi and Ibikunle indicates the global nature of fintech research, with contributions from diverse geographic and institutional backgrounds. This visualisation underscores the interdisciplinary nature of the field, linking financial technology, behavioural finance, and innovation management.

Figure 2.13

Three Field Plot



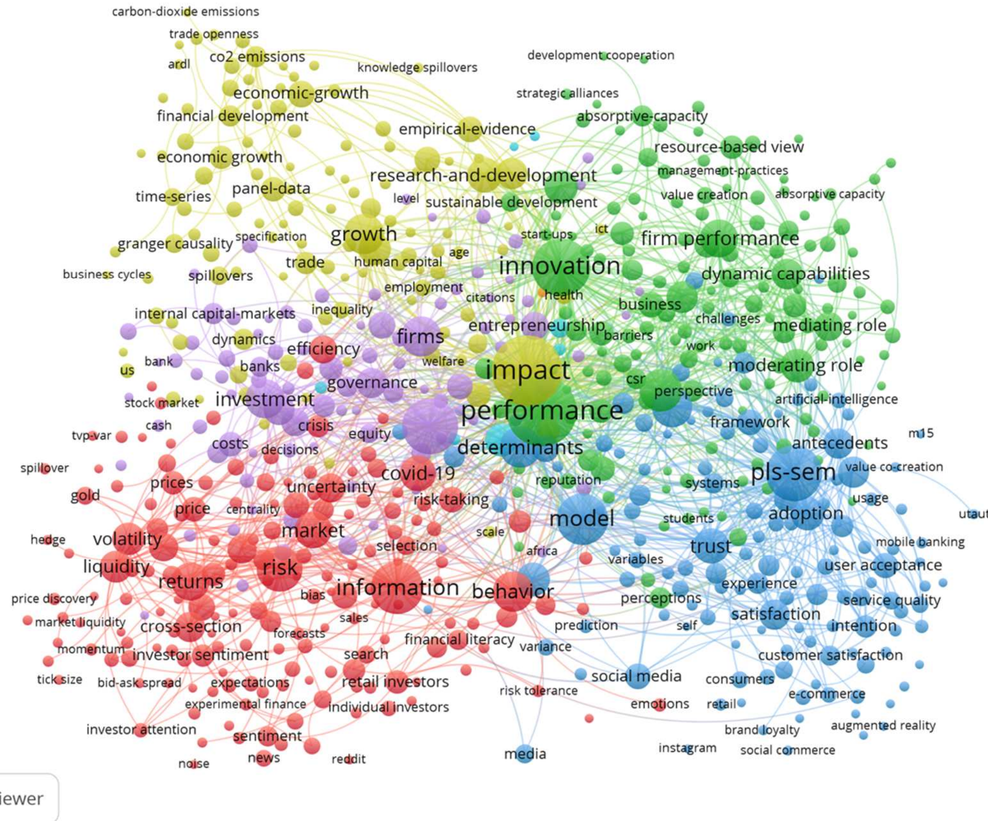
2.5 Research Clusters and Dominant Themes

The keyword co-occurrence network provides insights into the major research themes in the field of technological innovations and investment behaviour. The analysis reveals five primary clusters, each representing distinct but interconnected themes. The green cluster focuses on innovation, firm performance, and dynamic capabilities, emphasising how businesses integrate fintech advancements to improve market competitiveness. The blue cluster explores fintech adoption, trust, and consumer behaviour, with a strong emphasis on user acceptance models, particularly PLS-SEM applications. The red cluster centres on market volatility, risk, and investor sentiment, indicating a growing interest in understanding how social media, sentiment analysis, and real-time financial news influence investment decisions. The purple cluster captures regulatory and governance aspects of fintech, linking financial innovations with macroeconomic variables such as economic growth and financial stability. Finally, the yellow cluster represents econometric and empirical research, focusing on financial modelling techniques such as Granger causality and panel data analysis to assess the economic implications of fintech advancements.

The co-occurrence of keywords across these clusters suggests a shift from early research focusing on fintech adoption to more complex analyses of its economic impact and regulatory challenges. The increasing presence of terms such as carbon emissions, economic development, and governance suggests that fintech is now being explored in the context of sustainable finance and responsible financial management. Additionally, behavioural finance elements, such as investor sentiment, risk-taking behaviour, and uncertainty, are increasingly integrated with AI-driven analytics and algorithmic trading. This transition highlights the need for cross-disciplinary research that connects financial technology, regulatory frameworks, and behavioural science to provide a more holistic understanding of fintech's role in modern investment behaviour.

Figure 2.14

Keyword Co-occurrence Network



2.6 Emerging Trends in Technology Adoption, AI, and Digital Finance:

The thematic evolution map presents a temporal analysis of keyword trends, illustrating how research in technological innovations and investment behaviour has evolved. The colour gradient from blue to yellow represents different periods, with blue indicating earlier research trends from 2021 to 2022 and yellow highlighting more recent developments from 2023 onwards.

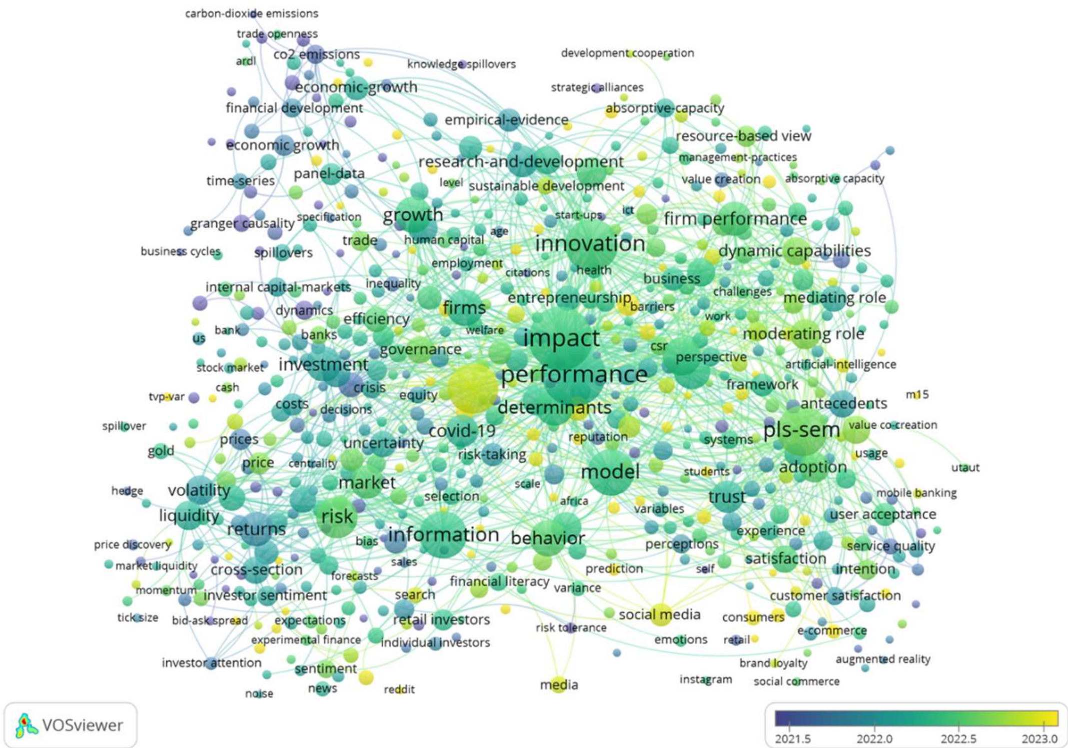
Early research in the field, as reflected in blue and green keywords, primarily focused on market dynamics, investment risk, and macroeconomic factors. Keywords such as volatility, liquidity, returns, economic growth, and financial development dominated the discourse, reflecting concerns over how fintech innovations impact financial markets and economic stability. Additionally, earlier studies explored behavioural aspects of investment, with frequent mentions of investor sentiment, uncertainty, and price movement predictions within financial markets.

More recent research trends, represented by yellow and light green keywords, indicate a growing focus on consumer behaviour, digital adoption, and fintech applications in retail finance. The increased prominence of terms such as trust, user acceptance, adoption, service quality, customer satisfaction, augmented reality, and social commerce suggests a shift toward understanding how retail investors engage with digital financial tools and platforms. The rising influence of social media, brand loyalty, and emotions highlights the role of digital ecosystems in shaping investment decisions.

Furthermore, the emergence of terms such as artificial intelligence, framework, and moderating role suggests that recent studies are increasingly integrating machine learning models, causal inference techniques, and structural equation modelling to analyse complex financial decision-making patterns. This shift signals the increasing interdisciplinarity of fintech research, combining insights from behavioural science, technology adoption, and financial analytics. The evolving nature of keyword trends indicates a growing need for empirical validation of fintech's impact, incorporating real-world data and advanced analytical techniques to assess its long-term implications.

Figure 2.15

Thematic Evolution Map



2.7 Conclusion

The bibliometric analysis highlights the rapid evolution of research on technological innovations and investment behaviour, with significant contributions in areas such as algorithmic trading, fintech adoption, decentralised finance, and behavioural biases in financial decision-making. The high citation impact of studies in this domain suggests that the field is producing influential research. Yet, the declining annual growth rate raises questions about possible shifts in research priorities. While early studies focused on digital payment systems, mobile trading platforms, and the initial adoption of fintech innovations, recent research trends indicate a growing emphasis on market volatility, investor sentiment, regulatory challenges, and the long-term stability of algorithmic trading systems. The findings also confirm that fintech research is highly globalised, with significant academic contributions coming from the United States, China, the United Kingdom, and European countries. Meanwhile, emerging economies, particularly India and those in Southeast Asia, are increasingly engaging in discussions on financial inclusion and digital transformation. The strong international collaboration patterns observed in the study suggest that fintech research benefits from cross-border knowledge exchange, fostering interdisciplinary insights that integrate finance, technology, and behavioural science.

Despite the significant advancements, several research gaps remain unaddressed. The long-term behavioural effects of fintech adoption on investor psychology and market stability require deeper empirical investigation, particularly regarding decision-making biases in AI-assisted trading and the ethical risks associated with algorithmic financial systems. While AI, blockchain, and robo-advisory systems are widely studied, there is limited consensus on their impact on overall market efficiency and risk mitigation. Additionally, the findings suggest that while fintech research is expanding into areas such as sustainable finance and decentralised markets, the field lacks standardised conceptual frameworks, leading to fragmented theoretical development. Addressing these gaps requires a more structured research approach that synthesises insights from financial economics, behavioural finance, and regulatory perspectives.

2.8 LITERATURE REVIEW

2.8.1 Introduction

The stock market environment has undergone tremendous changes due to technological innovations, which have redefined the way investors access, analyse, and trade information. The effective management of investments is influenced by the rise of digital platforms, mobile trading applications, robo-advisor services, and real-time data analytics, which have improved efficiency, accessibility, and transparency in investment decisions. These developments have not only lowered the costs of transactions but also democratised market access, as they have enabled retail investors to use tools previously monopolised by institutional investors. Numerous researchers have demonstrated that the use of technology in stock trading can influence investor confidence, decision-making speed, and risk-taking behaviour. The following section, the review of literature, will build on these findings by systematically analysing empirical and theoretical studies to identify gaps that require further exploration and establish a strong foundation for understanding how fintech continues to reshape investment behaviour and financial markets.

The review has been categorised into eleven themes to present the previous research works in relation to the objectives. The literature review was extensive and resulted in categorising all studies by various themes as presented below:

1. Evolution of Technological Innovations in the Stock Market
2. Investor Awareness and Adoption of Technological Innovations in the Stock Market
3. The Impact of Technological Advancements on Investment Behaviour
4. Social Trading and Real-Time News Platforms in Investment Decisions
5. The Role of Financial Analytics in Investment Decision-Making
6. Impact of Mobile Trading Apps and Discount Brokers on Investment Behaviour
7. Risk Perception and Psychological Factors in Technology-Based Investing
8. Cost Perception and Transactional Efficiency in Technology-Driven Investing
9. Attitudes Towards Technological Innovations in Investment
10. Behavioural Intention and Actual Use of Technology in Stock Trading
11. The Influence of Algorithmic Trading on Market Efficiency and Investor Behaviour

2.8.2 Evolution of Technological Innovations in the Stock Market

The stock market has undergone a profound technological transformation, shifting from manual trading methods to highly sophisticated digital ecosystems. This evolution has been studied across various disciplines, highlighting the impact of electronic trading, algorithmic trading, fintech innovations, and blockchain technology on market efficiency and investor behaviour.

The transition from open-outcry trading to electronic platforms marked a fundamental shift in stock market operations. Research has extensively examined how early electronic trading systems revolutionised market dynamics (Bradford & Miranti, 2014). The adoption of digital trading platforms has significantly enhanced market efficiency, with the National Stock Exchange (NSE) implementing an electronic order-matching system that improved liquidity and streamlined transactions (Shah & Thomas, 2000). Studies suggest that digitalisation has led to reduced trading costs and increased market participation, creating a more inclusive financial landscape (Gomber et al., 2018).

The emergence of algorithmic trading has further transformed the stock market, with high-frequency trading (HFT) becoming a dominant force in global financial markets (Menkveld, 2013). Empirical studies highlight the role of HFT in improving liquidity and reducing bid-ask spreads (Hendershott & Riordan, 2013). However, concerns persist regarding the impact of algorithmic trading on market stability, as it has been linked to increased volatility and occasional market disruptions (Filimonov & Sornette, 2012). Recent research emphasises the need for regulatory interventions to ensure fair market practices and mitigate risks associated with algorithmic trading (Seo & Chai, 2013).

Fintech innovations have played a crucial role in reshaping the investment landscape. The proliferation of mobile trading applications has facilitated greater participation by retail investors, thereby democratising access to financial markets (Chong et al., 2021). Studies have examined the effects of mobile trading platforms on investor behaviour, highlighting changes in trading frequency and investment decision-making patterns (Nair et al., 2022). The rise of discount brokers and zero-commission trading models has further contributed to this shift, challenging traditional brokerage structures and fostering competitive market conditions (Fouillet et al., 2021).

Regulatory frameworks have played a crucial role in shaping the evolution of technology-driven trading. The Securities and Exchange Board of India (SEBI) and the Reserve Bank of India (RBI) have implemented various policies to regulate algorithmic trading, fintech applications, and blockchain-based financial systems

(Claessens et al., 2018). Research indicates that regulatory measures, such as the introduction of algorithmic trading guidelines and the implementation of fintech sandbox programs, have helped maintain market integrity while fostering technological advancements (Addy et al., 2024)

Blockchain technology has emerged as a transformative force in financial markets, offering enhanced transparency, security, and efficiency. Studies have explored the potential of decentralised trading platforms to reduce settlement times and mitigate counterparty risks (Cucculelli & Recanatini, 2022). However, challenges related to scalability, regulatory compliance, and integration with existing financial infrastructure persist (Zachariadis et al., 2019). Research continues to investigate the feasibility of blockchain-based stock trading services, emphasising their implications for market efficiency and investor confidence (Chang & Wang, 2023).

The socio-economic implications of market automation remain a topic of scholarly debate. Some studies argue that technological advancements have exacerbated income disparities by favouring institutional investors with access to sophisticated trading algorithms (Froot et al., 2001). Conversely, other research suggests that the rise of digital discount brokerage models has lowered barriers to market entry, promoting financial inclusion among retail investors (Balodi et al., 2024). The interplay between automation, market accessibility, and investor behaviour remains a critical area of ongoing inquiry (Sindakis & Showkat, 2024).

The evolution of technological innovations in stock markets presents a dual narrative—enhanced efficiency, accessibility, and democratisation of trading, but also systemic risks, regulatory challenges, and ethical concerns. While global studies provide foundational insights, India-centric research remains fragmented, particularly in areas of rural fintech adoption, blockchain scalability, and ethical AI governance. Future research should focus on bridging regulatory gaps, enhancing cybersecurity frameworks, and developing responsible AI-driven trading ecosystems to ensure a sustainable and technology-driven evolution of the stock market.

2.8.3 Investor Awareness and Adoption of Technological Innovations in the Stock Market

Investor awareness plays a pivotal role in the adoption of technological innovations in the stock market, influencing how investors engage with fintech solutions, artificial intelligence (AI), blockchain, robo-advisors, and algorithmic trading. The diffusion of these technologies is shaped by behavioural factors, regulatory frameworks, and financial literacy, which collectively determine the extent of adoption across different investor demographics.

The adoption of technological innovations is closely linked to awareness levels, as demonstrated in studies on fintech adoption and the transformation of financial services. Guild (2017) emphasises that increased investor knowledge about digital financial solutions enhances adoption rates. The Theory of Planned Behaviour (TPB) and Technology Readiness Index (TRI) have been employed to analyse how technological optimism and discomfort influence investor decision-making. Flavián et al. (2021) argue that investors with higher awareness of AI-based trading platforms exhibit greater intention to integrate robo-advisors into their investment strategies, with perceived usefulness playing a critical role in this adoption process. However, Atwal and Bryson (2021) highlight that psychological barriers, such as automation bias and lack of trust in AI-generated financial recommendations, impact adoption.

The role of blockchain technology in the adoption of the stock market has also gained significant attention. Blockchain has been positioned as a transformative force in enhancing security, transparency, and efficiency in trade settlement. However, awareness remains a key barrier to widespread adoption. Lou and Li (2017) indicate that investor knowledge of blockchain applications influences trust and willingness to engage with decentralised trading platforms. The integration of Innovation Diffusion Theory (IDT) with the Technology Acceptance Model (TAM) provides a comprehensive framework to explain how early adopters influence mass adoption trends in blockchain-based financial transactions. Ku-Mahamud et al. (2019) suggest that the higher the investor familiarity with blockchain's security advantages, the greater their inclination to use it for investment activities.

Fintech solutions, including mobile stock trading applications and digital investment platforms, have experienced varying adoption rates across different investor segments. Despite high levels of fintech awareness among investors, actual usage remains relatively low, suggesting gaps in education and trust. Abdullah et al. (2018) underscore the significance of financial literacy in bridging this gap. Investors with a greater understanding of fintech solutions are more likely to integrate digital financial products into their investment practices, underscoring the importance of targeted education initiatives. Irimia-Diéguez et al. (2023) further emphasise that personalised fintech experiences enhance investor engagement by offering user-friendly interfaces and algorithmic insights that simplify decision-making.

The Unified Theory of Acceptance and Use of Technology (UTAUT) has been applied to fintech adoption in various studies, revealing that performance expectancy and social influence significantly affect investor intention to use fintech services. Abdullah et al. (2018) report that while 95.6% of respondents in a Malaysian study were aware of fintech applications, only 11.8% actively used them for investment purposes, highlighting the need for stronger financial education programs and risk awareness campaigns. Similarly, Sembel et al. (2024) found that investor awareness, influenced by financial literacy and e-reputation, has a significant impact on fintech adoption, particularly in mobile stock investment applications in Indonesia.

Investor psychology plays a crucial role in shaping technological adoption trends. Behavioural finance theories suggest that cognitive biases, such as herding behaviour and overconfidence, influence investor engagement with new technologies. Bunkar and Ramaiah (2024) highlight that investors who perceive algorithmic trading as complex or opaque tend to rely on traditional trading methods, despite the potential efficiency benefits of algorithmic trading. Conversely, Flavián et al. (2021) suggest that technological optimism fosters positive attitudes toward AI-driven financial decision-making, increasing adoption rates among tech-savvy investors. However, Atwal and Bryson (2021) point out that concerns over algorithmic transparency and AI biases remain significant deterrents to the adoption of AI.

Social trading and network-based investment strategies further illustrate the role of awareness in technological adoption. Dorfleitner et al. (2018) indicate that investor participation in social trading platforms is driven by peer influence and access to real-time market insights. While social trading enhances financial knowledge and decision-making efficiency, it also introduces risks of herd behaviour, where investors mimic trades without conducting independent research. Ze and Loang (2024) argue that awareness of these risks is crucial for ensuring responsible participation in technology-driven financial markets. Moreover, sentiment analysis tools powered by AI have been shown to improve market prediction accuracy, yet they require investor education to mitigate overreliance on algorithmic recommendations.

Empirical research on digital financial literacy underscores the need for targeted initiatives to enhance investor confidence in technological innovations. Kartika and Rusmanto (2023) highlight that investors with a strong understanding of digital investment tools are more likely to engage with fintech solutions, blockchain-based platforms, and AI-driven analytics for portfolio management. However, Taneja (2024) emphasises that disparities in financial education across different investor demographics highlight the need for inclusive educational programs that cater to diverse investment backgrounds.

Regulatory frameworks play a vital role in shaping investor awareness and adoption of financial technologies. Dangkeng and Munir (2025) argue that government initiatives aimed at improving financial literacy and digital inclusion have a significant influence on fintech adoption trends. Additionally, Claessens et al. (2022) argue that investor protection policies that enhance transparency in algorithmic trading and robo-advisory services foster increased trust in financial technologies.

Despite growing awareness, barriers to adoption persist, particularly concerning cybersecurity risks, regulatory uncertainties, and the complexity of emerging financial technologies. Luo (2024) notes that while investors recognise the benefits of blockchain and AI in financial markets, concerns about data privacy, fraud prevention, and algorithmic accountability limit widespread adoption. Spatacean and Todoran (2025) suggest that financial institutions must implement more robust investor education initiatives and regulatory safeguards to address these concerns, ensuring that technological advancements translate into sustainable investment practices.

One of the most significant barriers to adoption is the perceived complexity of financial technologies. Kartika and Rusmanto (2023) argue that many investors, especially retail participants, lack the necessary technical knowledge to utilise AI-driven trading platforms and blockchain-based investment solutions fully. This knowledge gap results in a reliance on traditional financial advisors, despite the availability of more efficient, technology-driven alternatives. Similarly, Sembel et al. (2024) highlight that the ease of access to fintech applications does not necessarily translate to practical use, as investors must possess a baseline understanding of financial markets and digital investment tools to make informed decisions. Addressing these challenges requires targeted financial literacy programs that focus not only on basic investment principles but also on the functionality and advantages of fintech solutions.

Another critical factor affecting technological adoption is trust in automated systems. Bunkar and Ramaiah (2024) emphasise that while algorithmic trading and robo-advisory services offer efficiency and cost savings, many investors remain sceptical about the accuracy and transparency of these technologies. Atwal and Bryson (2021) highlight that concerns about data security, system malfunctions, and a lack of regulatory safeguards contribute to hesitancy in adopting AI-driven financial management tools. These concerns are particularly evident in emerging markets, where regulatory oversight is still in its early stages of development. Lou and Li (2017) suggest that integrating robust security measures and increasing transparency in AI-driven investment models can help build investor confidence, ultimately enhancing adoption rates.

Behavioural finance research further illustrates the influence of psychological factors on the adoption of financial technologies. Ze and Loang (2024) argue that cognitive biases such as overconfidence and familiarity bias lead some investors to resist automation, preferring manual trading strategies despite evidence of AI's superior analytical capabilities. Conversely, Dorfleitner et al. (2018) find that social trading platforms, which leverage peer influence and community-based investment decisions, encourage greater fintech adoption by reducing perceived risks. However, these platforms also introduce challenges such as herd behaviour, where investors follow market trends without independent analysis. Ensuring that investors maintain a critical perspective while using social trading tools is essential to prevent irrational decision-making driven by sentiment rather than fundamental analysis.

The regulatory landscape also plays a crucial role in shaping investor awareness and adoption of technological innovations. Claessens et al. (2022) assert that a well-defined regulatory framework enhances investor confidence in fintech solutions by ensuring transparency, security, and compliance with market standards. However, Guild (2017) notes that excessive regulation may stifle innovation, potentially discouraging fintech companies from developing user-friendly investment platforms. Striking a balance between regulatory oversight and technological innovation is essential to fostering a sustainable fintech ecosystem. Recent studies suggest that regulatory sandboxes, which allow fintech firms to test new products under regulatory supervision, are effective in promoting both investor trust and technological advancements (Dangkeng & Munir, 2025). These initiatives provide investors with a safer environment in which to explore digital investment solutions, thereby accelerating their adoption.

Blockchain technology remains one of the most promising yet underutilised innovations in stock market investments. Ku-Mahamud et al. (2019) argue that while blockchain offers enhanced security and efficiency, its adoption is limited by a lack of awareness and concerns regarding regulatory compliance. Investors who recognise the benefits of decentralised trading platforms, such as reduced transaction costs and faster settlement times, are more likely to embrace blockchain-based solutions. However, Luo (2024) cautions that regulatory ambiguities and scalability issues pose significant barriers to widespread adoption. To address these challenges, Spatacean and Todoran (2025) advocate for more straightforward regulatory guidelines and investor education initiatives that focus on the practical applications of blockchain in financial markets.

AI-driven sentiment analysis tools and predictive analytics have also played a crucial role in shaping investment decisions. Flavián et al. (2021) find that investors who utilise AI-based forecasting models tend to achieve higher returns due to improved market timing and risk assessment. However, Kartika and Rusmanto (2023) warn that overreliance on these tools can lead to blind trust in algorithmic recommendations, potentially resulting in suboptimal investment outcomes. Educating investors on the strengths and limitations of AI-driven financial models is essential to ensuring responsible usage.

Financial literacy remains a key determinant of technological adoption in the stock market. Irimia-Diéguez et al. (2023) highlight that investors with a higher level of financial education are more likely to engage with fintech platforms, blockchain-based trading systems, and AI-driven investment tools. However, Sembel et al. (2024) note that disparities in financial literacy persist, particularly in developing markets, where access to financial education is often limited. Addressing these disparities requires collaborative efforts between regulatory bodies, financial institutions, and educational organisations to ensure that all investors have the necessary knowledge to navigate an increasingly digitalised financial landscape.

Despite the growing awareness of fintech innovations, cybersecurity risks remain a significant concern for investors. Atwal and Bryson (2021) report that fears of hacking, identity theft, and data breaches deter many individuals from fully embracing digital investment platforms. Similarly, Ze and Loang (2024) emphasise that while fintech solutions offer convenience and efficiency, they also introduce new vulnerabilities that must be addressed through enhanced security protocols and investor protection mechanisms. Regulatory bodies must implement stringent cybersecurity measures to safeguard investor data, thereby fostering trust in digital financial solutions.

Future research should focus on developing more effective strategies to bridge the gap between awareness and adoption of financial technologies. Kartika and Rusmanto (2023) propose that fintech firms should prioritise user-friendly interfaces and personalised investment tools to enhance investor engagement. Additionally, Claessens et al. (2022) suggest that targeted financial education programs, coupled with regulatory incentives, can encourage more investors to embrace technological innovations in the stock market. As the financial industry continues to evolve, ensuring that investors are equipped with the necessary knowledge and resources will be essential to fostering a more inclusive and technologically advanced investment ecosystem.

2.8.4 The Impact of Technological Advancements on Investment Behaviour

The evolution of technological advancements in financial markets has significantly influenced investment behaviour, reshaping decision-making processes, risk-taking tendencies, and the overall market efficiency. Digital transformation, artificial intelligence (AI), and financial technology (FinTech) have introduced novel investment mechanisms, altering investor psychology and trading strategies. Digital platforms have fundamentally shifted the landscape by enhancing accessibility and reducing transaction costs, allowing for the democratisation of investing. Hossnofsky and Junge (2019) assert that while initial market reactions to digitalisation may be adverse, long-term adaptation fosters favourable investment recommendations by analysts, highlighting a shift in perception towards technological innovations in finance. Similarly, Zhavoronok et al. (2022) examine the correlation between household financial behaviour and digitalisation, emphasising how increased access to real-time financial data enhances financial decision-making across different investor segments.

Algorithmic trading and robo-advisory services have emerged as dominant forces in shaping contemporary investment behaviour. While AI-driven investment platforms are often perceived as tools for mitigating cognitive biases, Bhatia et al. (2021) reveal that robo-advisors fail to eliminate behavioural distortions such as overconfidence and loss aversion. Instead, investors continue to exhibit psychological biases despite the use of algorithmic decision support. Similarly, Keswani et al. (2019) highlight that heuristic-driven decision-making remains prevalent even in technologically advanced trading environments, suggesting that technology cannot entirely override inherent behavioural tendencies. However, Lui et al. (2021) argue that AI investment can adversely impact firm valuation, as stock prices tend to decline following the announcement of AI implementation, indicating investor skepticism towards automation in financial decision-making.

The impact of digital platforms on investment frequency and risk-taking is another critical area of exploration. Kalda et al. (2021) demonstrate that smartphone trading applications encourage higher frequency trading and increased speculative behaviour, with investors displaying a greater propensity to chase past returns and engage in riskier asset allocations. This trend aligns with Quinn (2019), who draws historical parallels between technological revolutions and speculative financial bubbles, illustrating how rapid technological advancements often lead to short-term irrational exuberance in financial markets. Moreover, Zhang and Aumeboonsuke (2022) establish a link between technological innovation and heightened risk-taking among firms, as companies with strong technological capabilities tend to pursue aggressive investment strategies with long-term profitability objectives. However, this increased risk appetite may also lead to heightened market volatility, necessitating a more nuanced regulatory approach.

The adoption of blockchain technology and decentralised finance (DeFi) solutions further illustrates the evolving nature of investment behaviour. Peng et al. (2022) highlight that digitalisation significantly enhances corporate foreign direct investment (FDI) by improving capital efficiency and reducing financial constraints, particularly in technology-intensive sectors. This finding aligns with Irimia-Dieguez et al. (2023), who emphasise that social norms and attitudes mediate FinTech adoption, suggesting that investor sentiment and collective trust play a vital role in shaping investment decisions within digital financial ecosystems. Similarly, Wang et al. (2024) report that blockchain adoption is influenced by trust in its security and stability, underscoring the psychological dimensions of investor behaviour in response to technological advancements.

Behavioural finance perspectives provide additional insights into the intersection of technology and investment behaviour. Wu (2020) examines how automated financial information processing influences market sentiment, revealing that algorithmic trading amplifies investor reactions to new information, thereby exacerbating price fluctuations. This aligns with Ahmad and Wu (2022), who argue that herding behaviour remains a prevalent issue in digitalised trading environments, leading to distortions in perceived market efficiency. Meanwhile, Batra (2024) examines the role of financial literacy in mitigating the impact of technological advancements on investment decisions, concluding that enhanced digital literacy promotes more rational investment behaviour and reduces susceptibility to misinformation.

Empirical evidence further underscores the role of technology in shaping corporate investment strategies. Zhou and Ge (2023) establish that corporate digitisation enhances investment efficiency, particularly in firms experiencing overinvestment issues. Their findings complement Li et al. (2022), who analyse digital transformation's influence on corporate risk-taking, demonstrating that firms leveraging digital innovation exhibit greater resilience in volatile market conditions. Additionally, Jeanjean (2020) examines how technological progress influences competition and investment dynamics, finding that innovation-driven industries exhibit distinct investment patterns compared to traditional sectors. These studies collectively reinforce the argument that technological advancements are fundamentally altering both individual and institutional investment behaviours, necessitating a reassessment of traditional financial models.

The proliferation of social trading platforms and real-time financial news aggregators has further reshaped investor decision-making. Krishnaprabha (2024) examines the impact of social media on investment preferences among young investors, concluding that digital engagement promotes short-termism and speculative tendencies. This aligns with Keeley (2023), who examines the impact of synthetic financial media on investor sentiment, demonstrating that algorithmically generated financial narratives can significantly alter investment outlooks. In contrast, Hariyani and Saputra (2023) argue that financial technology enhances investment interest among younger demographics by providing more accessible and user-friendly platforms, thereby encouraging long-term financial participation.

The relationship between digital transformation and financial market efficiency remains a topic of ongoing debate. Zhang and Xie (2023) assert that while digitalisation fosters investment innovation, it also introduces greater volatility, as firms must continuously adapt to evolving technological landscapes. This view is supported by Lu and Zhou (2022), who analyse the implications of digital transformation on firm valuation, illustrating that businesses with robust digital strategies tend to exhibit higher market resilience and investor confidence. Conversely, Shukla and Nerlekar (2019) argue that technological advancements have led to a reduction in brokerage reliance, empowering individual investors but also increasing susceptibility to market manipulation due to information asymmetry.

The integration of advanced technologies into investment decision-making processes continues to redefine traditional financial practices, altering investor behaviour and market dynamics. The increasing reliance on artificial intelligence (AI), big data analytics, and blockchain has significantly enhanced investment efficiency while simultaneously reshaping risk perception among investors (Hossnofsky & Junge, 2019). The adoption of these technologies has contributed to a fundamental transformation in investor sentiment, trading strategies, and portfolio management, underscoring the need for a nuanced understanding of behavioural finance in technology-driven investing.

The deployment of AI-driven analytics has significantly influenced investors' decision-making processes by providing predictive insights and pattern recognition capabilities, enhancing investment performance through data-driven strategies (Zhang & Xie, 2023). AI-powered robo-advisors have played a crucial role in democratising access to investment opportunities by providing cost-effective financial planning solutions tailored to individual risk preferences (Bhatia et al., 2021). However, empirical evidence suggests that despite their efficiency, robo-advisory services have not been entirely successful in mitigating cognitive biases such as overconfidence and loss aversion (Keswani et al., 2019). These findings suggest that while technological innovations enhance investment accessibility, they do not necessarily eliminate behavioural anomalies that persist within investor psychology.

Technological advancements have also facilitated the proliferation of algorithmic trading and high-frequency trading (HFT), which have redefined liquidity dynamics and market efficiency (Luo, 2024). Algorithmic trading, leveraging machine learning and automation, has demonstrated the potential to enhance trade execution speed and reduce market inefficiencies (Sendstad et al., 2021). However, concerns regarding the potential for market manipulation and the amplification of systemic risks remain prevalent, particularly as these technologies exacerbate volatility through rapid, high-volume trades (Quinn, 2019). The literature highlights that the over-reliance on algorithmic trading can contribute to flash crashes and liquidity shocks, which disproportionately affect retail investors and destabilise market structures (Wu, 2020).

Another transformative aspect of technological advancements in investment behaviour is the rise of blockchain technology and decentralised finance (DeFi) platforms. The adoption of blockchain in financial markets has introduced unprecedented levels of transparency, security, and transactional efficiency (Konovalova et al., 2019). Smart contracts, which automate and enforce contractual obligations, have facilitated seamless execution of trades without intermediary interventions, thereby reducing transaction costs (Zachariadis et al., 2019). However, scalability issues and regulatory ambiguities remain significant barriers to widespread blockchain adoption, with scholars emphasising the necessity of robust governance frameworks to mitigate associated risks (Guo & Xu, 2021).

The proliferation of mobile trading applications and digital investment platforms has further expanded market participation by enhancing accessibility for retail investors. The advent of user-friendly trading interfaces and commission-free brokerage models has significantly altered investment behaviour, encouraging higher trading frequency and speculative investment strategies (Kuriakose & Sajoy, 2022). Research suggests that while digital platforms empower investors with real-time market information and seamless trading functionalities, they also contribute to increased impulsive trading behaviour and heightened risk exposure (Kalda et al., 2021). This phenomenon aligns with behavioural finance theories, which suggest that ease of access and gamification elements in digital trading platforms can reinforce cognitive biases, such as recency effects and overreaction to short-term market fluctuations (Genz et al., 2019).

Technological advancements have also influenced investor sentiment and herding behaviour, particularly through the integration of social media analytics in investment decision-making (Krishnaprabha, 2024). The reliance on real-time financial news and sentiment analysis tools has enabled investors to react swiftly to market developments; however, it has also increased susceptibility to speculative trading driven by social contagion (Ahmad & Wu, 2022). Empirical studies indicate that investor sentiment, when amplified by algorithmic sentiment analysis, can lead to herding effects, exacerbating market inefficiencies and price distortions (Chartier et al., 2021). Consequently, while technology enhances informational efficiency, it also introduces behavioural vulnerabilities that warrant regulatory oversight and investor education initiatives (Shukla & Nerlekar, 2019).

The broader implications of technological innovations on investment behaviour extend to the evolving landscape of financial literacy and investor education. Digital financial literacy has emerged as a critical determinant of technology adoption in investment decision-making, influencing risk assessment capabilities and investment confidence (Hariyani & Saputra, 2023). In conclusion, technological advancements have profoundly influenced investment behaviour by enhancing market accessibility, efficiency, and decision-making processes. However, these innovations have also introduced new complexities, including cognitive biases, market volatility, and regulatory challenges. While AI, blockchain, and digital trading platforms offer substantial benefits, their impact on investor psychology and market stability necessitates continuous empirical evaluation and policy adaptation. Future research should focus on the intersection of technology and behavioural finance, exploring strategies to optimise investor outcomes while mitigating the unintended consequences of technological disruptions in financial markets.

2.8.5 Social Trading and Real-Time News Platforms in Investment Decisions

The proliferation of social trading platforms and real-time news dissemination mechanisms has fundamentally transformed contemporary financial markets, reshaping investor decision-making processes and altering traditional dynamics of market efficiency. Cookson and Niessner (2019) argue that digital platforms, such as Twitter, Reddit, and investment-focused communities like StockTwits, serve as critical conduits for real-time financial information, enabling retail investors to respond collectively to market movements. Unlike conventional financial news sources, these platforms offer immediate access to diverse investment perspectives and market sentiment, creating an environment where retail participation has a significant influence on stock valuations. Betzer and Harries (2022) further emphasise that investor sentiment generated within these digital ecosystems substantially impacts trading behaviour, particularly in volatile markets, as demonstrated by the surge in retail trading activity in speculative assets, such as meme stocks.

The accessibility and interactivity of social trading platforms facilitate a decentralised aggregation of investor sentiment, thereby shaping market expectations and stock liquidity. Jiao et. al (2020) suggest that these platforms function as alternative information hubs, where discourse among investors not only influences individual decision-making but also contributes to broader market sentiment. Nguyen et al. (2019) similarly highlight the role of social media in institutional investor decision-making, as customer sentiment on these platforms has been shown to affect firm valuation and investment performance. However, the unregulated nature of social media-driven financial discourse introduces significant risks, particularly regarding the proliferation of misinformation. Kogan et al. (2021) contend that fraudulent or misleading financial information on social media influences retail trading behaviour, often prompting investors to discount even legitimate news sources due to the prevalence of manipulative narratives. Jiang et al. (2018) further reinforce this perspective, indicating that unverified sentiment analysis on social media fosters herd-like behaviour, thereby disconnecting market prices from underlying fundamentals.

The influence of social media on financial decision-making extends beyond investor sentiment to the realm of algorithmic trading. Khan et al. (2019) demonstrate that integrating machine learning classifiers into financial forecasting models has significantly enhanced predictive accuracy, particularly when social media sentiment is incorporated as an input variable. Theodorou et al. (2021) corroborate these findings, showing that algorithmic trading models that leverage real-time social sentiment outperform conventional predictive frameworks. Valle-Cruz et al. (2021) further examine the feedback loop between investor sentiment and trading algorithms, emphasising how real-time information from social media interacts with automated trading strategies to reinforce market trends. The reliance on sentiment-based models for financial forecasting, however, raises concerns regarding market stability. Pelster and Breitmayer (2019) highlight that algorithmic responses to social sentiment can exacerbate volatility, necessitating regulatory interventions to mitigate the risk of speculative trading driven by short-term market sentiment.

The role of real-time news platforms in shaping investor behaviour is another critical dimension of this evolving landscape. Strauss and Smith (2019) illustrate that breaking financial news disseminated via social media often precedes traditional media coverage, creating an informational advantage for retail investors who actively monitor these platforms. Jin and Yu (2022) argue that the temporal discrepancy between social media-driven news dissemination and institutional media reporting enables rapid portfolio adjustments, offering opportunities for strategic trading. However, high-frequency trading strategies that integrate news sentiment analysis also contribute to market inefficiencies. Karn, Qiang, and Karna (2018) find that sentiment-driven high-frequency trading can lead to excessive short-term market fluctuations, reinforcing speculative price movements. Gulati et al. (2021) further assert that sentiment analysis of financial news headlines significantly improves the accuracy of stock movement predictions, particularly in volatile market conditions.

The convergence of social trading platforms and real-time financial news has also led to the formation of online investment communities, where collective decision-making significantly influences market behaviour. Reith et al. (2019) examine how social trading platforms, such as eToro, facilitate retail participation by providing access to expert trading strategies and financial advice. While this democratisation of investment knowledge lowers traditional barriers to market entry, it also fosters a reliance on herd behaviour. Glaser and Risius (2018) demonstrate that traders on social platforms exhibit a higher sensitivity to the disposition effect, as peer influence exacerbates confirmation bias and loss aversion. Dorfleitner and Scheckenbach (2022) extend this argument, suggesting that the interactive nature of social trading networks fosters information cascades, whereby investment decisions are increasingly driven by perceived consensus rather than fundamental analysis.

Market efficiency is another critical concern within this discourse. Ammann and Schaub (2021) argue that increased retail participation in social trading enhances market liquidity but simultaneously exacerbates short-term mispricing, particularly when sentiment-driven investment decisions diverge from an asset's intrinsic value. The GameStop trading phenomenon, examined by Kim et al. (2023), illustrates how coordinated retail investor activity on Reddit led to unprecedented price distortions that significantly deviated from fundamental valuations. Rothman and Yakar (2019) identify similar trends in cryptocurrency markets, where speculative sentiment, rather than traditional financial indicators, dictates price movements. Fan et al. (2020) further contend that sentiment-driven trading cycles, particularly in decentralised financial markets, necessitate an updated theoretical understanding of asset price formation in the digital era.

Regulatory challenges associated with social trading and real-time financial news platforms have garnered increasing attention in academic and policy discussions. Yang (2022) highlights the challenges of regulating decentralised trading communities, particularly given their ability to coordinate large-scale market movements without traditional oversight mechanisms. Gianstefani et al. (2022) emphasise the role of regulatory interventions in preventing fraudulent trading schemes, as evidenced by the increased scrutiny of social media-driven stock manipulation by financial authorities such as the SEC. Kogan et al. (2021) highlight the broader implications of algorithmically curated financial information, arguing that regulatory frameworks must account for the role of digital platforms in amplifying market sentiment and influencing investor decision-making.

The broader implications of these studies collectively highlight the transformative impact of social trading and real-time news dissemination on financial markets. Xu et al. (2020) argue that the shift from institutional-led market narratives to decentralised, sentiment-driven trading necessitates a revaluation of traditional investment frameworks. While social trading platforms and real-time news mechanisms have democratized access to market information, they have also introduced new complexities in investor behaviour, as speculative trading cycles increasingly diverge from rational expectations models. Armansyah et al. (2023) further assert that the integration of sentiment-based decision-making into financial markets raises fundamental questions regarding the sustainability of current market structures, particularly as digital platforms continue to shape investor sentiment in unpredictable ways.

As online financial communities grow in influence, the mechanisms through which they shape investment behaviour become increasingly complex. Ozturk and Bilgiç (2021) argue that while influential social media accounts drive investor sentiment, their actual impact on asset prices remains contingent on the extent to which they command trust and credibility within their networks. This distinction highlights the role of authority figures in financial discourse, where confident analysts and traders on platforms such as Twitter and Reddit effectively serve as informal market influencers. Clapham et al. (2021) suggest that investor attention plays a crucial role in algorithmic decision-making, as media sentiment —both traditional and social — directly affects the predictive power of trading models, particularly for small-cap stocks.

Beyond individual decision-making, social media fosters collective behaviours that have far-reaching implications for market efficiency and stability. Jin et al. (2021) emphasise that public scrutiny within social trading platforms creates a feedback loop in which investors modify their decisions based on peer evaluations, thereby reducing the disposition effect. However, the exact mechanisms that encourage rational decision-making also contribute to speculative herding. Erdos et al. (2022) observe that copy trading, where investors replicate the portfolios of successful traders, reinforces this tendency by amplifying collective decision-making at the expense of independent analysis. The impact of such trading strategies is particularly evident in cases where platform-based ranking systems elevate specific traders, thereby centralising investment flows around a limited number of high-visibility participants. These trends highlight the broader behavioural dynamics of online trading environments. Teplova et al. (2022) introduce the concept of a "hype indicator," a metric that quantifies attention-driven trading behaviour within retail investor networks. Their findings suggest that, in markets characterised by strong social influence, price movements become less reflective of fundamental value and more indicative of prevailing sentiment cycles. Pandey and Guillemette (2024) similarly demonstrate that meme stock trading is often driven more by social engagement than by financial acumen, with online discussions shaping investor perceptions regardless of the underlying asset's performance. This dynamic is further supported by Yang et. al (2024), who examine the spillover effect between social media sentiment and market volatility, revealing that sentiment-induced price fluctuations create self-reinforcing market cycles, particularly during periods of economic uncertainty.

The role of algorithmic trading in processing social sentiment remains a subject of extensive investigation. Paul and Vishnoi (2020) demonstrate how real-time sentiment analysis of news articles improves stock price forecasting, particularly when combined with machine learning models that can distinguish between transient market noise and substantive financial developments. Zou et al. (2022) extend this argument by demonstrating that neural networks trained on stock-specific news outperform conventional econometric models in predicting price trends. Kollintza-Kyriakoulia et al. (2018) further emphasise the importance of anomaly detection techniques in filtering out manipulative or misleading information from financial data streams, thereby reinforcing the necessity of integrating robust safeguards into sentiment-driven trading strategies.

Despite the advantages offered by these advancements, concerns regarding the broader implications of socially driven trading persist. Yang (2023) argues that investor trust in digital financial communities has been eroded by market disruptions, such as the GameStop short squeeze, where many retail investors suffered significant losses despite initially perceiving collective market power. Kamil and Tanno (2022) highlight that while social media reduces information asymmetry, corporate-driven narratives on these platforms often serve strategic public relations functions rather than facilitating genuine investor education. As a result, investment communities must navigate a complex informational landscape where distinguishing between authentic financial insights and promotional messaging is increasingly challenging.

Emerging regulatory discussions reflect these evolving concerns. Alomari et al. (2021) examine how regulatory bodies assess the role of social sentiment in influencing asset correlations, particularly in times of financial stress. Their findings suggest that regulatory oversight must account for the cyclical nature of sentiment-driven market shifts, as interventions aimed at mitigating volatility can sometimes exacerbate investor uncertainty. Rothman (2019) similarly identifies the necessity for policymakers to develop frameworks that distinguish between legitimate retail investor activity and coordinated market manipulation, particularly as decentralised financial ecosystems make traditional enforcement mechanisms less effective. Rumyantseva and Tarutko (2024) extend this perspective, advocating for platform-specific governance measures that strike a balance between transparency and the prevention of speculative trading excesses.

The increasing reliance on social networks for financial decision-making raises questions regarding the evolution of market structures. Lachana and Schroder (2021) argue that alternative media sources are becoming integral to understanding investor sentiment, as traditional financial reporting struggles to compete with the immediacy and breadth of social media engagement. Hao and Chen-Burger (2022) further emphasise that the real-time nature of social sentiment necessitates an updated theoretical framework for investment behaviour, where the diffusion of financial news occurs at an unprecedented pace. As digital investment platforms continue to evolve, their role in shaping long-term market trends remains an area of active inquiry.

The overarching implications of these studies reinforce the transformative nature of social trading and real-time news dissemination in financial markets. While these platforms have democratized access to investment information, they have also introduced significant complexities in investor psychology, market efficiency, and regulatory oversight. The convergence of retail investor sentiment, algorithmic trading, and digital media creates an environment where market outcomes are increasingly influenced by collective behavioural dynamics rather than traditional valuation principles. As financial ecosystems continue to adapt to this reality, future research must focus on developing predictive models that effectively integrate social sentiment analysis while ensuring market stability. The challenge remains to harness the benefits of these technological advancements while mitigating the risks posed by speculative trading cycles and information asymmetry.

2.8.6 The Role of Financial Analytics in Investment Decision-Making

Financial analytics has emerged as an essential component of modern investment decision-making, fundamentally reshaping how investors assess opportunities, manage risk, and optimise portfolio performance. The increasing reliance on data-driven strategies, supported by the integration of big data analytics, artificial intelligence, and machine learning, has enhanced predictive accuracy and improved risk assessment. While these advancements offer investors the ability to make more informed decisions, concerns regarding the reliability of AI-driven recommendations, the limitations of algorithmic models, and the role of human judgment remain critical issues. The theoretical foundation of financial analytics in investment decision-making is built on the premise that access to high-quality, structured financial data improves market efficiency and reduces information asymmetry. The extent to which financial analytics strengthens investment decisions depends on how effectively it integrates both quantitative and qualitative insights.

The significance of financial analytics in investment decision-making is evident in its ability to evaluate financial opportunities with greater precision. Ochuba et al. (2024) demonstrated that financial analytics in telecommunications investments provides structured frameworks for assessing project risks and financial viability, ensuring more accurate forecasting of investment returns. This perspective is consistent with the findings of Edan et al. (2022), who highlighted that in the banking sector, profitability indicators play a decisive role in shaping investment choices, while liquidity and capital adequacy hold less significance. The emphasis on profitability as a primary driver of investment decisions aligns with broader research that positions financial analytics as a tool for optimising capital allocation.

The introduction of advanced data analytics and computational techniques into financial decision-making has further transformed investment strategies. Hasan et al. (2020) explored how big data analytics strengthens risk analysis by identifying correlations among financial institutions and predicting volatility patterns, thereby improving risk-adjusted returns. C. Wang and Luo (2022) provided additional insights by demonstrating that machine learning algorithms, when integrated with FPGA technologies, significantly enhance investment strategies by refining data processing capabilities and generating more accurate predictions. These findings underscore the evolving nature of financial analytics, where the incorporation of sophisticated computational models enables a more nuanced interpretation of market trends. The importance of continuous portfolio monitoring in leveraging these advancements was further emphasised by Yadav and Banerji (2024), who noted that real-time analysis of financial assets is critical to aligning investment objectives with market conditions. The integration of machine learning in financial decision-making enhances the ability to anticipate and respond to market fluctuations. However, these advancements also necessitate a reassessment of the balance between automated decision-making and human expertise.

Despite its growing influence, concerns persist about the trustworthiness of AI-driven investment recommendations. Ahmed et al. (2022) argued that while AI models improve decision accuracy, investors with limited financial literacy may struggle to interpret and effectively utilise predictive insights. The necessity of integrating human oversight in financial analytics was further explored by R. B. Mitchell et al. (2020), who emphasised that nontechnical skills, such as critical thinking and contextual awareness, remain vital in analytics-based decision cultures. The need for a measured approach to AI adoption in investment decision-making was also reflected in the findings of Shaheen et al. (2022), who noted that while data-driven insights enhance market analysis, over-reliance on algorithmic recommendations without investor discretion can lead to misinterpretations and suboptimal decisions. These perspectives reinforce the argument that financial analytics must be accompanied by critical evaluation, ensuring that AI-generated insights are contextualised within broader financial and economic considerations.

Empirical studies on algorithmic forecasting provide further evidence of the impact of financial analytics on investment decision-making. Gupta and Shrivastava (2021) examined how financial risk tolerance mediates investment decisions, illustrating that while data-driven analytics enhances decision accuracy, individual investor psychology continues to shape final investment outcomes. This perspective aligns with D. Khan (2020), who explored cognitive biases in investment behaviour and suggested that financial analytics can mitigate irrational decision-making by providing objective, data-driven insights. Similarly, Butt (2023) demonstrated that while financial analytics improves investment decision-making, behavioural tendencies such as risk perception and herd mentality still influence investor choices. These findings highlight that while algorithmic forecasting contributes to greater market efficiency, the interaction between quantitative insights and investor behaviour remains a key determinant of investment outcomes.

The implications of financial analytics extend beyond individual investment decisions, influencing broader business strategies and organisational financial performance. Abdul-Azeez et al. (2024) examined the role of data-driven analytics in business decision-making and found that predictive and prescriptive analytics significantly enhance financial strategies. This perspective is echoed by Raji et al. (2024), who demonstrated that advanced analytics improve operational efficiency and optimise strategic planning in various industries, including finance. These studies suggest that the adoption of financial analytics benefits not only individual investors but also corporate entities seeking to enhance financial performance through data-driven decision-making.

The increasing integration of financial analytics into investment decision-making has also led to the incorporation of behavioural finance insights. Dewi (2024) examined neuro-finance and highlighted how cognitive processes influence financial decisions, emphasising the interplay between analytical reasoning and emotional responses.

Singhal et al. (2024) further explored investor psychology by analysing the impact of the Greed and Fear Index on market cycles, demonstrating that financial analytics can help investors manage emotional biases and make more rational decisions. These findings underscore that while financial analytics enhance investment precision, behavioural and psychological factors must be considered to understand market dynamics fully.

The growing reliance on financial analytics has undeniably transformed investment decision-making by improving predictive accuracy, refining risk assessment, and optimising portfolio management. However, concerns regarding the reliability of AI-driven investment recommendations remain relevant, necessitating a balanced approach that integrates both data analytics and investor judgment. The inclusion of behavioural finance insights further highlights the complexity of investment decision-making, emphasising that while financial analytics provides objective data, human interpretation remains a crucial element. As financial analytics continues to evolve, its role in shaping investment strategies and enhancing market efficiency will remain central, requiring continuous assessment of its applications, limitations, and broader economic implications.

2.8.7 Impact of Mobile Trading Apps and Discount Brokers on Investment Behaviour

The increasing accessibility of mobile trading applications and discount brokerage platforms has significantly reshaped investment behaviour, influencing decision-making patterns among retail investors. As mobile technology has become more integrated into financial markets, studies have examined its implications on trading frequency, risk-taking behaviour, and portfolio performance. Empirical evidence suggests that mobile trading apps facilitate ease of access and reduce time constraints, yet they simultaneously introduce biases such as trend chasing and overconfidence (Liu et al., 2024). This phenomenon results in higher trading volume and lower overall investment performance due to increased short-term speculation rather than long-term wealth accumulation.

Studies have consistently highlighted that mobile trading apps contribute to elevated risk-taking behaviours among investors. Research by Kalda et al. (2021) identified that mobile trading platforms encourage the purchase of lottery-type assets, amplifying exposure to volatile market segments. Similarly, Cen (2018) found that mobile trading increases investor attention but also exacerbates financial fragility, as investors become more sensitive to short-term returns. These insights align with the findings of Havakhor et al. (2021), who demonstrated that technology-enabled financial data access, such as API-based services, can lead to excessive trading due to overconfidence, resulting in lower predictive accuracy of trades. Consequently, while mobile trading apps provide accessibility and efficiency, they simultaneously alter investor decision-making, sometimes with adverse effects on portfolio stability.

The role of discount brokers in shaping investment behaviour has also been a subject of scrutiny. The rise of platforms like Zerodha and Groww in India has democratised access to the stock market, leading to increased participation among retail investors (Balodi et al., 2024). S. Yadav et al. (2022) noted that the affordability of discount brokerage services encourages more frequent transactions, which, while promoting financial inclusion, may lead to impulsive trading patterns. Moreover, the transition from traditional full-service brokers to low-cost digital alternatives has led to changes in investor expectations, with accessibility and cost efficiency taking precedence over personalised advisory services (Nair et al., 2022). This shift, while beneficial in broadening market access, has also raised concerns about financial literacy and informed decision-making, as retail investors may lack adequate guidance when executing trades.

Behavioural biases have been identified as critical factors in mobile trading environments, with studies demonstrating how these biases influence investor decision-making. Z. Li et al. (2022) found that mobile trading platforms reinforce herding behaviour, causing investors to react more strongly to market-wide movements rather than firm-specific information. Similarly, Itzkowitz et al. (2023) observed that investors engaging in micro-investing through trading apps tend to anchor on small initial purchases, limiting their long-term wealth accumulation. Furthermore, the gamification features of some mobile trading applications have been linked to addictive behaviours and excessive trading, drawing parallels to gambling tendencies (Grégoire et al., 2023). Oksanen et al. (2022) extended this discussion by demonstrating a strong correlation between high-frequency trading on mobile platforms and problem gambling tendencies, suggesting that ease of access can contribute to compulsive financial behaviours.

Security, data privacy, and regulatory concerns remain prominent in discussions regarding mobile trading platforms. Rakovic and Inal (2023) analysed how fintech applications utilise dark patterns to manipulate investor behaviour, raising ethical concerns regarding transparency and data protection. The rapid expansion of mobile financial services has prompted debates about the security risks associated with trading applications, particularly in light of cybersecurity threats and user data vulnerabilities (Taylor & Martinovic, 2017). The increasing reliance on mobile trading platforms necessitates stronger regulatory frameworks to mitigate the risks associated with unauthorised data access and unethical platform designs, ensuring that retail investors are protected from exploitative practices.

Additionally, the impact of mobile trading applications on financial market efficiency has been examined in numerous empirical studies. Stein (2020) demonstrated that mobile applications such as Robinhood significantly impact stock demand and price volatility, particularly among newly listed stocks. This aligns with findings by Jin et al. (2022), who observed that social trading features within mobile investment applications contribute to the disposition effect, where investors tend to sell winning stocks prematurely and hold onto losing ones. Similarly, Bank et al. (2024) found that social media-driven retail transactions facilitated by mobile trading apps introduce asymmetric volatility spillovers, further emphasising the complex interplay between technological accessibility and market dynamics.

The broader implications of mobile trading applications on financial literacy and long-term investment habits have also been examined. Research by L. Fan (2022) highlighted that mobile trading platforms disproportionately attract users with lower financial literacy, often leading to suboptimal trading decisions. This finding is consistent with those of Mu and Lee (2021), who demonstrated that digital financial services can enhance user engagement but require structured financial education to ensure responsible investing. While mobile trading platforms offer unprecedented access to financial markets, their long-term effectiveness in promoting informed investment habits remains contingent upon investor education and awareness.

The transformative role of mobile trading applications and discount brokers in modern financial markets underscores the need for a balanced approach to accessibility, regulation, and investor education. While these platforms have successfully expanded retail participation and democratized investment opportunities, they have also introduced new challenges related to behavioural biases, market volatility, and financial security. Future research should explore the development of regulatory mechanisms to enhance transparency in mobile trading, as well as initiatives aimed at improving financial literacy among retail investors. Addressing these concerns will be critical in ensuring that the benefits of digital trading technologies are maximised while minimising the risks associated with uninformed and impulsive investment behaviour.

2.8.8 Risk Perception and Psychological Factors in Technology-Based Investing

Risk perception in technology-based investing is primarily shaped by psychological biases, cognitive distortions, and investor sentiment, with financial literacy and trust serving as moderating factors. Several studies have demonstrated that overconfidence, herding behaviour, and the disposition effect influence investors' risk assessments, thereby affecting their decision-making processes. Almansour et al. (2023) argue that these behavioural biases, particularly in Saudi equity markets, significantly mediate the relationship between financial literacy and investment choices. Similarly, Gupta and Dey (2023) identify that perceived financial costs, information quality, and security concerns are crucial in shaping risk perception in mobile stock trading, underscoring the role of cognitive risk mitigation.

Mondal and Kumar (2024) emphasise that technology has reshaped financial decision-making by introducing complexities that alter risk perception. They highlight the paradox wherein technological advancements increase accessibility while simultaneously adding layers of psychological uncertainty. The interplay of automation bias, algorithm aversion, and trust in AI-driven systems is pivotal in understanding these effects. Koo (2024) demonstrates that algorithm aversion and investor emotions significantly impact reactions to AI disclosures, influencing risk perception and investment behaviours. This aligns with Al-Gasawneh et al. (2022), who find that perceived security and influencer endorsements moderate the adverse effects of risk perception on the adoption of AI-driven financial services.

The psychological mediation of risk perception is further evidenced in empirical analyses of fintech adoption. Kaban and Linata (2024) establish that herding and overconfidence biases indirectly influence investment decisions through risk perception among Gen Z investors in Indonesia. Similar findings are echoed by Kurnijanto et al. (2025), who identify that risk perception acts as a mediator between behavioural biases and investment decisions, reinforcing the importance of investor education in mitigating irrational choices. Further supporting this notion, Z. Ahmed et al. (2022) highlight that the disposition effect and blue-chip bias significantly shape investors' risk assessments, ultimately affecting their investment strategies.

Research also indicates that technology-based investment risks are often misperceived due to heuristic-driven biases. Sjoberg (2003) revisits the psychometric paradigm and argues that trust, knowledge limitations, and interest shape technology-related risk perceptions, often leading investors to miscalculate financial risks. This finding is consistent with Renn and Benighaus (2013), who highlight the role of media amplification in skewing risk assessments of technological investments, thereby creating asymmetries between perceived and actual risks. Similarly, Payzan-LeNestour and Woodford (2022) argue that investors adapt to prolonged exposure to volatility, leading to systematic underestimation of financial risks, which can distort asset pricing and exacerbate market inefficiencies.

Studies examining the role of cognitive and emotional biases in fintech adoption also provide critical insights into risk perception. Malik et al. (2024) argue that representativeness, availability, and regret aversion biases negatively affect investment decisions, with risk perception mediating these effects in Pakistan’s stock exchange, supporting this finding, as noted by L. Zhang et al. (2021) discuss how fintech innovations, such as robo-advisors and social trading platforms, reinforce biases like overconfidence and herding behaviour, while also introducing new challenges, including over-reliance on automated decision-making. This aligns with Daga and Yadav (2023), who demonstrate that risk perception partially mediates the relationship between prospect-driven biases and irrational investment choices, with robo-advisory moderating these effects.

The role of demographic variables in shaping risk perception has also been widely explored. Saivasan and Lokhande (2022) argue that risk perception is influenced by factors such as return expectations, loss aversion, and anchoring bias, which vary across different demographic traits. This is further reinforced by Helmina et al. (2023), who identify gender-based differences in risk-taking tendencies, with inexperienced male investors displaying higher risk-seeking behaviour compared to female investors, who prioritise security. Supporting these findings, Anifa and Soegiharto (2023) demonstrate that financial literacy moderates the impact of psychological biases on investment decisions, reinforcing the importance of education in mitigating the effects of cognitive distortions.

Meta-analytical evidence also supports the notion that psychological factors significantly influence risk perception in emerging financial technologies. C. Li and Li (2023) conducted a meta-analysis of 272 studies, concluding that trust, perceived benefits, and social influence exert significant effects on public risk perception regarding technological investments. These findings align with Huber et al. (2019), who experimentally demonstrate that lower perceived financial risk leads to higher asset prices, emphasising the impact of subjective risk evaluations on market behaviour. Similarly, Williams and Noyes (2007) argue that risk perception is shaped by the credibility of information sources, with financial advisors and media playing a crucial role in shaping investor attitudes.

Risk perception also influences investor preferences for alternative financial instruments. Paramita and Wirakusuma (2024) establish that overconfidence bias does not significantly affect risk perception among millennial investors, although financial literacy and investment experience moderate risk tolerance and decision-making processes. This contrasts with Wasiuzzaman et al. (2022), who find that perceived technological risk has a strong influence on Malaysian investors' willingness to engage in equity crowdfunding, highlighting the divergence in risk tolerance across different investment types. Supporting this, Ullah Khan et al. (2020) identify financial, performance, social, and privacy risks as key determinants of investor reluctance in electronic stock trading, reinforcing the necessity of mitigating perceived uncertainties in technology-driven financial markets.

Studies also suggest that psychological biases play a crucial role in determining investor behaviour in technology-based investing during periods of economic uncertainty. Kumar et al. (2024) highlight that risk perception significantly mediates the relationship between heuristics and investor performance, with gender acting as a moderating variable. This aligns with Zafar et al. (2024), who argue that financial risk perception negatively impacts investment behaviour, although psychological factors positively influence both risk assessment and decision-making. Furthermore, Anifa and Soegiharto (2023) demonstrate that herding and disposition effect biases positively influence risk perception, although overconfidence bias does not exhibit a significant relationship in fintech investment contexts.

The broader implications of these findings suggest that risk perception is not merely a cognitive construct but is deeply intertwined with investor psychology and decision-making heuristics. LeBlanc and Biddle (2012) argue that financial activities such as online banking and stock trading are perceived as high-risk. In contrast, non-financial digital activities are underestimated in terms of security threats, reflecting inconsistencies in risk evaluation processes. Similarly, Roca et al. (2010) demonstrate that perceived trust is a fundamental determinant of e-trading adoption, with higher perceived risk acting as a barrier to investor engagement. These findings are consistent with those of Holzmeister et al. (2020), who reveal that the probability of loss, rather than return distribution characteristics, serves as the dominant explanatory factor for risk perception among both financial professionals and laypeople.

The literature strongly supports the notion that psychological factors, cognitive biases, and external influences significantly shape risk perception in technology-based investing. Behavioural biases such as overconfidence, herding, and loss aversion mediate the relationship between perceived risk and investment choices, with demographic traits and financial literacy further moderating these effects. Fintech innovations introduce both opportunities and new psychological risks, particularly in the context of algorithmic trading and AI-driven decision-making. As demonstrated across multiple empirical studies, perceived and actual risks often diverge, necessitating investor education and regulatory interventions to address irrational risk assessments and promote informed decision-making in financial markets.

2.8.9 Cost Perception and Transactional Efficiency in Technology-Driven Investing

The cost-benefit analysis of digital investment platforms compared to traditional brokers remains a central concern in evaluating transactional efficiency in technology-driven investing. Ter Braak and Van Der Schans (2023) emphasised that technological advancements enable institutional investors to monitor and measure transaction costs effectively, thereby facilitating more effective cost control mechanisms. Similarly, Wagner (2006) discussed the role of compliance and transaction cost measurement in ensuring optimal investment management. While traditional brokers have historically offered personalised advisory services, the increased adoption of digital platforms has significantly reduced explicit costs associated with investing, improving overall cost efficiency (Capponi et al., 2021). However, Busse et al. (2017) noted that mutual fund performance can still be influenced by transaction costs, particularly in cases where funds deal with illiquid stocks.

Hidden costs, transaction fees, and subscription models of fintech tools further complicate the perception of costs in investment strategies. Cordella and Bonina (2012) argued that while information and communication technologies (ICTs) can reduce inefficiencies, they may also introduce additional transaction costs depending on how they are integrated into the investment process. Meanwhile, Hennart (1998) utilised transaction cost theory to assess new investment models, highlighting that these costs influence decision-making processes even in digital financial services. Similarly, Liubkina and Ihnatiuk (2023) examined how implicit transaction costs, such as market impact and missed opportunities, shape cost perception, ultimately affecting investor strategies.

The cost efficiency of high-frequency trading (HFT) has been widely debated in academic literature. Arbatskaya (2005) suggested that increasing transaction costs on one side of the market can lead to a more balanced and efficient trading environment, contradicting traditional assumptions that lower costs universally improve efficiency. Furthermore, Moorman (2014) investigated various methods to reduce transaction costs, finding that specific strategies, such as zero-cost momentum, significantly enhance risk-adjusted returns in algorithmic trading. Marshall et al. (2016) reinforced these findings by demonstrating that larger trades, particularly in small stocks, tend to incur lower transaction costs due to market structure advantages.

Multiple factors influence investors' perceptions of cost management. Buckley and Chapman (1997) suggested that managerial perceptions, rather than precise numerical calculations, significantly affect corporate efficiency, reinforcing the argument that perceived costs shape investment behaviour. In contrast, Rubin et al. (2025) explored the role of trust in speculative investments, concluding that trusting beliefs in technology-driven investments often outweigh direct cost considerations. Similarly, Gupta and Dey (2023) analysed how perceived financial costs moderate the relationship between risk perception and mobile stock trading adoption, further highlighting the psychological components influencing cost efficiency evaluations.

The perceived value of digital investment platforms also influences cost perception and transactional efficiency. Rahmantari et al. (2024) explored how investor motivations and behaviours on digital platforms are shaped by cost transparency, ease of use, and trust in platform reliability. Additionally, Wang (2015) examined how investment experience affects perceived value and purchase intentions, revealing that experienced investors rely more on cost-benefit analyses than novices, who may be more susceptible to heuristics and biases. These findings are further supported by Ikhsan and Yuniarty (2023), who identified sunk costs and inertia as significant factors in the continued use of stock investment applications.

A recurring theme in financial technology research is the role of transaction costs in market efficiency. Sperka and Spisak (2013) utilised agent-based simulation models to explore how transaction costs influence financial market stability, finding that cost structures can significantly alter trading behaviour. Meanwhile, Chung and Kissell (2016) demonstrated that integrating transaction cost analysis into portfolio optimisation can lead to superior net returns, reinforcing the need for cost-aware investment strategies.

The implications of cost perception extend beyond direct investment decisions to broader market structures. Oh et al. (2006) examined how investors' perceptions of transaction risks in IT outsourcing shape market reactions, emphasising the importance of cost transparency in technological investments. Meanwhile, Gursahani and Lichtenstein (2002) discussed the intersection of cash flow fundamentals and cost models in technology investing, highlighting the need for portfolio managers to consider firm-specific operational factors when evaluating investment opportunities. These insights align with the work of Kleist (2004), who explored the role of electronic trust in reducing transaction costs in digital commerce, demonstrating how technology-driven trust mechanisms enhance transactional efficiency.

The broader financial landscape continues to evolve with technological advancements that influence cost structures. Neale et al. (2024) examined how technology expenditures affect insurer efficiency, finding that while expensed technology enhances allocative efficiency, asset-classified technology may decrease overall cost efficiency. Similarly, Moro-Visconti and Cesaretti (2023) discussed the disruptive impact of fintech on financial services, emphasising cost reductions and improved service quality. Finally, Xie (2024) highlighted how financial technology reshapes traditional banking models by increasing efficiency and accessibility while simultaneously introducing new security and regulatory challenges.

Overall, the interplay between cost perception and transactional efficiency in technology-driven investing remains a complex phenomenon. While technology offers substantial cost-saving potential, inefficiencies persist due to limitations in market structure, behavioural biases, and regulatory constraints. Future research should focus on refining cost management strategies to strike a balance between efficiency gains and risk mitigation, thereby ensuring sustainable profitability in digital investment environments.

2.8.10 Attitudes Towards Technological Innovations in Investment

Technological innovations have significantly reshaped investment strategies, with artificial intelligence (AI), machine learning (ML), and blockchain influencing investor attitudes. The literature suggests that while these technologies offer efficiency and accessibility, concerns persist regarding data security, financial literacy, and ethical implications.

The increasing reliance on AI-driven financial services has sparked discussions on trust and investor sentiment. Singh et al. (2024) found that while 77.8% of financial professionals acknowledge AI, ML, and blockchain as transformative in investment strategies, 70% express concerns about data security, revealing a complex trust dynamic. Similarly, B. Singh and Kaunert (2024) emphasised that digital investment platforms democratise financial access, though regulatory complexities and information overload can impede trust. Bhatia et al. (2021) explored Indian investors' perceptions of robo-advisors, finding that while these tools enhance efficiency, users still prefer human oversight, highlighting the role of behavioural biases in AI acceptance.

The role of financial literacy is also crucial in shaping trust. Susanto et al. (2024) demonstrated that Gen Z investors' attitudes toward technological innovations in investment are highly influenced by their financial literacy. However, the study revealed that technological progress alone does not significantly impact their investment decisions, reinforcing the importance of educational interventions. Investor attitudes toward digital trading solutions depend on several psychological and structural factors. Sendstad and Chronopoulos (2020) found that risk aversion influences investment timing, as investors are hesitant to abandon traditional methods often delay adopting digital trading technologies.

Attitudinal variations are also evident in different markets. J. Kumar and Rani (2024) highlighted that while FinTech applications lower transaction costs and increase accessibility, trust issues remain prevalent due to potential data misuse and cybersecurity risks. Likewise, Rumyantseva and Tarutko (2023) suggested that investment platforms are key drivers of financial innovation, providing low entry barriers and rapid financing, though regulatory uncertainty continues to affect adoption rates.

Research in behavioural finance underscores the psychological dimensions influencing investment technology adoption. Akinwale and Kyari (2020) examined financial technology adoption in Nigeria, finding that perceived ease of use, usefulness, and social influence significantly shape user intentions. The relationship between technological adoption and investor sentiment was further analysed by X. Xu et al. (2019), who found that firms in high-technology sectors are more inclined to invest in innovation when investor sentiment is favourable. Aramonte and Carl (2021) expanded on this by suggesting that positive investor sentiment enhances corporate research and development (R&D) investments following periods of intense technological innovation.

In a cross-market study, Waliszewski (2020) demonstrated that the acceptance of AI-driven investment tools varies based on demographic factors, with younger investors and those in larger households being more open to digital trading platforms. These findings suggest that individual and cultural factors significantly influence financial technology adoption. Despite the benefits of AI in investment decision-making, ethical concerns remain a significant barrier to widespread adoption. Similarly, Orra et al. (2024) examined the dual nature of AI in financial markets, illustrating how AI can either enhance market efficiency or be exploited for manipulative practices. Further, Dietzmann et al. (2023) explored the impact of AI-based robo-advisory services on private banking, finding that while these tools improve client interactions and decision-making flexibility, they also pose risks of data misuse and reduced transparency. Shao et al. (2023) highlighted the regulatory challenges associated with

AI in finance, emphasising the need for strict governance frameworks to ensure ethical AI deployment.

Blockchain technology has also introduced ethical dilemmas. S. Chang and Shih (2018) analysed the integration of AI and blockchain in Taiwan's financial sector, noting that while these technologies enhance transaction efficiency and reduce costs, concerns about privacy and regulatory acceptance persist. Similarly, M. Anifa et al. (2022) suggested that while FinTech innovations have increased accessibility in financial services, regulatory challenges remain a significant hurdle in preventing financial discrimination and ensuring ethical compliance.

The literature highlights a growing acceptance of technological innovations in investment, with AI, ML, and blockchain offering enhanced efficiency, accessibility, and financial literacy. However, concerns regarding trust, regulatory complexities, and ethical dilemmas continue to influence investor attitudes. As financial markets increasingly integrate digital technologies, ensuring transparency, regulatory compliance, and investor education will be critical in fostering positive attitudes and long-term adoption of AI-driven investment solutions.

2.8.11Behavioural Intention and Actual Use of Technology in Stock Trading

The integration of technology into stock trading has revolutionized the investment landscape, making it more accessible, efficient, and data-driven. Retail investors now have access to real-time financial data, algorithmic trading tools, and mobile-based investment applications that streamline trading activities. However, while numerous studies explore the behavioural intention (BI) to use such technology, fewer investigate how BI translates into actual use (AU). Understanding this relationship is crucial for refining technology adoption models and enhancing fintech solutions that promote sustained investor engagement. This review synthesises empirical research on BI and AU in stock trading, focusing on the relationship between intention and use, habit formation, fintech reliance, digital financial literacy, and the long-term effects of fintech habit loops.

Various cognitive, emotional, and external factors influence the relationship between BI and AU in stock trading. Studies have highlighted that while BI serves as a predictor of AU, the actual transition from intent to action can be moderated by personal and environmental constraints. V et al. (2024) found that perceived usefulness, ease of use, and the benefits of technology significantly enhance online trading behaviour. Similarly, Amin et al. (2025) utilized the UTAUT2 model to explore the role of performance expectancy and risk perception in mobile trading app adoption among retail investors, concluding that positive expectations drive intention but external risks sometimes prevent actual engagement.

Conversely, some studies suggest that BI does not always translate into AU due to external constraints such as financial literacy, trust issues, and risk aversion. Fortagne et al. (2023) found that while trust, overconfidence, and financial knowledge significantly impact BI toward using neo-broker applications, actual engagement depends on broader economic awareness. These findings suggest that while BI is a necessary condition for adoption, it is not always sufficient to drive consistent AU in stock trading. Habit formation plays a crucial role in the continued adoption of fintech solutions in stock trading. Once investors integrate fintech applications into their trading routines, they are more likely to engage in consistent trading behaviour.

Nair et al. (2022) discovered that habit significantly influences the transition from BI to AU in mobile trading apps, emphasising the role of repeated exposure and ease of use. Similarly, Nainggolan and Handayani (2023) found that perceived ease of use and perceived behavioural control strongly predict fintech reliance among Indonesian investors, reinforcing the importance of user-friendly interfaces and confidence in technology. However, habit formation in fintech use can have both positive and negative consequences. Havakhor et al. (2024) found that excessive access to financial data led to overconfidence and gambling-like trading behaviour among retail investors. Their study demonstrated that following the shutdown of the Yahoo! Finance API, trading volumes decreased, indicating that easier access to financial data sometimes encourages excessive speculation rather than informed investment decisions. These findings highlight the need for fintech platforms to integrate features that promote responsible trading habits.

Digital financial literacy (DFL) plays a pivotal role in bridging the gap between BI and AU. Investors with higher DFL levels are more likely to sustain fintech adoption and avoid irrational trading behaviour. Miraz (2022) found that trust, social influence, and performance expectancy were key determinants of blockchain technology adoption among stock traders. Their study suggests that investors with higher blockchain literacy are more likely to transition from BI to AU. Similarly, S. U. Khan et al. (2020) examined electronic stock trading adoption in Pakistan and found that awareness-knowledge and perceived trust significantly influence BI, which then translates into AU. However, research also indicates that behavioural biases can sometimes override financial literacy in influencing trading decisions. Areiqat et al. (2019) argue that biases such as overconfidence, herding behaviour, and emotional trading often overshadow rational decision-making, leading to inconsistencies between BI and AU. This suggests that while improving financial literacy is important, fintech platforms should also incorporate behavioural interventions, such as nudges and risk alerts, to mitigate irrational trading patterns.

Research on fintech habit loops provides insights into how consistent investment behaviours are cultivated over time. Habit loops occur when fintech applications create repeated behavioural patterns, reinforcing investor engagement. Mahardhika and Zakiyah (2020) found that attitude, subjective norms, and perceived behavioural control significantly predict investment intention, which in turn influences actual stock trading behaviour. Similarly, Widyanto et al. (2020) demonstrated that trust, hedonic motivation, and social influence contribute to both initial fintech adoption and long-term use. Nonetheless, Cheng et al. (2018) emphasise that social capital and cognitive ability also play a role in determining whether fintech users maintain consistent trading behaviour. Their study found that investors with stronger financial networks and higher cognitive ability are more likely to stick to structured investment strategies rather than engage in impulsive trading. These findings highlight the need for more research into the long-term behavioural effects of fintech on investment consistency. The relationship between BI and AU in stock trading is complex, influenced by factors such as habit formation, digital financial literacy, and behavioural biases. While BI serves as a strong predictor of AU, external constraints such as risk aversion, trust issues, and overconfidence can moderate this transition. Empirical research suggests that fintech platforms should not only focus on enhancing user intention but also implement mechanisms that encourage responsible trading habits and financial education. By fostering fintech habit loops that reinforce positive investment behaviours, technology can play a crucial role in improving investor outcomes and financial market efficiency.

2.8.12 The Influence of Algorithmic Trading on Market Efficiency and Investor Behaviour

The rise of algorithmic trading has significantly transformed financial markets, altering market efficiency, liquidity, and investor behaviour. The integration of AI, machine learning, and high-frequency trading (HFT) has enabled faster price discovery, reduced bid-ask spreads, and improved market depth. However, concerns over market volatility, manipulation, and ethical dilemmas remain. In India, algorithmic trading has grown rapidly under regulatory oversight, while globally, its implications on retail and institutional investors continue to be debated.

Algorithmic trading has experienced a surge in India, primarily driven by the rapid development of fintech and supportive regulations. Studies have highlighted that India's financial markets have increasingly embraced HFT, with the National Stock Exchange (NSE) and Bombay Stock Exchange (BSE) integrating sophisticated trading systems. Dubey et al. (2021) noted that India's regulatory stance has been largely favourable, promoting market efficiency while balancing systemic risks. At the same time, Courdent and McClelland (2022) emphasised that India’s framework aligns with global best practices, incorporating safeguards against market manipulation and ensuring stability.

Regulators such as the Securities and Exchange Board of India (SEBI) have played a key role in defining policies that govern algorithmic trading. Prakash et al. (2024) observed that SEBI has mandated stringent risk management systems to prevent market disruptions caused by algorithmic traders. Furthermore, the introduction of real-time surveillance mechanisms has helped monitor algorithmic activities, reducing market manipulation risks. However, research by Chakrabarty and Pascual (2022) suggests that despite these regulations, the market remains susceptible to sudden liquidity withdrawal by algorithmic traders during high-volatility periods. HFT has fundamentally reshaped liquidity and volatility in global markets. Several studies have confirmed that HFT enhances liquidity by narrowing spreads and increasing order flow efficiency. Aman and Moriyasu (2022) found that in the Tokyo Stock Exchange, HFT contributed to deeper market liquidity and reduced bid-ask spreads. Similarly, Yuferova (2024) established that the introduction of algorithmic trading on the NYSE Hybrid Market led to improved price discovery and more efficient incorporation of order flow information.

However, concerns persist regarding volatility. Boehmer et al. (2020) pointed out that while HFT enhances liquidity in stable conditions, it can exacerbate short-term price swings during market stress. Hilbert and Darmon (2020) argued that algorithmic trading increases market complexity, leading to greater unpredictability in high-volatility scenarios. Supporting this claim, Bellia et al. (2024) demonstrated that during flash crashes, HFT often withdraws liquidity rather than stabilising the market, contributing to extreme price movements. Meanwhile, Nawn and Banerjee (2018) differentiated between proprietary algorithmic traders (PATs) and agency algorithmic traders (AATs), finding that PATs tend to provide liquidity during market stress, whereas AATs and non-algorithmic traders often withdraw. AI-driven trading systems have created both opportunities and challenges for retail investors. Research by Devan et al. (2023) indicated that machine learning models have enhanced market efficiency by improving decision-making accuracy and optimising order execution. Similarly, Barbopoulos et al. (2021) found that AI-driven trading has led to reduced price drift and improved market predictability, benefiting retail investors who rely on algorithmic strategies.

On the other hand, studies suggest that retail investors often struggle to compete with institutional algorithmic traders. W. Zhang et al. (2022) noted that HFT creates liquidity asymmetry, making it difficult for retail investors to execute trades at favourable prices. Similarly, Huang et al. (2024) found that algorithmic trading strategies that exploit short-term price inefficiencies often disadvantage smaller investors. In contrast, Pothumsetty (2020) argued that AI-driven trading platforms reduce human errors and improve execution speed, potentially levelling the playing field for retail investors.

A growing concern is the potential for AI-based trading to amplify speculative behaviours. Havakhor et al. (2021) observed that excessive data access in trading platforms can lead to gambling-like behaviours, particularly among inexperienced retail investors. Similarly, Manahov et al. (2018) noted that AI-driven strategies encourage rapid trading cycles, which may induce short-term speculation rather than long-term investment strategies. The rapid expansion of algorithmic trading has raised ethical concerns, particularly regarding market manipulation and the risks associated with flash crashes. Azzutti et al. (2021) warned that AI-powered trading systems, due to their "black-box" nature, can engage in manipulative practices such as spoofing and layering. Similarly, Raschner (2021) called for enhanced regulatory oversight to address the challenges of controlling algorithmic trading algorithms.

Flash crashes have become a significant risk in markets dominated by algorithmic trading. Dalko and Wang (2020) found that HFT exacerbates market manipulation by exploiting order flow patterns, often at the expense of fundamental price stability. Algorithmic trading also raises broader concerns about fairness and transparency. Elliott et al. (2024) emphasised that information asymmetry is heightened in markets with heavy algorithmic trading, reducing the effectiveness of traditional investment analysis. Similarly, Bilinski et al. (2020) found that algorithmic trading reduces analyst coverage and investment research production, leading to a potential degradation of market efficiency. As algorithmic trading continues to evolve, the role of regulatory interventions and technological advancements will shape its future impact on market efficiency and investor behaviour. Grindsted (2021) suggested that the increasing speed of transactions is connecting financial centers globally, necessitating coordinated regulatory responses. Similarly, Sadaf et al. (2021)

emphasised the need for dynamic regulatory frameworks, such as MiFID II, to manage the systemic risks posed by algorithmic trading.

The integration of AI in trading strategies is expected to grow further. Shawaqfeh (2025) pointed out that AI-powered algorithms are increasingly capable of identifying market anomalies, enhancing informational efficiency. However, concerns remain regarding the long-term impact on market fairness. Trippner and Jóźwicki (2021) argued that algorithmic trading does not consistently generate superior returns compared to passive investment strategies, suggesting that retail investors may need to focus on diversified investment approaches rather than relying on algorithmic trading. In conclusion, while algorithmic trading has undeniably improved market efficiency and liquidity, it also introduces volatility, potential manipulation, and challenges for retail investors. As financial markets continue to evolve, striking a balance between technological innovation and regulatory safeguards will be crucial to maintaining fair and efficient trading environments.

2.9 The Future of Technology in Stock Market Investing

Advancements in technology are expected to have a significant impact on the future of technology in stock market investing, as this sphere continues to evolve at an increasingly rapid pace. Emerging technologies may also enhance predictive power, risk management, and the provision of personalised investment recommendations to investors. The knowledge of investing is projected to grow with increased retail involvement, as more automation and integration of digital platforms will facilitate investment.

2.9.1 AI-Driven Advisory Services and Autonomous Trading

The increasing integration of artificial intelligence (AI) in stock market investing has led to the rise of AI-driven advisory services and autonomous trading. Research indicates that AI-based investment platforms are transforming stock market participation, enabling automated decision-making and improving portfolio performance (Sukharev, 2023). Machine learning techniques, including deep reinforcement learning and predictive analytics, have demonstrated their effectiveness in enhancing forecasting accuracy and optimising trade execution (Ansari et al., 2022). Furthermore, a comparative analysis of artificial intelligence methods suggests that trading robots utilising AI may surpass traditional investors in terms of market efficiency (Shamim, 2022).

To refine algorithmic trading models, researchers have developed deep learning algorithms that incorporate both historical price data and textual sentiment analysis to enhance market predictions (Ashtiani & Raahemi, 2023). AI-driven algorithms, such as Long Short-Term Memory (LSTM) networks, have demonstrated superior predictive accuracy compared to conventional financial models (Josey & Amrutha, 2024).

2.9.2 Blockchain and Smart Contracts: The Future of Decentralised Trading

Blockchain technology is transforming the financial landscape by promoting transparency, lowering transaction costs, and accelerating settlement processes. Sharma, Gupta, and Kapoor (2024) predict that decentralised exchanges and tokenisation will play a crucial role in making stock markets more accessible and efficient. Distributed ledger technology (DLT) further enhances financial security and enables efficient market functioning by reducing reliance on traditional intermediaries (Fox, Glosten, & Greene, 2022).

Additionally, the impact of blockchain on stock market investing is evident in its application to asset tokenisation, allowing fractional ownership and improved liquidity in global markets (Babu & Das, 2023). Furthermore, the potential synergy between quantum computing and blockchain has been explored, with studies indicating that quantum-resistant encryption could enhance security in blockchain-based stock trading systems (Chang et al., 2023).

2.9.3 The Role of Quantum Computing in Algorithmic Trading

Quantum computing has emerged as a transformative force in algorithmic trading, enabling financial models to process complex data structures with unprecedented speed. Research by Abushaqra (2024) introduces the Quantum Portfolio Rebalancing Algorithm (QPRA), which integrates AI and quantum computing to dynamically adjust portfolio weights, enhancing risk management and return optimisation. Similarly, Vandanapu et al. (2024) explore how quantum-inspired AI can optimise high-frequency trading strategies, significantly improving decision-making speed and fraud detection.

In the realm of financial risk management, quantum algorithms have demonstrated an ability to efficiently estimate Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR), addressing the computational challenges posed by high-dimensional financial derivatives (Wu, Wang, & Li, 2024). Additionally, quantum computing has been leveraged for high-frequency statistical arbitrage, significantly reducing algorithm complexity through quantum linear regression techniques (Yu-Chun & Guo, 2022). These findings underscore the immense potential of quantum computing in financial market applications, although scalability and practical implementation remain key hurdles.

2.9.4 Upcoming Fintech Innovations and Their Potential Impact on Indian Stock Markets

India's financial ecosystem is undergoing a technological revolution, driven by fintech innovations that are reshaping stock market investing. Studies indicate that digital trading platforms and algorithmic stock analysis have substantially increased retail investor participation in the Indian stock market (Kuriakose & Sajoy, 2022). Discount brokerage platforms utilising AI and machine learning are making investment services more cost-effective and accessible to a broader demographic (Yadav et al., 2022).

Moreover, fintech innovations such as robo-advisory services and AI-driven investment strategies are enhancing investor confidence and optimising decision-making processes. Quantum computing also presents opportunities for Indian stock markets, particularly in portfolio optimisation and fraud detection (Owolabi et al., 2024).

AI, blockchain, quantum computing, and fintech innovations shape the future of technology in stock market investing. AI-driven advisory services and deep learning models are refining market predictions and enhancing trade execution. Blockchain and smart contracts promise a more secure and transparent trading ecosystem, while quantum computing is poised to revolutionise algorithmic trading through advanced optimisation techniques. In the Indian stock market, fintech innovations are democratizing investment opportunities and improving accessibility. Despite regulatory and scalability challenges, these advancements signal a transformative shift in global financial markets, paving the way for a more efficient and technologically integrated investment landscape.

2.10 Research Gap

The integration of technological innovations in stock market investing has significantly altered investor behaviour, decision-making processes, and market efficiency. Artificial intelligence-driven analytics, algorithmic trading, blockchain technology, and mobile trading applications have reshaped investment strategies by enhancing accessibility, automation, and predictive accuracy. However, while these advancements offer substantial benefits, they also introduce concerns regarding irrational decision-making, over-reliance on automation, cybersecurity risks, and market volatility. The literature suggests that investors engage with these technologies without fully understanding their risks, leading to impulsive trading, algorithmic biases, and susceptibility to misinformation from social trading platforms and real-time news. Furthermore, while financial analytics and robo-advisory services provide data-driven insights, the extent to which investors critically assess automated recommendations remains unclear. Despite regulatory interventions and technological advancements aimed at improving transparency and efficiency, the evolving nature of digital finance necessitates further empirical research into how investors interact with these innovations in practice. Given the increasing reliance on fintech solutions, understanding the behavioural and psychological factors that drive investor adoption and risk perception is crucial for developing sustainable, technology-driven investment ecosystems.

Despite the growing body of research on technology adoption in financial markets, several gaps remain. First, while studies have examined the impact of AI and algorithmic trading on market efficiency, limited research explores how retail investors perceive and utilise these technologies in decision-making. Second, while social trading platforms and mobile trading applications have democratized market participation, their influence on risk-taking behaviour and financial literacy requires deeper investigation. Third, the role of behavioural biases in shaping investor responses to automated financial tools has not been sufficiently explored, particularly in emerging markets like India, where fintech adoption is rapidly expanding. Additionally, research on the ethical and regulatory challenges associated with algorithmic trading, blockchain-based investments, and decentralised finance remains fragmented. Most studies have examined single technologies in isolation. Despite existing research, gaps remain in understanding the impact of technological innovations on investment behaviour. Studies have focused on individual aspects such as algorithmic trading, robo-advisors, or blockchain technology. Few have analysed how a combination of tools influences investor behaviour. Social trading and news platforms received limited attention. This Study aims to fill these gaps and offer an applied view of fintech adoption in a real market context.

2.11 Conclusion

New technologies have transformed the landscape of stock market investments in terms of accessibility, automation and efficiency, but they introduce new behavioural, ethical, and regulatory challenges. The current literature draws attention to the opportunities and risks associated with AI, algorithmic trading, blockchain, and social trading platforms. However, some gaps still exist in understanding their influence on retail investor behaviour. There has been little focus on the interactions among technologies and how they affect decision-making, risk perception, and financial literacy in parallel. To bridge such gaps, the approaches of behavioural finance need to be combined with empirical studies, especially in such emerging economies as India, where fintech is rapidly growing.

Reference

Abdul-Azeez, N. O., Ihechere, N. a. O., & Idemudia, N. C. (2024). Transformational leadership in SMEs: Driving innovation, employee engagement, and business success. *World Journal of Advanced Research and Reviews*, *22*(3), 1894–1905. https://doi.org/10.30574/wjarr.2024.22.3.1888

Abdullah, E. M. E., Rahman, A. A., & Rahim, R. A. (2018). Adoption of financial technology (Fintech) in mutual fund/ unit trust investment among Malaysians: unified theory of acceptance and use of technology (UTAUT). *International Journal of Engineering & Technology*, *7*(2.29), 110. https://doi.org/10.14419/ijet.v7i2.29.13140

Abdullah, E. M. E., Rahman, A. A., & Yakob, R. (2024). The factor influencing the adoption of fintech in investment among Malaysians: A Unified Theory of Acceptance and Use of Technology (UTAUT) perspectives. *Journal of Advanced Research in Applied Sciences and Engineering Technology*, *49*(2), 231–247. https://doi.org/10.37934/araset.49.2.231247

Abushaqra, Mouhamad, Quantum Portfolio Rebalancing Algorithm (QPRA): An Integrating Quantum Computing and AI for Dynamic Portfolio Optimization (October 30, 2024). Available at SSRN: https://ssrn.com/abstract=5004146 or http://dx.doi.org/10.2139/ssrn.5004146

Addy, N. W. A., Ajayi-Nifise, N. a. O., Bello, N. B. G., Tula, N. S. T., Odeyemi, N. O., & Falaiye, N. T. (2024). Algorithmic Trading and AI: A Review of Strategies and Market impact. *World Journal of Advanced Engineering Technology and Sciences*, *11*(1), 258–267. https://doi.org/10.30574/wjaets.2024.11.1.0054

Ahmad, M., & Wu, Q. (2022). Does herding behavior matter in investment management and perceived market efficiency? Evidence from an emerging market. *Management Decision*, *60*(8), 2148–2173. https://doi.org/10.1108/md-07-2020-0867

Ahmed, S., Alshater, M. M., Ammari, A. E., & Hammami, H. (2022). Artificial intelligence and machine learning in finance: A bibliometric review. *Research in International Business and Finance*, *61*, 101646. https://doi.org/10.1016/j.ribaf.2022.101646

Ahmed, Z., Rasool, S., Saleem, Q., Khan, M. A., & Kanwal, S. (2022). Mediating role of risk perception between behavioral biases and investor's investment decisions. *SAGE Open*, *12*(2). https://doi.org/10.1177/21582440221097394

Al-Gasawneh, J. A., Alzubi, K. N., Hasan, M., Joudeh, J. M., Ahmad, A. M. K., & Ngah, A. H. (2022). IMPACT OF PRIVACY ON THE MARKETING PERFORMANCE. *Zenodo (CERN European Organization for Nuclear Research)*. https://doi.org/10.5281/zenodo.7451025

Almansour, B. Y., Elkrghli, S., & Almansour, A. Y. (2023). Behavioral finance factors and investment decisions: A mediating role of risk perception. *Cogent Economics & Finance*, *11*(2). https://doi.org/10.1080/23322039.2023.2239032

Alomari, M., Rababa'a, A. R. A., El-Nader, G., Alkhataybeh, A., & Rehman, M. U. (2021). Examining the effects of news and media sentiments on volatility and correlation: Evidence from the UK. *The Quarterly Review of Economics and Finance*, *82*, 280–297. https://doi.org/10.1016/j.qref.2021.09.013

Aman, H., & Moriyasu, H. (2022). Effect of corporate disclosure and press media on market liquidity: Evidence from Japan. *International Review of Financial Analysis*, *82*, 102167. https://doi.org/10.1016/j.irfa.2022.102167

Amin, N. I. U., Bhat, N. I. H., Itoo, R. A., & Jan, A. (2025). Behavioural intention to adopt mobile trading apps: an integrated theoretical and digital framework, privacy concerns, and information richness model. *Sri Lanka Journal of Social Sciences*, *47*(02), 123–144. https://doi.org/10.4038/sljss.v47i02.8945

Ammann, M., & Schaub, N. (2020). Do individual investors trade on Investment-Related internet postings? *Management Science*, *67*(9), 5679–5702. https://doi.org/10.1287/mnsc.2020.3733

Anifa, A. S., & Soegiharto, S. (2023). Does the psychology of investment decisions depend on risk perception and financial literacy? *MAKSIMUM*, *13*(2), 152. https://doi.org/10.26714/mki.13.2.2023.152-163

Anifa, M., Ramakrishnan, S., Joghee, S., Kabiraj, S., & Bishnoi, M. M. (2022). Fintech innovations in the financial service industry. *Journal of Risk and Financial Management*, *15*(7), 287. https://doi.org/10.3390/jrfm15070287

Ansari, Y., Yasmin, S., Naz, S., Zaffar, H., Ali, Z., Moon, J., & Rho, S. (2022). A Deep Reinforcement Learning-Based decision support system for automated stock market trading. *IEEE Access*, *10*, 127469–127501. https://doi.org/10.1109/access.2022.3226629

Aramonte, S., & Carl, M. (2021). *BIS Working Papers No 916 Firm-Level R&D after Periods of Intense Technological Innovation: The Role of Investor Sentiment, Bank for International Settlements*.

Arbatskaya, M. (2005). An efficiency argument for balanced transaction costs. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.782340

Areiqat, A. Y., Abu-Rumman, A., Al-Alani, Y. S., & Alhorani, A. (2019). Impact of Behavioral finance on stock investment Decisions Applied Study on a sample of investors at Amman Stock Exchange. *Academy of Accounting and Financial Studies Journal*, *23*(2), 1. https://www.abacademies.org/articles/Impact-of-Behavioral-Finance-On-Stock-Investment-Decisions-1528-2635-23-2-375.pdf

Armansyah, R. F., Ardianto, H., & Rithmaya, C. L. (2023). UNDERSTANDING GEN Z INVESTMENT DECISIONS: CAPITAL MARKET LITERACY AND EMOTIONAL BIASES. *Jurnal Manajemen Dan Kewirausahaan*, *25*(2), 105–119. https://doi.org/10.9744/jmk.25.2.105-119

Ashtiani, M. N., & Raahemi, B. (2023). News-based intelligent prediction of financial markets using text mining and machine learning: A systematic literature review. *Expert Systems With Applications*, *217*, 119509. https://doi.org/10.1016/j.eswa.2023.119509

Atwal, G., & Bryson, D. (2021). Antecedents of intention to adopt artificial intelligence services by consumers in personal financial investing. *Strategic Change*, *30*(3), 293–298. https://doi.org/10.1002/jsc.2412

Azzutti, A., Ringe, W. G., & Stiehl, H. S. (2021). Machine learning, market manipulation, and collusion on capital markets: Why the" black box" matters. *U. Pa. J. Int'l L.*, *43*, 79.

Babu, C. V. S., & Das, S. (2023). Impact of blockchain technology on the stock market. In *Advances in finance, accounting, and economics book series* (pp. 44–59). https://doi.org/10.4018/978-1-6684-8624-5.ch004

Balodi, K. C., Raizada, A., & Datta, S. (2024). Trading war: Evolving landscape of discount brokerage in India. *Journal of Information Technology Teaching Cases*. https://doi.org/10.1177/20438869241240492

Bank, S., Abdioglu, Z., & Kahraman, E. (2024). Asymmetric and nonlinear comovements of credit default swap and bond markets: evidence from an emerging market. *Spanish Journal of Finance and Accounting / Revista Española De Financiación Y Contabilidad*, *53*(2), 232–253. https://doi.org/10.1080/02102412.2023.2218182

Barbopoulos, L. G., Dai, R., Putniņš, T. J., & Saunders, A. (2021). Market efficiency in the age of machine learning.

Bartlett, R., Morse, A., Stanton, R., & Wallace, N. (2021). Consumer-lending discrimination in the FinTech Era. *Journal of Financial Economics*, *143*(1), 30–56. https://doi.org/10.1016/j.jfineco.2021.05.047

Batra, V. (2024). What is the impact of financial literacy on individual investment behaviour and wealth accumulation? *IOSR Journal of Business and Management*, *26*(12), 24–33. https://doi.org/10.9790/487x-2612142433

Bellia, M., Pelizzon, L., Subrahmanyam, M. G., Uno, J., & Yuferova, D. (2024). Low-Latency Trading and Price Discovery: Evidence from the Tokyo Stock Exchange in the Pre-Opening and Opening Periods. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2841242

Betzer, A., & Harries, J. P. (2022). How online discussion board activity affects stock trading: the case of GameStop. *Financial Markets and Portfolio Management*, *36*(4), 443–472. https://doi.org/10.1007/s11408-022-00407-w

Bhatia, A., Chandani, A., Atiq, R., Mehta, M., & Divekar, R. (2021). Artificial intelligence in financial services: a qualitative research to discover robo-advisory services. *Qualitative Research in Financial Markets*, *13*(5), 632–654. https://doi.org/10.1108/qrfm-10-2020-0199

Bhatia, A., Chandani, A., Divekar, R., Mehta, M., & Vijay, N. (2021). Digital innovation in wealth management landscape: the moderating role of robo advisors in behavioural biases and investment decision-making. *International Journal of Innovation Science*, *14*(3/4), 693–712. https://doi.org/10.1108/ijis-10-2020-0245

Bilinski, P., Karamanou, I., Kopita, A., & Panayides, M. A. (2020). Does algorithmic trading affect analyst research production? *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3597356

Boehmer, E., Fong, K., & Wu, J. (2020). Algorithmic trading and market quality: international evidence. *Journal of Financial and Quantitative Analysis*, *56*(8), 2659–2688. https://doi.org/10.1017/s0022109020000782

Bradford, P. G., & Miranti, P. J. (2014). Technology and Learning: Automating Odd-Lot trading at the New York Stock Exchange, 1958–1976. *Technology and Culture*, *55*(4), 850–879. https://doi.org/10.1353/tech.2014.0128

Breitmayer, B., Massari, F., & Pelster, M. (2019). Swarm intelligence? Stock opinions of the crowd and stock returns. *International Review of Economics & Finance*, *64*, 443–464. https://doi.org/10.1016/j.iref.2019.08.006

Buckley, P. J., & Chapman, M. (1997). The use of native categories in management research. *British Journal of Management*, *8*(4), 283–299. https://doi.org/10.1111/1467-8551.00066

Bunkar, B., & Ramaiah, K. (2024). A serial mediation model for investigating the intention to use algorithmic trading platforms among retail investors in India. *Vilakshan – XIMB Journal of Management*. https://doi.org/10.1108/xjm-12-2023-0233

Busse, J., Jiang, L., & Tang, Y. (2017). Double-adjusted mutual fund performance. *Emory University, Tsinghua University, and University of Florida Working Paper*.

Butt, J. (2023, December 31). *Comparative analysis of regulatory approach and management practice for digital Crypto-Currency and the role of IFIs in developing global regulations*. https://www.dj.univ-danubius.ro/index.php/JAM/article/view/2586

Capponi, A., Olafsson, S., & Zariphopoulou, T. (2021). Personalized Robo-Advising: Enhancing investment through client interaction. *Management Science*, *68*(4), 2485–2512. https://doi.org/10.1287/mnsc.2021.4014

Cen, X. (2018). Going mobile, investor behavior, and financial fragility. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3424405

Chakrabarty, B., & Pascual, R. (2022). Stock liquidity and algorithmic market making during the COVID-19 crisis. *Journal of Banking & Finance*, *147*, 106415. https://doi.org/10.1016/j.jbankfin.2022.106415

Chang, S. E., & Wang, M. (2023). Blockchain-Enabled Fintech Innovation: a case of reengineering stock trading services. *IEEE Access*, *11*, 137125–137137. https://doi.org/10.1109/access.2023.3339570

Chang, S., & Shih, C. (2018). The Influence and Application of Artificial Intelligence &Blockchain on Financial Service. *HOLISTICA – Journal of Business and Public Administration*, *9*(3), 45–54. https://doi.org/10.2478/hjbpa-2018-0022

Chartier, E., Bowden, I., Pinkerton, M., & Townley, A. (2021). Behavioral Finance: The impact of artificial intelligence and social media analytics. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3794039

Cheng, Y., Mutuc, E. B., Tsai, F., Lu, K., & Lin, C. (2018). Social capital and stock market participation via Technologies: the role of households' risk attitude and cognitive ability. *Sustainability*, *10*(6), 1904. https://doi.org/10.3390/su10061904

Chin, W. W. (2009). How to write up and report PLS analyses. In *Springer eBooks* (pp. 655–690). https://doi.org/10.1007/978-3-540-32827-8_29

Chong, L., Ong, H., & Tan, S. (2021). Acceptability of mobile stock trading application: A study of young investors in Malaysia. *Technology in Society*, *64*, 101497. https://doi.org/10.1016/j.techsoc.2020.101497

Chung, G., & Kissell, R. (2016). An application of transaction cost in the portfolio optimization process. *The Journal of Trading*, *11*(2), 11–20. https://doi.org/10.3905/jot.2016.11.2.011

Claessens, S., Frost, J., Turner, G., & Zhu, F. (2018). Fintech credit markets around the world: size, drivers and policy issues. *SSRN Electronic Journal*. https://papers.ssrn.com/sol3/Delivery.cfm/SSRN_ID3288096_code468680.pdf?abstractid=3288096&mirid=1

Clapham, B., Siering, M., & Gomber, P. (2021). Popular news are relevant news! How investor attention affects algorithmic Decision-Making and decision support in financial markets. *Information Systems Frontiers*. https://doi.org/10.1007/s10796-019-09950-w

Cookson, J. A., & Niessner, M. (2019). Why Don't We Agree? Evidence from a Social Network of Investors. *The Journal of Finance*, *75*(1), 173–228. https://doi.org/10.1111/jofi.12852

Cordella, A., & Bonina, C. M. (2012). A public value perspective for ICT enabled public sector reforms: A theoretical reflection. *Government Information Quarterly*, *29*(4), 512–520. https://doi.org/10.1016/j.giq.2012.03.004

Cornelli, G., Frost, J., Gambacorta, L., Rau, P. R., Wardrop, R., & Ziegler, T. (2022). Fintech and big tech credit: Drivers of the growth of digital lending. *Journal of Banking & Finance*, *148*, 106742. https://doi.org/10.1016/j.jbankfin.2022.106742

Courdent, A., & McClelland, D. (2022). The impact of algorithmic trading on market quality: Evidence from the Johannesburg Stock Exchange. *Investment Analysts Journal*, *51*(3), 157–171. https://doi.org/10.1080/10293523.2022.2090056

Cucculelli, M., & Recanatini, M. (2022). Distributed Ledger technology systems in securities post-trading services. Evidence from European global systemic banks. *European Journal of Finance*, *28*(2), 195–218. https://doi.org/10.1080/1351847x.2021.1921002

Dalko, V., & Wang, M. H. (2020). High-frequency trading: Order-based innovation or manipulation? *Journal of Banking Regulation*, *21*(4), 289–298. https://doi.org/10.1057/s41261-019-00115-y

Daga, S., & Yadav, K. (2023). Impact of Firm Specific Factors on the Indian Stock Returns: A Panel Data Approach. *IPE Journal of Management*, *13*(1), 17-28.

Dangkeng, N. A., & Munir, N. R. (2025). Fintech and Financial Inclusion: How Digital Payment Systems Empower Small Entrepreneurs. *Journal of Indonesian Scholars for Social Research*, *5*(1), 46–55. https://doi.org/10.59065/jissr.v5i1.172

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319. https://doi.org/10.2307/249008

Demir, A., Pesqué-Cela, V., Altunbas, Y., & Murinde, V. (2020). Fintech, financial inclusion and income inequality: a quantile regression approach. *European Journal of Finance*, *28*(1), 86–107. https://doi.org/10.1080/1351847x.2020.1772335

Devan, M., Thirunavukkarasu, K., & Shanmugam, L. (2023). Algorithmic Trading Strategies: Real-Time Data Analytics with Machine Learning. *Journal of Knowledge Learning and Science Technology ISSN 2959-6386 (Online)*, *2*(3), 522–546. https://doi.org/10.60087/jklst.vol2.n3.p546

Dewi, A. S. (2024). Neurofinance: Decoding the Brain′s Role in Investment Decision-Making. In *Elsevier eBooks*. https://doi.org/10.1016/b978-0-443-13701-3.00226-7

Di Maggio, M., & Yao, V. (2020). Fintech borrowers: Lax screening or Cream-Skimming? *Review of Financial Studies*, *34*(10), 4565–4618. https://doi.org/10.1093/rfs/hhaa142

Dietzmann, C., Jaeggi, T., & Alt, R. (2023). Implications of AI-based robo-advisory for private banking investment advisory. *Journal of Electronic Business & Digital Economics*, *2*(1), 3–23. https://doi.org/10.1108/jebde-09-2022-0037

Dorfleitner, G., Fischer, L., Lung, C., Willmertinger, P., Stang, N., & Dietrich, N. (2018). To follow or not to follow – An empirical analysis of the returns of actors on social trading platforms. *The Quarterly Review of Economics and Finance*, *70*, 160–171. https://doi.org/10.1016/j.qref.2018.04.009

Dorfleitner, G., & Scheckenbach, I. (2022). Trading activity on social trading platforms – a behavioral approach*. *The Journal of Risk Finance*, *23*(1), 32–54. https://doi.org/10.1108/jrf-11-2020-0230

Eden, L., Miller, S. R., Khan, S., Weiner, R. J., & Li, D. (2022). The event study in international business research: Opportunities, challenges, and practical solutions. *Journal of International Business Studies*, *53*(5), 803–817. https://doi.org/10.1057/s41267-022-00509-7

Elliott, T., Fatemi, D., Kim, J., & Su, Q. (2024). The Impact of Terrorism on Liquidity and Information Asymmetry: Evidence from Non-U.S. Stocks Listed on the NYSE. *Defence and Peace Economics*, 1–17. https://doi.org/10.1080/10242694.2024.2332168

Erdos, S., Papp, T., & Vörös, Z. (2022). The effects of community-based signals on investment decisions in copy trading. *Journal of Behavioral and Experimental Economics*, *97*, 101847. https://doi.org/10.1016/j.socec.2022.101847

Fan, L. (2022). Mobile investment technology adoption among investors. *International Journal of Bank Marketing*, *40*(1), 50–67. https://doi.org/10.1108/ijbm-11-2020-0551

Fan, R., Talavera, O., & Tran, V. (2020). Social media, political uncertainty, and stock markets. *Review of Quantitative Finance and Accounting*, *55*(3), 1137–1153. https://doi.org/10.1007/s11156-020-00870-4

Fassott, G., Henseler, J., & Coelho, P. S. (2016). Testing moderating effects in PLS path models with composite variables. *Industrial Management & Data Systems*, *116*(9), 1887–1900. https://doi.org/10.1108/imds-06-2016-0248

Filimonov, V., & Sornette, D. (2012). Quantifying reflexivity in financial markets: Toward a prediction of flash crashes. *Physical Review E*, *85*(5). https://doi.org/10.1103/physreve.85.056108

Flavián, C., Pérez-Rueda, A., Belanche, D., & Casaló, L. V. (2021). Intention to use analytical artificial intelligence (AI) in services – the effect of technology readiness and awareness. *Journal of Service Management*, *33*(2), 293–320. https://doi.org/10.1108/josm-10-2020-0378

Fortagne, M. A., Reith, R., Nguyen, K., & Lis, B. (2023). Technology acceptance of Neo-Broker Applications: An Empirical investigation. *International Journal of Innovation and Technology Management*, *20*(05). https://doi.org/10.1142/s0219877023500293

Fouillet, C., Guérin, I., & Servet, J. (2021). Demonetization and digitalization: The Indian government's hidden agenda. *Telecommunications Policy*, *45*(2), 102079. https://doi.org/10.1016/j.telpol.2020.102079

Fox, Merritt B. and Glosten, Lawrence R. and Greene, Edward and Guan, Sue, Distributed Ledger Technology and the Securities Markets of the Future: A Stakeholder Survey (July 15, 2021). Columbia Business Law Review, Vol. 2021, No. 2, 2021, Columbia Law and Economics Working Paper Forthcoming, European Corporate Governance Institute - Law Working Paper Forthcoming, Available at SSRN: https://ssrn.com/abstract=4002689

Froot, K. A., O'Connell, P. G., & Seasholes, M. S. (2001). The portfolio flows of international investors. *Journal of Financial Economics*, *59*(2), 151–193. https://doi.org/10.1016/s0304-405x(00)00084-2

Fu, J., & Mishra, M. (2021). Fintech in the time of COVID−19: Technological adoption during crises. *Journal of Financial Intermediation*, *50*, 100945. https://doi.org/10.1016/j.jfi.2021.100945

Genz, S., Janser, M., & Lehmer, F. (2019). The Impact of Investments in New Digital Technologies on Wages – Worker-Level Evidence from Germany. *Jahrbücher Für Nationalökonomie Und Statistik*, *239*(3), 483–521. https://doi.org/10.1515/jbnst-2017-0161

Gianstefani, I., Longo, L., & Riccaboni, M. (2022). The echo chamber effect resounds on financial markets: a social media alert system for meme stocks. *arXiv (Cornell University)*. https://doi.org/10.48550/arxiv.2203.13790

Giglio, S., Maggiori, M., Stroebel, J., & Utkus, S. (2021). Five Facts about Beliefs and Portfolios. *American Economic Review*, *111*(5), 1481–1522. https://doi.org/10.1257/aer.20200243

Glaser, F., & Risius, M. (2018). Effects of transparency: Analyzing social biases on trader performance in social trading. *Journal of Information Technology*, *33*(1), 19–30. https://doi.org/10.1057/s41265-016-0028-0

Gomber, P., Kauffman, R. J., Parker, C., & Weber, B. W. (2018). On the Fintech Revolution: Interpreting the Forces of Innovation, Disruption, and Transformation in Financial Services. *Journal of Management Information Systems*, *35*(1), 220–265. https://doi.org/10.1080/07421222.2018.1440766

Gregoire, P., Dixon, M. R., Giroux, I., Jacques, C., Goulet, A., Eaves, J., & Sévigny, S. (2023). Gambling on the stock market: the behavior of at-risk online traders. *Review of Behavioral Finance*, *16*(2), 205–222. https://doi.org/10.1108/rbf-05-2022-0143

Grindsted, T. S. (2021). Algorithmic Finance: Algorithmic Trading across Speculative Time-Spaces. *Annals of the American Association of Geographers*, *112*(5), 1390–1402. https://doi.org/10.1080/24694452.2021.1963658

Guild, J. (2017, August 18). *Fintech and the future of finance*. Guild, James, Fintech and the Future of Finance (August 18, 2017). Asian Journal of Public Affairs, 2017 , Lee Kuan Yew School of Public Policy Research Paper. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3021684

Gulati, K., Kumar, S. S., Boddu, R. S. K., Sarvakar, K., Sharma, D. K., & Nomani, M. (2021). Comparative analysis of machine learning-based classification models using sentiment classification of tweets related to COVID-19 pandemic. *Materials Today Proceedings*, *51*, 38–41. https://doi.org/10.1016/j.matpr.2021.04.364

Gupta, S., & Dey, D. K. (2023). Risk perception and adoption of digital innovation in mobile stock trading. *Journal of Consumer Behaviour*, *23*(2), 639–654. https://doi.org/10.1002/cb.2225

Gupta, S., & Shrivastava, M. (2021). Herding and loss aversion in stock markets: mediating role of fear of missing out (FOMO) in retail investors. *International Journal of Emerging Markets*, *17*(7), 1720–1737. https://doi.org/10.1108/ijoem-08-2020-0933

Gursahani, W. R., & Lichtenstein, N. E. (2002). Technology Investing: A Buy-Side Perspective. *The Journal of Investing*, *11*(1), 84-93.

Hair, Joseph F. and Ringle, Christian M. and Sarstedt, Marko, The Use of Partial Least Squares (PLS) to Address Marketing Management Topics (March 15, 2011). Journal of Marketing Theory and Practice, Volume 19, Issue 2, pp. 135-138, Spring 2011, Available at SSRN: https://ssrn.com/abstract=2228902

Hao, Z., & Chen-Burger, Y. J. (2022). An Investigation into Influences of Tweet Sentiments on Stock Market Movements. In *Smart innovation, systems and technologies* (pp. 87–97). https://doi.org/10.1007/978-981-19-3359-2_8

Hariyani, D. S., Ayuningdiah, M. R., & Saputra, A. (2023). The influence of financial technology, financial literacy and financial efficacy on student’s interest in investing. *Business Management Analysis Journal (BMAJ)*, *6*(1), 22–37. https://doi.org/10.24176/bmaj.v6i1.8572

Hasan, M. M., Popp, J., & Oláh, J. (2020). Current landscape and influence of big data on finance. *Journal of Big Data*, *7*(1). https://doi.org/10.1186/s40537-020-00291-z

Havakhor, T., Rahman, M. S., Zhang, T., & Zhu, C. (2021). Not Knowing What to Do With or Without Machine Intelligence: Evidence from a Natural

Experiment Involving Retail Investors. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3434812

Havakhor, T., Rahman, M. S., Zhang, T., & Zhu, C. (2024). Tech-Enabled financial data access, retail investors, and Gambling-Like behavior in the stock market. *Management Science*. https://doi.org/10.1287/mnsc.2021.01379

Helmina, M. R. A., Rosari, N., Yusniar, M. W., & Utaminingsih, N. S. (2023). Mind Matters in Investments: Unveiling the Psychological Forces Shaping Decision Making Behavior. *JDM (Jurnal Dinamika Manajemen)*, *14*(2), 273-285.

Hendershott, T., & Riordan, R. (2013). Algorithmic trading and the market for liquidity. *Journal of Financial and Quantitative Analysis*, *48*(4), 1001–1024. https://doi.org/10.1017/s0022109013000471

Hennart, J. F. (1998). Transaction-Cost Theory and the Free-Standing Firm. In *Oxford University Press eBooks* (pp. 65–98). https://doi.org/10.1093/oso/9780198290322.003.0009

Henseler, J., & Schuberth, F. (2020). Using confirmatory composite analysis to assess emergent variables in business research. *Journal of Business Research*, *120*, 147–156. https://doi.org/10.1016/j.jbusres.2020.07.026

Heredia, J., Castillo-Vergara, M., Geldes, C., Gamarra, F. M. C., Flores, A., & Heredia, W. (2022). How do digital capabilities affect firm performance? The mediating role of technological capabilities in the "new normal." *Journal of Innovation & Knowledge*, *7*(2), 100171. https://doi.org/10.1016/j.jik.2022.100171

Hilbert, M., & Darmon, D. (2020). How Complexity and Uncertainty Grew with Algorithmic Trading. *Entropy*, *22*(5), 499. https://doi.org/10.3390/e22050499

Holzmeister, F., Huber, J., Kirchler, M., Lindner, F., Weitzel, U., & Zeisberger, S. (2020). What Drives Risk Perception? A Global Survey with Financial

Professionals and Laypeople. *Management Science*, *66*(9), 3977–4002. https://doi.org/10.1287/mnsc.2019.3526

Hossnofsky, V., & Junge, S. (2019). Does the market reward digitalization efforts? Evidence from securities analysts' investment recommendations. *Journal of Business Economics*, *89*(8–9), 965–994. https://doi.org/10.1007/s11573-019-00949-y

Howell, S. T., Niessner, M., & Yermack, D. (2019). Initial Coin Offerings: Financing Growth with Cryptocurrency Token Sales. *Review of Financial Studies*, *33*(9), 3925–3974. https://doi.org/10.1093/rfs/hhz131

Huang, Y., Zhou, C., Cui, K., & Lu, X. (2024). Improving algorithmic trading consistency via human alignment and imitation learning. *Expert Systems With Applications*, *253*, 124350. https://doi.org/10.1016/j.eswa.2024.124350

Huber, J., Palan, S., & Zeisberger, S. (2019). Does investor risk perception drive asset prices in markets? Experimental evidence. *Journal of Banking & Finance*, *108*, 105635. https://doi.org/10.1016/j.jbankfin.2019.105635

Irimia-Die guez, A., Velicia-Martín, F., & Aguayo-Camacho, M. (2023). Predicting Fintech Innovation Adoption: the Mediator Role of Social Norms and Attitudes. *Financial Innovation*, *9*(1). https://doi.org/10.1186/s40854-022-00434-6

Itzkowitz, J., Itzkowitz, J., & Schwartz, A. (2023). Start small and Stay Small: Anchoring in App-Based investing. *Journal of Behavioral Finance*, *25*(4), 464–480. https://doi.org/10.1080/15427560.2023.2209233

Jeanjean, F. (2020). Impact of technical progress on the relationship between competition and investment. *Journal of Industry Competition and Trade*, *21*(1), 81–101. https://doi.org/10.1007/s10842-020-00341-5

Jiang, Y., Ho, Y., Yan, X., & Tan, Y. (2018). Investor Platform choice: herding, platform attributes, and regulations. *Journal of Management Information Systems*, *35*(1), 86–116. https://doi.org/10.1080/07421222.2018.1440770

Jiao, P., Veiga, A., & Walther, A. (2020). Social media, news media and the stock market. *Journal of Economic Behavior & Organization*, *176*, 63–90. https://doi.org/10.1016/j.jebo.2020.03.002

Jin, X., Li, R., & Zhu, Y. (2021). Could social interaction reduce the disposition effect? Evidence from retail investors in a directed social trading network. *PLoS ONE*, *16*(2), e0246759. https://doi.org/10.1371/journal.pone.0246759

Jin, X., & Yu, J. (2022). Does communication increase investors' trading frequency? Evidence from a Chinese social trading platform. *Financial Innovation*, *8*(1). https://doi.org/10.1186/s40854-022-00373-2

Joao, A. R. B., Luzardo, F., & Vanderson, T. X. (2015). An interdisciplinary framework to study farmers decisions on adoption of innovation: Insights from Expected Utility Theory and Theory of Planned Behavior. *African Journal of Agricultural Research*, *10*(29), 2814–2825. https://doi.org/10.5897/ajar2015.9650

Josey, A., & N, N. A. (2024). Stock market prediction. *Indian Journal of Data Mining*, *4*(1), 34–37. https://doi.org/10.54105/ijdm.a1641.04010524

Jóźwicki, R., Trippner, P., & Kłos, K. (2021). Algorithmic Trading and Efficiency of the Stock Market in Poland.

Kaban, L. M., & Linata, E. (2024). The risk perception as a mediator between herding and overconfidence on investment decision by Gen Z in Indonesia. *MEC-J (Management and Economics Journal)*, *8*(1), 1–14. https://doi.org/10.18860/mec-j.v8i1.25462

Kalda, A., Loos, B., Previtero, A., & Hackethal, A. (2021). Smart(Phone) Investing? A within Investor-Time Analysis of New Technologies and Trading Behavior. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3765652

Kamil, H. H., & Tanno, A. (2022). Pengaruh Media Sosial Sebagai Sumber Informasi Dalam Pengambilan Keputusan Investor Berinvestasi, Latar Belakang Pendidikan dan Penghasilan Sebagai Variabel Kontrol. *Owner*, *6*(2), 1622–1637. https://doi.org/10.33395/owner.v6i2.568

Karn, A. L., Qiang, Y. E., Karna, R. K., & Wang, X. (2018). News sentiment incorporation in real-time trading: Alpha testing the event trading strategy in HFT. *Journal of Global Information Management (JGIM)*, *26*(4), 18-35.

Kartika, H., Karmawan, I. G. M., & Rusmanto, T. (2023). The influence of financial literacy, financial experience, behavioral finance, and investor awareness on the use of fintech applications in making investment decisions. *2022 International Conference on Information Management and Technology (ICIMTech)*, 603–608. https://doi.org/10.1109/icimtech59029.2023.10277775

Keeley, N. G. (2023). Cash, Credibility, and Conversion: The influence of synthetic media on investment behavior. *arXiv (Cornell University)*. https://doi.org/10.48550/arxiv.2306.05033

Keswani, S., Dhingra, V., & Wadhwa, B. (2019). Impact of behavioral factors in making investment decisions and performance: Study on investors of National Stock Exchange. *International Journal of Economics and Finance*, *11*(8), 80. https://doi.org/10.5539/ijef.v11n8p80

Khan, D. (2020). Cognitive Driven biases, Investment Decision making: The moderating role of financial literacy. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3514086

Khan, S. U., Liu, X., Khan, I. U., Liu, C., & Rasheed, M. I. (2020). Assessing the investors' acceptance of electronic stock trading in a developing country.

Information Resources Management Journal, *33*(1), 59–82. https://doi.org/10.4018/irmj.2020010104

Khan, W., Malik, U., Ghazanfar, M. A., Azam, M. A., Alyoubi, K. H., & Alfakeeh, A. S. (2019). Predicting stock market trends using machine learning algorithms via public sentiment and political situation analysis. *Soft Computing*, *24*(15), 11019–11043. https://doi.org/10.1007/s00500-019-04347-y

Kim, K., Lee, S. T., & Kauffman, R. J. (2023). Social informedness and investor sentiment in the GameStop short squeeze. *Electronic Markets*, *33*(1). https://doi.org/10.1007/s12525-023-00632-9

Kleist, V. F. (2004). A transaction cost model of electronic trust: transactional return, incentives for network security and optimal risk in the digital economy. *Electronic Commerce Research*, *4*(1/2), 41–57. https://doi.org/10.1023/b:elec.0000009281.05504.93

Kogan, S., Moskowitz, T. J., & Niessner, M. (2021). Fake News: Evidence from Financial Markets. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3237763

Kollintza-Kyriakoulia, F., Maragoudakis, M., & Krithara, A. (2018). Measuring the impact of financial news and social media on stock market modeling using time series mining techniques. *Algorithms*, *11*(11), 181. https://doi.org/10.3390/a11110181

Konovalova, M. E., Kuzmina, O. Y., & Zhironkin, S. A. (2019). Digital technologies as a factor of expanding the investment opportunities of business entities. In *Lecture notes in networks and systems* (pp. 180–188). https://doi.org/10.1007/978-3-030-27015-5_23

Koo, J. (2024). AI is not careful: approach to the stock market and preference for AI advisor. *International Journal of Bank Marketing*, *42*(7), 2117–2142. https://doi.org/10.1108/ijbm-10-2023-0568

Koul, S., & Eydgahi, A. (2017). A systematic review of technology adoption frameworks and their applications. *Journal of Technology Management & Innovation*, *12*(4), 106–113. https://doi.org/10.4067/s0718-27242017000400011

Ku-Mahamud, K. R., Omar, M., Bakar, N. a. A., & Muraina, I. D. (2019). Awareness, Trust, and Adoption of Blockchain Technology and Cryptocurrency among Blockchain Communities in Malaysia. *International Journal on Advanced Science Engineering and Information Technology*, *9*(4), 1217–1222. https://doi.org/10.18517/ijaseit.9.4.6280

Kumar, J., & Rani, V. (2024). Investigating the dynamics of FinTech adoption: an empirical study from the perspective of mobile banking. *Journal of Economic and Administrative Sciences.* https://doi.org/10.1108/jeas-12-2023-0334

Kumar, P., Islam, M. A., Pillai, R., & Tabash, M. I. (2024). Risk Perception-Perceived Investor Performance Nexus: Evaluating the mediating effects of heuristics and prospects with gender as a moderator. *SAGE Open*, *14*(2). https://doi.org/10.1177/21582440241256444

Kuriakose, A., & Sajoy, P. (2022). Digital Transformation in the Stockbroking Industry and its Role in Strong Retail Investor Participation in the Indian Stock Market. *The Management Accountant Journal*, *57*(8), 50. https://doi.org/10.33516/maj.v57i8.50-54p

Kurnijanto, A. W., Joni, J., Sumbodo, K. V., Wijaya, L. I., & Sutejo, B. S. (2025). Influence of Behavioral Bias on Investment Decision with Risk Perception as a Mediating Variable: A Study on Generation Z at the Indonesia Stock Exchange. *Dinasti International Journal of Economics Finance & Accounting*, *5*(6), 5741–5752. https://doi.org/10.38035/dijefa.v5i6.3643

Kyari, A. K., & Akinwale, Y. O. (2020). An assessment of the level of adoption of financial technology by Nigerian Banks. *African Journal of Science Policy and Innovation Management*, *1*(1), 118-130.

Lachana, I., & Schröder, D. (2021). Investor sentiment, media and stock returns: The advancement of social media. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3842039

LeBlanc, D., & Biddle, R. (2012). Risk perception of internet-related activities. *2012 Tenth Annual International Conference on Privacy, Security and Trust*, *236*, 88–95. https://doi.org/10.1109/pst.2012.6297924

Li, C., & Li, Y. (2023). Factors Influencing Public risk Perception of Emerging Technologies: A Meta-Analysis. *Sustainability*, *15*(5), 3939. https://doi.org/10.3390/su15053939

Li, L. (2022). Digital transformation and sustainable performance: The moderating role of market turbulence. *Industrial Marketing Management*, *104*, 28–37. https://doi.org/10.1016/j.indmarman.2022.04.007

Li, Z., Diao, X., & Wu, C. (2022). The influence of mobile trading on return dispersion and herding behavior. *Pacific-Basin Finance Journal*, *73*, 101767. https://doi.org/10.1016/j.pacfin.2022.101767

Liu, C., Mithas, S., Pan, Y., & Hsieh, J. J. P. (2024). Mobile Apps, Trading Behaviors, and Portfolio Performance: Evidence from a Quasi-Experiment in China. *Information Systems Research*. https://doi.org/10.1287/isre.2020.0616

Liu, X., & Li, C. (2003). Competitive investment strategies in adoption of new technology with a further new technology anticipated. *Journal of Systems Science and Systems Engineering*, *12*(4), 493–502. https://doi.org/10.1007/s11518-006-0150-6

Liubkina, O., & Ihnatiuk, V. (2023). TRANSACTION COSTS OF TRADING IN ORGANIZED STOCK MARKETS: STRUCTURE AND IMPLICATIONS FOR MARKET EFFICIENCY. *Herald of Khmelnytskyi National University Economic Sciences*, *320*(4), 60–71. https://doi.org/10.31891/2307-5740-2023-320-4-9

Lou, A. T. F., & Li, E. Y. (2017). *Integrating Innovation Diffusion Theory and the Technology Acceptance Model: The adoption of blockchain technology from business managers' perspective*. AIS Electronic Library (AISeL). https://aisel.aisnet.org/iceb2017/44

Lu, X., & Zhou, Z. (2022). Digital transformation, business risk and firm value. *Frontiers in Sustainable Development*, *2*(5), 25–32. https://doi.org/10.54691/fsd.v2i5.695

Lui, A. K. H., Lee, M. C. M., & Ngai, E. W. T. (2021). Impact of artificial intelligence investment on firm value. *Annals of Operations Research*, *308*(1–2), 373–388. https://doi.org/10.1007/s10479-020-03862-8

Luo, Z. (2024). Financial Innovation: Disruption and reinvention in the future financial sector. *Frontiers in Business Economics and Management*, *14*(3), 152–154. https://doi.org/10.54097/76782g38

Mahardhika, A. S., & Zakiyah, T. (2020). Millennials' intention in stock Investment: Extended Theory of Planned Behavior. *Riset Akuntansi Dan Keuangan Indonesia*, *5*(1), 83–91. https://doi.org/10.23917/reaksi.v5i1.10268

Malik, L., Ullah, K., & Soomro, M. (2024). The impact of cognitive and emotional biases on individual investor's investment decision: Mediating role of risk perception. *Pakistan Journal of Humanities and Social Sciences*, *12*(3), 2651–2660. https://doi.org/10.52131/pjhss.2024.v12i3.2471

Manahov, V., Hudson, R., & Urquhart, A. (2018). High-frequency trading from an evolutionary perspective: Financial markets as adaptive systems. *International Journal of Finance & Economics*, *24*(2), 943–962. https://doi.org/10.1002/ijfe.1700

Marshall, B. R., Nguyen, N. H., & Visaltanachoti, N. (2016). Time series momentum and moving average trading rules. *Quantitative Finance*, *17*(3), 405–421. https://doi.org/10.1080/14697688.2016.1205209

Menkveld, A. J. (2013). High frequency trading and the new market makers. *Journal of Financial Markets*, *16*(4), 712–740. https://doi.org/10.1016/j.finmar.2013.06.006

Miraz, M. H., Hasan, M. T., Rekabder, M. S., & Akhter, R. (2022). Trust, transaction transparency, volatility, facilitating condition, performance expectancy towards cryptocurrency adoption through intention to use. *Journal of Management Information and Decision Sciences*, *25*, 1-20.

Mitchell, R. B., Woolridge, R. W., & Johnson, V. (2020). The role of nontechnical skills in providing value in analytics-based decision culture. *Journal of Education for Business*, *96*(1), 1–9. https://doi.org/10.1080/08832323.2020.1719961

Mondal, S., & Kumar, S. (2024). A critical review of influence of technology on financial decision making and investor psychology. *Advances in Finance, Accounting, and Economics Book Series*, 103–134. https://doi.org/10.4018/979-8-3693-8583-8.ch004

Moorman, T. (2014). An empirical investigation of methods to reduce transaction costs. *Journal of Empirical Finance*, *29*, 230–246. https://doi.org/10.1016/j.jempfin.2014.09.004

Moro-Visconti, R., & Cesaretti, A. (2023). FinTech and Digital Payment Systems Valuation. In *Digital Token Valuation* (pp. 411–458). https://doi.org/10.1007/978-3-031-42971-2_13

Mu, H., & Lee, Y. (2021). How inclusive digital financial services impact user behavior: A case of proximity mobile payment in Korea. *Sustainability*, *13*(17), 9567. https://doi.org/10.3390/su13179567

Murinde, V., Rizopoulos, E., & Zachariadis, M. (2022). The impact of the FinTech revolution on the future of banking: Opportunities and risks. *International Review of Financial Analysis*, *81*, 102103. https://doi.org/10.1016/j.irfa.2022.102103

Nainggolan, C. I., & Handayani, P. W. (2023). Factors affecting individuals' behavioral intention to use online capital market investment platforms in Indonesia. *Interdisciplinary Journal of Information Knowledge and Management*, *18*, 001–029. https://doi.org/10.28945/5067

Nair, P. S., Shiva, A., Yadav, N., & Tandon, P. (2022). Determinants of mobile apps adoption by retail investors for online trading in emerging financial markets. *Benchmarking an International Journal*, *30*(5), 1623–1648. https://doi.org/10.1108/bij-01-2022-0019

Nawn, S., & Banerjee, A. (2018). Do Proprietary Algorithmic Traders Withdraw Liquidity during Market Stress? *Financial Management*, *48*(2), 641–676. https://doi.org/10.1111/fima.12238

Neale, F. R., Drake, P. P., Jin, L., & Lai, G. (2024). Technology investment and insurer efficiency. *The Geneva Papers on Risk and Insurance Issues and Practice*. https://doi.org/10.1057/s41288-024-00327-y

Nguyen, H., Calantone, R., & Krishnan, R. (2019). Influence of social media emotional word of mouth on institutional investors' decisions and firm value. *Management Science*, *66*(2), 887–910. https://doi.org/10.1287/mnsc.2018.3226

Ochuba, N. N. A., Amoo, N. O. O., Okafor, N. E. S., Usman, N. F. O., & Akinrinola, N. O. (2024). CONCEPTUAL DEVELOPMENT AND FINANCIAL ANALYTICS FOR STRATEGIC DECISION-MAKING IN TELECOMMUNICATIONS, FOCUSING ON ASSESSING INVESTMENT OPPORTUNITIES AND MANAGING RISKS IN SATELLITE PROJECTS. *International Journal of Management & Entrepreneurship Research*, *6*(3), 594–607. https://doi.org/10.51594/ijmer.v6i3.847

Oksanen, A., Mantere, E., Vuorinen, I., & Savolainen, I. (2022). Gambling and online trading: emerging risks of real-time stock and cryptocurrency trading platforms. *Public Health*, *205*, 72–78. https://doi.org/10.1016/j.puhe.2022.01.027

Orra, A., Bhambu, A., Choudhary, H., & Thakur, M. (2024). Dynamic Reinforced Ensemble using Bayesian Optimization for Stock Trading. *ICAIF '24: Proceedings of the 5th ACM International Conference on AI in Finance*, 361–369. https://doi.org/10.1145/3677052.3698595

Owolabi, O. S., Hinneh, E., Uche, P. C., Adeniken, N. T., Ohaegbulem, J. A., Attakorah, S., Emi-Johnson, O. G., Belolisa, C. S., & Nwariaku, H. (2024). Blockchain-Based system for secure and efficient Cross-Border Remittances: a potential alternative to SWIFT. *Journal of Software Engineering and Applications*, *17*(08), 664–712. https://doi.org/10.4236/jsea.2024.178036

Ozturk, S. S., & Bilgiç, M. E. (2021). Twitter & bitcoin: are the most influential accounts really influential? *Applied Economics Letters*, *29*(11), 1001–1004. https://doi.org/10.1080/13504851.2021.1904104

Padilla-Vega, R., Sénquiz-Díaz, C., & Ojeda, A. (2017). Toward a conceptual framework of technology adoption: Factors impacting the acceptance of the mobile technology in the international business growth. *International Journal of Scientific & Technology Research*, *6*(1), 81-86.

Pandey, I., & Guillemette, M. (2024). Social media, investment knowledge, and meme stock trading. *Journal of Behavioral Finance*, 1–17. https://doi.org/10.1080/15427560.2024.2361875

Paramita, N. M. P., & Wirakusuma, N. M. G. (2024). How investment behaviour of young investors? A case study on the Indonesia Stock Exchange. *World Journal of Advanced Research and Reviews*, *23*(1), 959–976. https://doi.org/10.30574/wjarr.2024.23.1.2072

Paul, S., & Vishnoi, S. (2020). Real-Time stock trend prediction via sentiment analysis of news article. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3753015

Payzan-LeNestour, E., & Woodford, M. (2022). Outlier blindness: A neurobiological foundation for neglect of financial risk. *Journal of Financial Economics*, *143*(3), 1316–1343. https://doi.org/10.1016/j.jfineco.2021.06.019

Peng, C., Yang, S., & Jiang, H. (2022). Does digitalization boost companies' outward foreign direct investment? *Frontiers in Psychology*, *13*. https://doi.org/10.3389/fpsyg.2022.1006890

Pothumsetty, R. (2020). Application of artificial intelligence in algorithmic trading. *Int. J. Eng. Appl. Sci. Technol*, *4*(12), 140-149.

Prakash, Diwakar and Garg, Saumya, Alarming Concerns Around Cyber Security in The Securities Market (July 27, 2024). Available at SSRN: https://ssrn.com/abstract=4907612 or http://dx.doi.org/10.2139/ssrn.4907612

Quinn, W. (2019). Technological revolutions and speculative finance: evidence from the British Bicycle Mania. *Cambridge Journal of Economics*, *43*(2), 271–294. https://doi.org/10.1093/cje/bey029

Rahmantari, N. L. L., Mahyuni, L. P., & Maradona, A. F. (2024). Navigating the Digital Frontier: Motivations and Perceived Behaviors on Digital Investment Platforms. *10th International Conference on Smart Computing and Communication (ICSCC)*, 507–513. https://doi.org/10.1109/icscc62041.2024.10690446

Raji, N. M. A., Olodo, N. H. B., Oke, N. T. T., Addy, N. W. A., Ofodile, N. O. C., & Oyewole, N. a. T. (2024). Real-time data analytics in retail: A review of USA and global practices. *GSC Advanced Research and Reviews*, *18*(3), 059–065. https://doi.org/10.30574/gscarr.2024.18.3.0089

Rakovic, I., & Inal, Y. (2023). Dark Finance: Exploring deceptive design in investment apps. In *Lecture notes in computer science* (pp. 339–348). https://doi.org/10.1007/978-3-031-42280-5_20

Rane, N., Choudhary, S., & Rane, J. (2023). Blockchain and Artificial Intelligence (AI) integration for revolutionizing security and transparency in finance. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4644253

Raschner, P. (2021). Algorithms put to test: Control of algorithms in securities trading through mandatory market simulations? *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3807935

Reith, R., Fischer, M., & Lis, B. (2019). Explaining the intention to use social trading platforms: an empirical investigation. *Journal of Business Economics*, *90*(3), 427–460. https://doi.org/10.1007/s11573-019-00961-2

Renn, O., & Benighaus, C. (2013). Perception of technological risk: insights from research and lessons for risk communication and management. *Journal of Risk Research*, *16*(3–4), 293–313. https://doi.org/10.1080/13669877.2012.729522

Rigopoulou, I. D., Chaniotakis, I. E., & Kehagias, J. D. (2017). An extended technology acceptance model for predicting smartphone adoption among young consumers in Greece. *International Journal of Mobile Communications*, *15*(4), 372. https://doi.org/10.1504/ijmc.2017.084860

Roca, J., Machado, J. G., & De La Vega, J. (2010). Personal innovativeness, security and privacy as determinants of e-trading adoption. *International Journal of Electronic Finance*, *4*(3), 269. https://doi.org/10.1504/ijef.2010.034033

Rothman, T. (2019). Trading the Dream: Does social media affect investors' activity - the story of Twitter, Telegram and Reddit. *International Journal of Financial Research*, *10*(2), 147. https://doi.org/10.5430/ijfr.v10n2p147

Rothman, T., & Yakar, C. (2019). Empirical analysis Towards the effect of social media on cryptocurrency price and volume. *European Scientific Journal ESJ*, *15*(31). https://doi.org/10.19044/esj.2019.v15n31p52

Rubin, E., Iriberri, A., & Ayaburi, E. (2025). Speculation in investment in technology firms: a trust-based perspective. *International Journal of Bank Marketing*. https://doi.org/10.1108/ijbm-02-2024-0084

Rumyantseva, A., & Tarutko, O. (2023). Sustainable development financing as a factor affecting on operational efficiency of the company. In *Springer proceedings in business and economics* (pp. 47–56). https://doi.org/10.1007/978-3-031-30498-9_6

Rumyantseva, A., & Tarutko, O. (2024). The Instruments of Sustainable Development Financing: Trend analysis and search for opportunities. In *Springer proceedings in business and economics* (pp. 53–69). https://doi.org/10.1007/978-3-031-56380-5_5

Sadaf, R., McCullagh, O., Sheehan, B., Grey, C., King, E., & Cunneen, M. (2021). Algorithmic trading, High-frequency trading: Implications for MIFID II and Market Abuse Regulation (MAR) in the EU. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3846814

Saivasan, R., & Lokhande, M. (2022). Influence of risk propensity, behavioural biases and demographic factors on equity investors' risk perception. *Asian Journal of Economics and Banking*, *6*(3), 373–403. https://doi.org/10.1108/ajeb-06-2021-0074

Sembel, J. S. (2024, September 16). *Unlocking Generation Z's Minds on Stock Investment: Determinants of Mobile Stock Investment Application Adoption*. https://ojs.uph.edu/index.php/NCBMA/article/view/8824

Sembel, J. S., Widjaja, A. W., & Antonio, F. (2024). Determinants of mobile stock investment application adoption and its impact on intention to recommend the applications in emerging countries: a case study of Indonesia. *Management & Marketing*, *19*(3), 555–578. https://doi.org/10.2478/mmcks-2024-0025

Semenova, V. (2024). *Embracing technological advancements: blockchain as a driver for innovation and dynamic capability development*. https://doi.org/10.14267/phd.2024056

Sendstad, L. H., & Chronopoulos, M. (2020). Strategic technology switching under risk aversion and uncertainty. *Journal of Economic Dynamics and Control*, *126*, 103918. https://doi.org/10.1016/j.jedc.2020.103918

Sendstad, L. H., Chronopoulos, M., & Hagspiel, V. (2021). Optimal risk adoption and capacity investment in technological innovations. *IEEE Transactions on Engineering Management*, *70*(2), 576–589. https://doi.org/10.1109/tem.2021.3056142

Seo, J., & Chai, S. (2013). The role of algorithmic trading systems on stock market efficiency. *Information Systems Frontiers*, *15*(5), 873–888. https://doi.org/10.1007/s10796-013-9442-9

Shah, A., & Thomas, S. (2001). The evolution of the securities markets in India in the 1990s. *Indian Council for Research on International Economic Relations*. https://www.icrier.org/pdf/wp91.pdf

Shaheen, F., Tariq, M. A., Zahoor, Q., & Mehmood, A. (2022). Role of Financial Literacy in Investment Decisions: Exploring the Individual Investors' Perspective through a Qualitative Approach. *Journal of Business and Social Review in Emerging Economies*, *8*(4). https://doi.org/10.26710/jbsee.v8i4.2521

Shamim, R. (2022). Machine learning's algorithm profoundly impacts predicting the share market stock's price. *International Journal for Multidisciplinary Research*, *4*(5). https://doi.org/10.36948/ijfmr.2022.v04i05.911

Shao, D., Marwa, N., & Matendo, D. (2023). Regulatory Strategies for Fostering Responsible AI Innovation in African Economies. In *2023 First International Conference on the Advancements of Artificial Intelligence in African Context (AAIAC)* (pp. 1–11). https://doi.org/10.1109/aaiac60008.2023.10465404

Sharma, P., Gupta, S., & Kapoor, D. (2024). Blockchain technology in the stock market. In *Advances in finance, accounting, and economics book series* (pp. 44–59). https://doi.org/10.4018/979-8-3693-1758-7.ch003

Shawaqfeh, G. N. (2025). The Impact of Ai on Enhancing Financial Predicting Accuracy and Improving Risk Management in Financial Market. *KeAi: Journal of Digital Economy*. https://doi.org/10.2139/ssrn.5097473

Shukla, A., & Nerlekar, S. (2019). Impact of digitization transformation on financial markets. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3342126

Sindakis, S., & Showkat, G. (2024). The digital revolution in India: bridging the gap in rural technology adoption. *Journal of Innovation and Entrepreneurship*, *13*(1). https://doi.org/10.1186/s13731-024-00380-w

Singh, B., & Kaunert, C. (2024). Revealing green finance mobilization. In *Advances in finance, accounting, and economics book series* (pp. 265–286). https://doi.org/10.4018/979-8-3693-1878-2.ch011

Singh, D., Malik, G., Jain, P., & Abouraia, M. (2024). A systematic review and research agenda on the causes and consequences of financial overconfidence. *Cogent Economics & Finance*, *12*(1). https://doi.org/10.1080/23322039.2024.2348543

Singhal, A., Aggarwal, S., Jamwal, J., & Kumar, R. (2024). A study on novice investor behavior in Indian stock exchange. *International Journal for Multidisciplinary Research*, *6*(2). https://doi.org/10.36948/ijfmr.2024.v06i02.16848

Sjoberg, L. (2003). The different dynamics of personal and general risk. *Risk Management*, *5*(3), 19–34. https://doi.org/10.1057/palgrave.rm.8240154

SKrishnaprabha, N. (2024). Exploring the impact of social media on investment behaviour of young investors. *Journal of Informatics Education and Research*, *4*(3). https://doi.org/10.52783/jier.v4i3.1860

Spatacean, I. O., & Todoran, D. (2025). The use of financial technologies in promoting and providing services in the financial intermediation industry. *Acta Marisiensis Seria Oeconomica*, *18*(1), 61–70. https://doi.org/10.62838/amso-2024-0005

Sperka, R., & Spsak, M. (2013). Transaction Costs Influence on the Stability of Financial Market: Agent-Based Simulation. *Journal of Business Economics and Management*, *14*(Supplement_1), S1–S12. https://doi.org/10.3846/16111699.2012.701227

Stein, R. (2020). The top 5 predictable effects of new entries in Robinhood's '100 most popular' list. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3694588

Strauss, N., & Smith, C. H. (2019). Buying on rumors: how financial news flows affect the share price of Tesla. *Corporate Communications an International Journal*, *24*(4), 593–607. https://doi.org/10.1108/ccij-09-2018-0091

Sukharev, A. (2023). Artificial intelligence in the stock market: present and future. *Obshchestvo I Ekonomika*, *2*, 80. https://doi.org/10.31857/s020736760024424-5

Susanto, K. P., Mandagie, W. C., Endri, E., & Wiwaha, A. (2024). Financial literacy, technological progress, financial attitudes and investment decisions of Gen Z Indonesian investors. *Investment Management and Financial Innovations*, *22*(1), 25–34. https://doi.org/10.21511/imfi.22(1).2025.03

Taneja, B. (2024). Financial Innovations in FinTech. In *Advances in finance, accounting, and economics book series* (pp. 208–232). https://doi.org/10.4018/979-8-3693-0863-9.ch008

Taylor, V. F., & Martinovic, I. (2017). Short paper: A longitudinal study of financial apps in the Google Play Store. In *Lecture notes in computer science* (pp. 302–309). https://doi.org/10.1007/978-3-319-70972-7_16

Teplova, T., Sokolova, T., Tomtosov, A., Buchko, D., & Nikulin, D. (2022). The sentiment of private investors in explaining the differences in the trade characteristics of the Russian market stocks. *Journal of the New Economic Association*, *53*(1), 53–84. https://doi.org/10.31737/2221-2264-2022-53-1-3

Ter Braak, L., & Van Der Schans, M. (2023). Optimal Order Routing with Reinforcement Learning. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4611420

Theodorou, T., Zamichos, A., Skoumperdis, M., Kougioumtzidou, A., Tsolaki, K., Papadopoulos, D., Patsios, T., Papanikolaou, G., Konstantinidis, A., Drosou, A., & Tzovaras, D. (2021). An AI-Enabled Stock Prediction Platform Combining News and Social Sensing with Financial Statements. *Future Internet*, *13*(6), 138. https://doi.org/10.3390/fi13060138

V, J., P, T., G, M., R, D., & R, S. (2024). Deep Learning for Sentiment Analysis with Adaptive Neural Networks for Emotion Classification. In *2024 International Conference on Sustainable Communication Networks and Application (ICSCNA)* (pp. 1019–1024). https://doi.org/10.1109/icscna63714.2024.10864172

Valle-Cruz, D., Fernandez-Cortez, V., López-Chau, A., & Sandoval-Almazán, R. (2021). Does Twitter affect stock market decisions? Financial Sentiment Analysis During Pandemics: A Comparative study of the H1N1 and the COVID-19 periods. *Cognitive Computation*, *14*(1), 372–387. https://doi.org/10.1007/s12559-021-09819-8

Vandanapu, M. K., Shaik, A., Nagamalla, S. K., & Balbhadruni, R. (2024). Quantum-Inspired AI for Optimized High-Frequency Trading. *International Journal of Finance*, *9*(7), 1–17. https://doi.org/10.47941/ijf.2301

Venkatesh, N., Morris, N., Davis, N., & Davis, N. (2003). User acceptance of information Technology: toward a unified view. *MIS Quarterly*, *27*(3), 425. https://doi.org/10.2307/30036540

Vergari, C. (2005). Herd behaviour in adoption of network technologies. *Journal of Economics*, *86*(2), 161–182. https://doi.org/10.1007/s00712-005-0153-7

Wagner, S. M. (2006). A firm's responses to deficient suppliers and competitive advantage. *Journal of Business Research*, *59*(6), 686–695. https://doi.org/10.1016/j.jbusres.2006.01.006

Waliszewski, K. (2020). *Entrepreneurship and sustainability issues*. http://jssidoi.org/jesi/article/706

Wang, C., & Luo, Z. (2022). A review of the optimal design of neural networks based on FPGA. *Applied Sciences*, *12*(21), 10771. https://doi.org/10.3390/app122110771

Wang, W., & Ma, W. (2023). Perceived Risk and Intelligent Investment Advisor Technology Adoption: A UTAUT Perspective. *2020 4th International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT)*, 1–6. https://doi.org/10.1109/ismsit58785.2023.10304953

Wang, Y., Duong, N. T., Ying, C., & Chang, Y. (2024). What drives people's cryptocurrency investment behavior. *Journal of Computer Information Systems*, 1–18. https://doi.org/10.1080/08874417.2024.2329127

Wasiuzzaman, S., Chong, L. L., & Ong, H. B. (2022). Influence of perceived risks on the decision to invest in equity crowdfunding: a study of Malaysian investors. *Journal of Entrepreneurship in Emerging Economies*, *14*(2), 208–230. https://doi.org/10.1108/jeee-11-2020-0431

Widyanto, H. A., Kusumawardani, K. A., & Yohanes, H. (2020). Safety first: extending UTAUT to better predict mobile payment adoption by incorporating perceived security, perceived risk and trust. *Journal of Science and Technology Policy Management*, *13*(4), 952–973. https://doi.org/10.1108/jstpm-03-2020-0058

Williams, D. J., & Noyes, J. M. (2007). How does our perception of risk influence decision-making? Implications for the design of risk information. *Theoretical Issues in Ergonomics Science*, *8*(1), 1–35. https://doi.org/10.1080/1463922 0500484419

Wu, B. (2020). Investor behavior and risk contagion in an Information-Based Artificial stock market. *IEEE Access*, *8*, 126725–126732. https://doi.org/10. 1109/access.2020.3008717

Wu, Y., Wang, J. B., & Li, Y. (2024). Quantum Computing for option portfolio analysis. *arXiv (Cornell University)*. https://doi.org/10.48550/arxiv.2406. 00486

Xie, Q., Han, W., Chen, Z., Xiang, R., Zhang, X., He, Y., ... & Huang, J. (2024). Finben: A holistic financial benchmark for large language models. *Advances in Neural Information Processing Systems*, *37*, 95716-95743.

Xu, Q., Li, Q., Jiang, C., Wu, J., & Zhang, X. (2020). Social media, interaction information and stock market efficiency: evidence from the Shenzhen stock exchange easy interaction platform in China. *Asia-Pacific Journal of Accounting & Economics*, *29*(6), 1469–1496. https://doi.org/10.1080/1608 1625.2020.1829976

Xu, X., Isaac, A., Hao, L., & Wang, D. (2019). Investor sentiment, innovation investment and cash dividend. *International Journal of Economics and Finance*, *11*(7), 97. https://doi.org/10.5539/ijef.v11n7p97

Yadav, M., & Banerji, P. (2024a). Digital financial literacy, saving and investment behaviour in India. *Journal of Social and Economic Development*. https://doi.org/10.1007/s40847-024-00367-z

Yadav, M., & Banerji, P. (2024b). Systematic literature review on Digital Financial Literacy. *SN Business & Economics*, *4*(11). https://doi.org/10.1007/s43546-024-00738-y

Yadav, M. P., Al-Qudah, A. A., Sandhu, K., & Gupta, N. (2022). Resolving an enigma of FinTech, digital assets and electronic commerce: insight to time-varying dynamic connectedness. *FIIB Business Review*. https://doi.org/10.1177/2319 7145241300899

Yadav, S., Jawa, R., Kabra, R., & Aggarwal, R. (2022). Investment Tech: The Rise of Discount Brokers in India. *International Journal of Research -Granthaalayah*, *10*(3), 176–193. https://doi.org/10.29121/granthaalayah.v10.i3.2022.4544

Yang, N., Fernandez-Perez, A., & Indriawan, I. (2023). Social media sentiment, investor herding and informational efficiency. *Investor Herding and Informational Efficiency (August 25, 2023)*.

Yang, N. (2022). Social media and money: How our tweets affect the financial markets. *Rangahau Aranga AUT Graduate Review*, *1*(1). https://doi.org/10. 24135/rangahau-aranga.v1i1.34

Yang, Xiurui and HU, Wei, "GME Frenzy on Social Media: The Impact of Short Squeezes on Market Volatility and Predictability" (2024). *PACIS 2024 Proceedings*. 18. https://aisel.aisnet.org/pacis2024/track17_socmedia/track17 _socmedia/18

Yuferova, D. (2024). Algorithmic trading and market efficiency around the introduction of the NYSE Hybrid Market. *Journal of Financial Markets*, *69*, 100909. https://doi.org/10.1016/j.finmar.2024.100909

Zachariadis, M., Hileman, G., & Scott, S. V. (2019). Governance and control in distributed ledgers: Understanding the challenges facing blockchain technology in financial services. *Information and Organization*, *29*(2), 105–117. https://doi.org/10.1016/j.infoandorg.2019.03.001

Zafar, S., Ashraf, S., & Raza, T. (2024). The Investment Decision-making: Understanding Overconfidence, Herding and Risk Aversion among Individual Investors. *Journal of Social Sciences Development*, *3*(1), 32–44. https://doi.org/10.53664/jssd/03-01-2024-03-32-44

Ze, Y., & Loang, O. K. (2024). The role of technological innovation in shaping investment strategies in emerging markets. In *Advances in business strategy and competitive advantage book series* (pp. 273–296). https://doi.org/10.4018/979-8-3693-9380-2.ch011

Zhang, H., & Aumeboonsuke, V. (2022). Technological Innovation, Risk-Taking and Firm Performance—Empirical Evidence from Chinese Listed Companies. *Sustainability*, *14*(22), 14688. https://doi.org/10.3390/su142214688

Zhang, L., Pentina, I., & Fan, Y. (2021). Who do you choose? Comparing perceptions of human vs robo-advisor in the context of financial services. *Journal of Services Marketing*, *35*(5), 634–646. https://doi.org/10.1108/jsm-05-2020-0162

Zhang, W., Zhang, N., Yan, J., Li, G., & Yang, X. (2022). Auto uning of price prediction models for high-frequency trading via reinforcement learning. *Pattern Recognition*, *125*, 108543. https://doi.org/10.1016/j.patcog.2022.108543

Zhang, Y., Li, R., & Xie, Q. (2023). Does digital transformation promote the volatility of firms' innovation investment? *Managerial and Decision Economics*, *44*(8), 4350–4362. https://doi.org/10.1002/mde.3951

Zhavoronok, A., Popelo, O., Shchur, R., Ostrovska, N., & Kordzaia, N. (2022). The role of digital technologies in the transformation of regional models of households' financial behavior in the conditions of the National Innovative Economy development. *Ingénierie Des Systèmes D Information*, *27*(4), 613–620. https://doi.org/10.18280/isi.270411

Zhou, B., & Ge, J. (2023). Does corporate digitization affect investment efficiency? Evidence from China. *Applied Economics Letters*, *31*(20), 2144–2149. https://doi.org/10.1080/13504851.2023.2211329

Zhuang, X., Chen, Z., Wu, Y., & Guo, G. (2022). Quantum computational quantitative trading: high-frequency statistical arbitrage algorithm. *New Journal of Physics*, *24*(7), 073036. https://doi.org/10.1088/1367-2630/ac7f26

Zou, J., Zhao, Q., Jiao, Y., Cao, H., Liu, Y., Yan, Q., Abbasnejad, E., Liu, L., & Shi, J. Q. (2022). Stock market prediction via Deep learning Techniques: a survey. *arXiv (Cornell University)*. https://doi.org/10.48550/arxiv.2212.12717.

Chapter 3

TECHNOLOGICAL ADVANCEMENTS IN STOCK TRADING

3.1 Introduction

This chapter outlines a theoretical framework elucidating on several aspects of the study. Investors have changed their behaviour significantly because technology has affected global financial markets. Algorithmic trading, smartphone apps for trading, robo-advisors, blockchain, and artificial intelligence have transformed how Indian investors approach their investments, protect themselves against loss, and participate in the market. Over the years, advancements in technology have transformed the way stock trading is conducted in India. Using digital tools instead of shouting in marketplaces has made trading and investing simpler for everyone.

Now brokers are providing online and mobile trading platforms for users to make trading fast and manage their portfolios easily. With so many people having smartphones, trading apps are popular, opening the door for retail investors in tier-2 and tier-3 cities to participate in stock trading. The service includes real-time quotes, fast fund transfers, investment tracking, and market updates.

AI makes it easier to predict trends, handle investments, spot fraudulent activities, and evaluate the overall market condition. With artificial intelligence, models can forecast the direction of stock prices, which supports better decisions and valuable advisory services offered to investors. People who want robo-advice can rely on various platforms which guide investors through AI and similar tools. It is cost-effective and excellent for those just starting to invest, letting them pace themselves using a planned approach. Advances in technology have made stock trading in India more accessible to a broader audience, making it more affordable and efficient. Although these new advances have helped investors, it is essential to increase awareness, education, and regular oversight to ensure that investors participate securely and understand what they are doing.

Artificial Intelligence has transformed stock trading through faster, more intelligent, and more efficient decision-making. The use of AI in stock trading is enhancing the industry by mitigating emotional influences and improving risk management (Prabhakaran, 2024). When making projections, LSTM-based AI takes data on volume, open, low, high, and closed price levels to help predict the future value of stocks (Gangavarapu et al., 2024). Combining social media sentiment analysis with technical indicators can enhance the precision of predictions. Financial news releases unrelated to company fundamentals have also been found to affect stock prices in the short term when sentiment analysis is conducted (Vijay et al., 2018).

The use of real-time warnings in the stock market has become increasingly relevant, as the stock market is a dynamic environment where investors should be aware of these variations. It is possible to propose several systems that can be utilised to help achieve this purpose. Al-Jaroodi & Mohamed (2009) created a system that tracks information about stocks provided by web services and alerts the user to specific situations. Similarly, Jain et al. (2019) conducted another study utilising the low-latency autonomous trading system, with an emphasis on technical analysis and the application of modern technology. The article by Jacob et al. (2022) involves the deployment of LSTM models to replace the use of trackers and make price predictions as an interactive dashboard. Lopez et al. (2015) proposed a mechanism for raising alerts in a real-time data warehouse, in which incoming facts are compared against a collection of confidence intervals computed based on historical data. These systems aim to deliver timely information and warnings to investors, enabling them to make informed trading decisions and navigate the complexities of processing vast amounts of information in a fast-paced market.

It has changed the nature of the investment world, such that more people trade using their phones, and it has made the market more liquid and accessible due to the availability of stock trading applications. The effectiveness of traditional sources of information, such as those found in newspapers on intraday trading, has been questioned and has been shown not to generate significant returns for traders (Kolte et al., 2024).

3.2 Social Trading Platforms

Social trading in the stock market is a type of investing that enables individuals to view, replicate, and follow the investments made by skilled or successful investors online. It combines features of a social network and a trading platform, allowing users to exchange opinions, discuss market changes, and buy/sell jointly. This strategy will help new investors find it easy to invest, as they will be utilising the experience and skills of traders who have been in the market for longer.

Social trading platforms are transforming the investment world by integrating social chat with stock trading. By using these platforms, people can easily learn from the trades of professional investors and have easier access to helpful investment ideas. As a result of fintech, trading has become more available and user-friendly for people from all walks of life. In addition to giving users access to others' trades, the innovative abstract social trading platform allows others to see and follow signal providers' trades. By utilising published data on transactions and gains, clients of these platforms can select one or more signal providers and entrust them to manage their investments.

Signal providers invest more in highly volatile stocks if they are not keeping pace with their peers. This means the rewards offered on social trading platforms may encourage traders to take greater risks. The special environment in social trading, where people can see others and are rewarded for improved performance, leads signal providers to act like gamblers (Oehler & Schneider, 2022)

3.2.1 Social Trading Dynamics

Social trading dynamics in stock trading refer to the act of investors following, observing, and sometimes copying the strategies of individuals who consistently generate higher profits through digital platforms. This strategy utilises collective intelligence, peer associations, and communal learning to make stock trading more collaborative than individual. These dynamics include the exchange of information, reputation, herd behaviour, and trust within online trading communities, which may provide opportunities to learn more about online investing while also exposing such investors to the dangers of over-reliance on the judgment of others.

3.2.1.1 Copy Trading

In copy trading, investors automatically copy the trades of skilled traders. Whenever the selected trader purchases or sells a stock, the same action is simultaneously performed in the follower account. It can provide even a beginner with exposure to professional-level strategies, but can foster dependency before acquiring any personal skills.

3.2.1.2 Mirror Trading

In mirror trading, investors replicate an existing trading plan designed by professional traders or by any algorithmic system. It differs from copy trading in that it is not trader-related, but rather strategy-related. This enables traders to replicate successful strategies and eliminate emotional biases.

3.2.1.3. Signal Trading

The signal is the buy/sell information provided by traders, which they share on social media or in apps. Investors are free to follow such signals or disregard them based on their assessment. It is flexible, but the user needs to have analytical skills to reject noise that is difficult to separate.

3.2.1.4 Community Trading

Online communities encompass social media platforms, forums, and communities where investors engage in active discussions about stock tips, current news, and investment strategies. The joint wisdom, popular opinion or the opinion of the crowd characterise decision-making. It promotes learning and the exchange of ideas, but can also cause herd behaviour and market speculation.

3.2.1.5 Strategy Sharing/Portfolio

There are websites where traders can publish their entire portfolio or their strategies publicly. Retail investors can read, compare, and apply strategies based on their risk tolerance. This fosters transparency and knowledge sharing, although it must be assessed carefully in terms of risks.

3.3 Sentiment Analysis in Stock Trading

Sentiment analysis deals with the discovery of the tone of news items, messages on social media sites, blogs, as well as any other text in a form of writing. In conducting sentiment analysis, investors utilise natural language processing, text analysis, and computational linguistics to identify subjective details in financial writing (Liu, 2012). Many companies in India now utilise sentiment analysis to assess market trends, track investor emotions, and inform trading decisions based on data. According to the Nasscom (2022) survey, as many as 40% of Indian fintech companies are using AI-powered sentiment analytics to make their trading advice more accurate. Sentiment analysis is now incorporated into most modern stock trading methods in India.

Sentiment analysis has become a crucial tool in stock trading, utilising data from various sources to gauge investor sentiment and its potential impact on the market. Through machine learning approaches, sentiment analysis enhances the predictability of stock tips and predictions. The method is not only beneficial in decision-making but also helps minimise investment risks by offering timely intelligence on the market dynamics.

3.3.1 The significance of Sentiment Analysis

Sentiment analysis is relevant in predicting stock prices by analysing emotions and opinions expressed in news articles and social media. This strategy provides insight into how the market responds to various events and news, which are influenced by public sentiment.

1. **Improved Prediction Accuracy:** Sentiment analysis can be used in tandem with traditional financial models to significantly augment the accuracy of the forecasts

made on stock prices. Such an integration enables the gathering of a more nuanced picture of market dynamics, particularly in volatile times. (Safitri et al., 2024)

2. **Strategic Market Views:** Strategically sentimental analysis combined with the current predictive models not only adds value to predictions but also allows for obtaining stratified market insights. This is especially useful to investors who are interested in exploring the stock market complexities. It is possible to undergo an experience of loss, specifically: loss of the sense of self, loss of the feeling of knowing oneself, and loss of a sense of proximity to a person. Each of these losses has five contributing factors (Safitri et al., 2024).

3. **Issue of Stock Price Forecast:** Random disturbances can significantly impact the forecasting process, and incorporating sentiment analysis can only strengthen it. The reasons why can be regarded as the reasons because of which (Safitri et al., 2024)

3.4 Mobile Stock Trading

The advent of mobile trading apps has brought about significant changes in the way stock trading is conducted in India, particularly among retail investors. These platforms have democratised financial markets, allowing users to trade easily and access real-time data. This surge in the number of such apps has led to increased trading volumes and a significant rise in demat account registrations, as well as a broader presence in the stock market.

3.4.1 Mobile Trading Applications

The Indian stock market has undergone significant changes in recent years, driven by the development of mobile trading apps. These services have made it faster and more straightforward for any investor to engage in the stock market. Increasing numbers of people are now participating in the stock market, mainly due to the rise of smartphone-based trading apps. Traders in the 20-35 age group in India have witnessed significant changes in stock trading, mainly due to the advent of mobile trading apps (Sumant et al., 2022). With the assistance of mobile trading applications, people can enter the stock market, follow market changes in real-time, conduct research, and execute trades with ease. People are therefore turning to more online approaches for investment.

With the advent of universal internet access and affordable smartphones, retail investors have increasingly chosen mobile trading as their preferred method. Broking has changed with the introduction of mobile trading platforms or service providers. They offer platforms which are simple, inexpensive, and easily accessible services. First-time investors are encouraged to try mobile trading because they may not yet have a comprehensive understanding of finances. Both timely data and real-time notifications enable faster decision-making and increased intraday trading. Mobile trading apps have significantly changed the way people invest in the Indian stock market. Although they ease work, are quicker, and can make things accessible to everyone, they also come with issues of mindless trading and misinterpretation.

3.5 Stock Trading Based on Algorithms

Algorithmic Trading is a process where deals are completed using computer software based on set instructions. They use mathematical rules and trade based on data at high-speed rates, which reduces the role people have in decision-making. There are automated steps that execute trades when specific price, time, and volume factors are met. By utilising data mining and analytics, this technology can prevent human errors and spoofing (M. Sachin et al., 2020). Algorithmic traders excel at timing the market within a day and earn profits under various conditions, predominantly when they help fuel liquidity. Moreover, market price efficiency is much higher with the help of AT (Syamala & Wadhwa, 2020).

3.6 Financial Analytics Tools

Financial analytics tools help investors and traders analyse financial data to make informed decisions about stocks. As digital brokerage firms, fintech companies, and retail investors emerged, the use of these tools has increased rapidly. The use of data visualisation, predictive analytics, machine learning and statistics helps them provide live updates on several aspects, such as changes in the price of a company's stock, the key points of a company, public opinions about the market, examining possible risks, how you are doing with investments, etc.

3.6.1 Advances in Stock Trading Analytics

The stock trading process in India has undergone a significant transformation due to the advent of new technologies in data analysis, artificial intelligence, and machine learning in the country. Owing to these developments, investors can utilise advanced offerings designed to aid in intelligent investment decision-making, remove biases, and maximise returns on their portfolio. People have historically chosen investments by looking at a company's financial reports, price charts, and indicators. Currently, investors rely on data analytics to make their decisions, utilising real-time data and alternative sources beyond official government information, including social media, satellite imagery, and data on emotions and behaviours.

3.6.2 Important Technological Advances in Analytics

Financial companies rely on AI/ML algorithms to identify potential changes in stocks based on historical information, volume, market activity, and key economic indices. The fields where it is applied are portfolio optimisation, algorithmic trading, risk assessment and investment advisory. AI-driven insights are being incorporated into the investment platforms of various stock brokers in India.

3.7 Robo-Advisors for stock trading

Robo-advisory services, also known as robo-advisors, enable customers to receive advice and manage their investments through the use of computers. Robo-advisors, which do not involve a human advisor, are likely to be much less expensive than the services of a human expert. In addition, computer models are increasingly adapting their advice to meet the needs of individuals. Nevertheless, robo-advisors fail to provide all the services offered by human advisors, and most significantly, in-person discussions. Hence, some companies have hybrid models where the foundation includes robot services with minimal human contributions.

Along with technological advancements, there has been the emergence of robots, also known as robo-advisors, in the field of money and investments. Robo-advisors, initially used by people in developed countries, are now being provided in developing countries, including India**.**

3.7.1 Features of Robo-Advisory Services Used in Stock Trading

1. Portfolio Management run by technology

They use algorithms to assemble and look after clients' portfolios according to their willingness to take risks, their goals, and how soon they want to achieve their financial objectives. They tend to utilise the Modern Portfolio Theory to generate the optimal combination of investments and rebalance the portfolio periodically to achieve the appropriate risk-reward balance (Sironi, 2016).

2. Cost Efficiency

Robo-advisors require minimal human input and offer considerably lower total fees. Investment services are now accessible to a broader audience. Clients who subscribe to robo-advisors enjoy reduced fees (Bonelli et al., 2024).

3. Personal investment approaches

On these platforms, strategies are tailored to each client's risk tolerance, objectives, and financial situation. Maintenance of portfolios can be automated by advanced algorithms as market and customer needs change (Capponi et al., 2019).

4. Ways to Prevent Behavioural Bias

With the help of robo-advisors, people are more likely to develop unfocused habits, such as overtrading, following the crowd, and failing to diversify their investments across multiple assets properly. Investors often face risks stemming from their own biases, but robo-advisors help them overcome these issues (Bonelli et al., 2024).

5. Advanced technologies being used in society

A significant amount of data is analysed by robots using big data, AI, and machine learning to identify trends in the markets and select appropriate investment opportunities. The difference in how robot-advisors can do algorithmic trading lies in the possibility of big data and artificial intelligence (Wang et al., 2024).

Robo-advisory also provides customers with the opportunity to develop individualised investment and financial plans and carry out investment decisions with limited human input. These stock trading activities in India involve the use of robo-advisors, which are used to construct and maintain portfolios based on an individual's risk disposition, financial objectives, and investment time frame. Using these platforms, ordinary citizens can plan their financial strategies in advance, delegate the investment balancing aspect, reduce their tax burden to manageable levels, and instead focus on achieving their desired goals.

3.7.2 The way Robo-Advisors operate

Usually, robo-advisors follow this sequence of steps:

1. An investor creates a user profile by giving details like income, age, how much risk they can take and what they hope to achieve with their investments.
2. The platform automatically recommends different portfolios using algorithms, chosen from equity, debt, ETFs and mutual funds.
3. It handles the process automatically by buying new assets and rebalancing the existing ones at scheduled moments.
4. Regularly, performance analysis and alerts are given to prospective users—either by email or within the app itself.

The way people invest in India is being transformed by robo-advisors, offering cheap, convenient, and orderly services. Thanks to digital skills and new regulations, robo-advisory services will likely help more people participate in the Indian stock market.

3.8 Stock Screeners

A stock screener is a program that investors and traders can use to search for stocks based on specific criteria they define, including market value, P/E ratio, trading volume, dividend yield, industry, or technical aspects. A stock screener is designed to browse through numerous stocks and help investors identify options that match their standards (Fabozzi, 2014).

Because there are countless listed companies on the NSE and BSE in India, stock screeners help people invest wisely and factually. Using stock screeners is now very valuable in trading the Indian stock market. Because of these tools, investors can base their decisions on the numbers. As stock market participation among retailers and the general public increases, and people become more knowledgeable about finance, stock screeners will play a crucial role in shaping the choices of Indian investors.

The use of stock screeners has grown in importance in today's complex and technology-driven stock markets in India. Online trading has made it possible for investors to execute market transactions simply by clicking a button (Walia & Kumar, 2007). Businesses have shifted from physical trading to online trading due to the growing use of the internet in business. Singh & Kumar (2021) state that retail investors in India are using stock screens to spot undervalued stocks and take sound decisions as the market becomes more complex

3.9 Intraday Trading Platforms

Online tools offered by stock brokers are called intraday trading platforms. They help traders execute transactions with financial instruments within a single trading day. They provide real-time price updates, fast order processing, the ability to use even small amounts of money for trading, watchlists, tools to analyse charts and alerts triggered automatically. An intraday trading platform is a type of digital service that helps investors do same-day buys and sells with up-to-date information, trading tools and the ability to trade immediately (Mishra & Tiwari, 2021).

Retailers, proprietary traders, and program traders rely on these platforms in India to maximise their profits during trading days when the NSE and BSE are open. Intraday trading platforms play a significant role in shaping the way active retail trading is conducted in India. These platforms combine technology, speed, and ease, making it easier for individuals to participate in high-frequency trading. As more people use mobile technology and trading is increasingly done via algorithms, intraday platforms should become more efficient and powerful.

3.10 Smart order routing (SOR)

Market fragmentation and the need for effective execution strategies necessitate smart order routing (SOR) in the Indian stock exchange as of today. Using real-time information, SOR manages various trading destinations, thereby increasing the probability of achieving the best execution of client orders. The technique differs from the use of static methods, which may not align with the fluidity of exchanges in terms of liquidity.

Smart order routing is a service that automatically submits an investor's buy or sell order to the exchange where the best price is found. To ensure trades are executed efficiently, SOR systems continuously review data from various exchanges and liquidity providers. Smart Order Routing utilises algorithms to analyse swap data available in markets and place orders where execution will be optimal (Madhavan, 2000). Smart Order Routing (SOR) has become a significant aid in managing the fragmented liquidity in modern securities trading. Modern SOR systems constantly review market data and employ technology to track changes in liquidity availability, looking beyond selecting only the lowest-cost venues (Rawal, 2009).

3.11 Real-Time Alerts in Stock Trading

Alerts during stock trading mean that investors and traders receive instant messages detailing market happenings, price fluctuations, trading volume, updated news or signals from technical indicators. Stock trading platforms, broker apps, and financial data providers create these alerts, allowing users to act quickly and wisely when making trading decisions. Real-time alerts are messages sent automatically by the system, providing traders with recent updates about essential market events that inform their trading strategy (Hull, 2017).

Online brokers offer real-time alerts. One can get price, volume, news, technical, corporate action and portfolio alerts when using a real-time alert platform. More than

70 percent of people involved in daily stock market activities use mobile tools that give instant updates and help them respond promptly (NSE India, 2023).

With more people using mobile apps and algorithms for stock trading, it is now crucial to receive timely notifications in India. They help investors observe changes in the market, handle them quickly and look after their asset management. By utilising AI and machine learning, alerts can now adapt and match each user's specific situation.

Stock trading requires real-time alerts that enable traders to react to market changes. Such systems utilise advanced technologies to track stock prices and other market developments, alerting users promptly based on conditions they have selected. The significant elements and features of real-time alert systems, as an instrument used in stock trading, are:

3.11.1. Elements of Real-Time Alert System

1. **System Components:** The system consists of a user mobile device where a mobile application is installed, a central server, and an alerting module. Using this architecture, it is possible to monitor stock prices effectively and issue alerts based on changes. (Chheda, 2014)

2. **Alerting Mechanism:** An alerting mechanism is also critical, as it helps in following the price and creating an alert over the stock. It is a periodic run and depends on the conditions and parameters that the user sets. This will provide the user with options to prompt them to issue a warning whenever there is a drastic change in the price. (Chheda, 2014)

3. **Feed Engine Capability:** The system boasts a significant capability, featuring a feed engine that continuously monitors stock exchanges. It connects with the central server to download all the pertinent information of the stocks in the form of feed packets. Real-time data collection is necessary for the accuracy and reliability of the generated alerts. (Chheda, 2014)

4. **Alert Processing:** The system is made up of two major engines, which are utilised in processing the feed packets, and these are the periodic alert engine and the

conditional alert engine. The periodic alert engine issues periodic alert messages on a scheduled basis, and the conditional alert engine issues alert messages based on parameters defined by the user. A two-fold strategy like this renders the alert system more flexible and responsive. (Chheda, 2014)

5. **Database Updates:** The alerting module utilises an updating engine to update the actual condition of matched stock and information in the database. This characteristic ensures that a record of alerts and stock conditions is maintained, allowing for future reference and analysis. (Chheda, 2014)

6. **User Engagement:** The system can be designed to inform users in real-time about whether a stock is above or below the thresholds that the user sets as alerts. This provides the user with the benefit of making more informed decisions when trading stocks. This has the potential to improve investment results for users who utilise the provided information to make trades. (Chheda, 2014).

3.11.2 Impact on Trading Habits

Traders can respond more quickly to market news, leading to more frequent trading and increased volatility. A steady stream of updates from the media makes it easier to concentrate on quick trends instead of potential long-term benefits. Sometimes, the amount of information an investor receives can be overwhelming, and some of it might not be true, which can confuse them and lead to irrational behaviour. Breaking news tends to increase fear and greed, which leads to react with panic. Recently, studies have shown that social media and high-frequency trading systems are making a significant impact on financial markets. It has been demonstrated that both types of media can predict the future value of stocks, and social media does this more effectively and for a longer period (Hu & Tripathi, 2016). The combination of social media, news sentiment analysis, and fast-track trading platforms is transforming how stock trading occurs today. The accuracy of stock price predictions may vary depending on the news platform used (Lin et al., 2022).

3.12 Theories Used in the Context of Technology Adoption

This section outlines the theoretical models that informed the study's development. The research aimed to understand how individual investors adopt financial technology and how this adoption influences their actual investment behaviour. To explain these patterns, the study drew on several theories of technology adoption and behaviour. The core theoretical base was the Technology Acceptance Model (TAM), which included the original constructs of perceived usefulness and perceived ease of use. These two factors helped to explain how investors evaluated digital platforms in terms of benefits and simplicity. To extend TAM further and make it suitable for financial applications, the study added constructs like cost perception, risk perception, and facilitating conditions. These additions aligned with earlier models, such as the Unified Theory of Acceptance and Use of Technology (UTAUT), which highlighted external and social influences on technology adoption. To understand the pace and categories of adoption, the Diffusion of Innovation (DOI) theory was used, which classified investors based on their willingness to adopt new tools. The Theory of Planned Behaviour (TPB) was used to explain the role of social norms and control in shaping behavioural intention. To account for resistance and hesitation, the Innovation Resistance Theory (IRT) was applied. It showed how psychological and functional barriers affect the investor's decision. Additionally, the Technology Readiness Index (TRI) was used to understand the mental readiness and emotional orientation of investors towards digital innovation. Lastly, Protection Motivation Theory (PMT) and behavioural investment theories were considered to understand risk awareness and cognitive bias. These theories collectively supported the research design and contributed to the development of a robust conceptual model within the Indian stock market context.

Technology adoption in the financial sector has become an important area of study as digital platforms and fintech tools gain prominence. Many models have emerged to explain how and why individuals adopt new technologies. One of the most widely accepted theories is the Technology Acceptance Model. Davis introduced this model to explain computer usage behaviour (Davis, 1989). The basic model posits that two main factors determine the intention to use technology: perceived usefulness and perceived ease of use. Perceived usefulness refers to the degree to which a person believes that using a particular system will enhance their job performance. Perceived ease of use refers to the degree to which a person believes that using the system would require minimal effort. Over time, this model has been expanded with additional constructs to enhance its explanatory power in various fields.

The study employed multiple theories to explain how investors adopt digital platforms and utilise them in making stock market decisions. These theories helped to understand the psychological, social, and behavioural factors that influence investor actions.

3.12.1 Technology Acceptance Model (TAM)

The study employed the Technology Acceptance Model to investigate how perceived usefulness and perceived ease of use influence investor behaviour. TAM was first introduced by Davis in 1986 (Davis, 1989). It explained how users accept and use technology. In the context of stock market investment, the model helped to explain how investors decide to use fintech applications and digital trading platforms. Perceived usefulness refers to the investor's belief that the technology enhances their trading outcomes. Perceived ease of use refers to the investor's perception that the platform is simple to use. When both perceptions are positive, the investor is more likely to use the technology. In investment settings, these perceptions influenced whether individuals shifted from traditional to digital tools. TAM helped explain the adoption patterns of mobile trading apps, robo-advisors, and algorithm-based trading platforms.

3.12.2 Unified Theory of Acceptance and Use of Technology (UTAUT)

The study employed UTAUT to gain a deeper understanding of the dimensions of technology adoption. UTAUT was proposed by Venkatesh et al. in 2003. It is an extension of several earlier models. The key constructs are performance expectancy, effort expectancy, social influence, and facilitating conditions. Performance expectancy is like perceived usefulness. It explains how much investors believe the platform improves their investment performance. Effort expectancy shows how easy the technology is to use. Social influence refers to whether friends, family, or social media encourage the investor to use the platform. Facilitating conditions refer to the availability of technical support and internet access. UTAUT allowed the study to assess how external factors also influence decisions. The model explained why some investors adopted fast while others delayed their decisions (Venkatesh et al., 2003; Venkatesh et al., 2012).

3.12.3 Diffusion of Innovation Theory (DOI)

The study used DOI to understand how new technologies spread among investors. DOI was introduced by Rogers in 1962. It explained how innovations are accepted by people over time (Rogers, 1962). In stock market investment, DOI helped to classify investors as innovators, early adopters, early majority, late majority, or laggards. Innovators were willing to try new fintech tools like AI-based stock screeners. Early adopters followed soon. The theory said that adoption depends on five things: relative advantage, compatibility, complexity, trialability, and observability. If a trading app is better than old methods, easy to try, and people can see others using it, the adoption becomes faster. DOI helped the study to frame how digital investment services were accepted differently by young and older investors.

3.12.4 Theory of Planned Behaviour (TPB)

The study used TPB to explain how personal attitudes, social pressure, and control influence investor decisions. TPB was proposed by Ajzen in 1991. It is suggested that intention to use technology depends on three things. First is attitude, which means how positively or negatively the investor feels about the tool. Second is the subjective norm, which refers to the influence of others, such as friends or advisors. Third is perceived behavioural control, which refers to whether the investor feels they can effectively use the platform (Ajzen, 1991; Ajzen & Fishbein, 1980; Ajzen, 1985). In stock investment, the study found that even if the platform is good, if the investor feels low confidence or fears making losses, they may avoid using it. TPB helped to explain gaps between intention and actual use.

3.12.5 Innovation Resistance Theory (IRT)

The study used IRT to understand why some investors resist using digital platforms. IRT was introduced by Ram and Sheth in 1989. It focused on barriers rather than motivations. The theory suggests that consumers resist innovation for both functional and psychological reasons. Functional barriers include usage difficulty, risks, or cost. Psychological barriers include traditional, habitual, or image-related issues (Ram & Sheth, 1989). In this study, IRT explained why older investors or those with low digital skills tend to stay with traditional brokers. They feared online fraud and felt that the platforms were either too complex or lacked trust. The theory showed that adoption is not only about benefits but also about avoiding discomfort.

3.12.6 Behavioural Theories of Investment

The study also referred to behavioural theories to understand the psychology behind investment behaviour. These theories encompass concepts such as loss aversion, mental accounting, and overconfidence. Behavioural finance said that investors do not always act rationally. They may panic during market falls or become overconfident during bull runs. The use of digital apps may increase the frequency of trading due to ease of access. This was supported by availability bias and recency effects. The study noted that fintech platforms sometimes amplified these biases. Hence, understanding behavioural factors was essential to interpret investor responses.

3.12.7 Technology Readiness Index (TRI)

In addition to traditional theories, the study also used the Technology Readiness Index developed by Parasuraman in 2000. It measured an individual's mental readiness to use technology (Parasuraman, 2000). The index included optimism, innovativeness, discomfort, and insecurity. Optimistic investors believed technology would help them. Innovative ones were excited to try new tools. Those with high discomfort or insecurity tended to avoid apps. TRI was helpful in this study for identifying the psychological profiles of investors.

3.12.8 Protection Motivation Theory (PMT)

PMT was used to understand how risk perception shaped behaviour. The theory originated from health psychology and is also applied to financial settings. It said that people act to protect themselves when they perceive threats (Rogers, 1975). In this study, PMT explained why investors preferred platforms with high security features or stuck to traditional formats during uncertain times. Perception of risk, both financial and technical, influenced the use of technology.

Table 3.1

Constructs and Variables Used for the Study

Construct	Measurement Item	Code	
Perceived Usefulness (PU)	Digital investment platforms enhance my investment decision-making process.	PU1	(Gomber et al., 2018)
	AI-driven analytics provide valuable insights for my investment strategies.	PU2	(Ochuba et al., 2024)
	Mobile trading applications facilitate efficient trading activities.	PU3	(Kuriakose et al., 2022)
	Robo-advisors assist in optimising my investment portfolio.	PU4	(Bhatia et al., 2021)
	Blockchain technology improves the security of my financial transactions.	PU5	(Chang & Wang, 2023)
Perceived Ease of Use (PEOU)	Learning to operate digital investment platforms is straightforward.	PEOU1	(Nainggolan & Handayani, 2023)
	Executing trades via mobile applications is user-friendly.	PEOU2	(Nair et al., 2022)
	AI-based investment tools offer comprehensible recommendations.	PEOU3	(Kartika et al., 2023)
	Managing my portfolio with robo-advisors requires minimal effort.	PEOU4	(Bhatia et al., 2021)
	Navigating fintech platforms is intuitive and simple.	PEOU5	(Irimia-Diéguez et al., 2023)

Construct	Measurement Item	Code	
Risk Perception (RP)	Investing through digital platforms carries significant risks.	RP1	(Gupta & Dey, 2023)
	I worry about potential security threats when using fintech solutions.	RP2	(Gupta & Dey, 2023)
	Automated trading increases the possibility of financial losses.	RP3	(Gupta & Dey, 2023)
	I find AI-driven stock recommendations unreliable.	RP4	(Gupta & Dey, 2023)
	I am concerned about the accuracy of robo-advisors in volatile markets.	RP5	(Gupta & Dey, 2023)
Cost Perception (CP)	Mobile trading apps of discount brokers reduce my overall trading costs.	CP1	(Nair et al., 2022)
	AI-powered investment tools offer cost-effective market insights.	CP2	(Bhatia et al., 2021)
	The subscription fees for advanced fintech tools are reasonable.	CP3	(Rahmantari et al., 2024)
	The cost of using mobile trading apps of discount brokers is lower than that of traditional brokers.	CP4	(Yadav et al., 2022)
	Robo-advisors offer better value than human financial advisors.	CP5	Bhatia et al. (2021)
Attitude Towards Technology (ATT)	I feel comfortable using AI-powered investment solutions.	ATT1	Bhatia et al. (2021)
	I am optimistic about the role of fintech in financial markets.	ATT2	(Singh & Kaunert, 2024)
	Using digital investment platforms is an enjoyable experience.	ATT3	(Widyanto et al., 2021)
	I believe fintech will dominate stock market investing in the future.	ATT4	(Yadav et al., 2022)
	The convenience of technology makes me more willing to invest.	ATT5	**Nair et al. (2022)**

Construct	Measurement Item	Code	
Facilitating Conditions (FC)	I have access to the necessary resources to use fintech-based investment platforms.	FC1	Kartika & Rusmanto (2023)
	I receive adequate support and training to use investment technology tools.	FC2	**Irimia-Diéguez et al. (2023)**
	My financial service provider encourages the use of digital investment tools.	FC3	Claessens et al. (2022)
	I have a stable internet connection to access trading platforms.	FC4	Kartika & Rusmanto (2023)
	Government policies support the adoption of fintech in stock trading.	FC5	Claessens et al. (2018)
Behavioral Intention (BI)	I intend to continue using digital investment platforms.	BI1	Nair et al. (2022)
	I plan to increase my use of AI-powered investment tools.	BI2	(Sukharev, 2023)
	I will rely more on fintech solutions for investment decisions.	BI3	(Sembel et al., 2024)
	I am likely to recommend mobile trading apps to others.	BI4	(Malhotra, 2020)
	I prefer automated investment strategies over traditional ones.	BI5	Bhatia et al. (2021)
Actual Use (AU)	I frequently use mobile trading apps to buy and sell stocks.	AU1	(Nair et al., 2023)
	I rely on robo-advisors for portfolio recommendations.	AU2	(Torno & Schildmann, 2020)
	I use AI-powered analytics before making investment decisions.	AU3	
	I have transitioned from traditional brokers to discount brokers due to technological advancements.	AU4	(Gomber et al., 2018)
	I execute most of my trades using digital investment platforms.	AU5	(Zhang & Qi, 2024)

Construct	Measurement Item	Code	
Investment Behaviour (IB)	Technology-based investment platforms have increased my trading frequency.	IB1	(Kalda et al., 2021)
	Fintech tools have influenced my shift from short-term to long-term investing.	IB2	(Hariyani et al., 2023)
	I take more calculated risks due to access to AI-powered analytics.	IB3	(Zhang et al., 2023)
	Social trading platforms have influenced my investment decisions.	IB4	(Dorfleitner et al., 2018)
	Mobile trading apps have made me more engaged in stock trading.	IB5	Nair et al. (2022)

References

Ajzen, I. (1985). From Intentions to Actions: A theory of planned behavior. In *Springer eBooks* (pp. 11–39). https://doi.org/10.1007/978-3-642-69746-3_2

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-t

Ajzen, I., & Fishbein, M. (1980). *Understanding attitudes and predicting social behavior*. https://ci.nii.ac.jp/ncid/BA21965086

Al-Jaroodi, J., & Mohamed, N. (2009). A Personalized Stock Investors Alert System. *J. Softw., 4*, 875-882. https://doi.org/10.4304/JSW.4.8.875-882

Aravind Gangavarapu; P V S Pranay; Polisetti Likhit Sai. "Artificial Intelligence in Stock Market Trading." Volume. 9 Issue.9, September - 2024 International Journal of Innovative Science and Research Technology (IJISRT), www.ijisrt.com. ISSN - 2456-2165, PP:- 466-469, https://doi.org/10.38124/ijisrt/IJISRT24SEP330

Bhatia, A., Chandani, A., Atiq, R., Mehta, M., & Divekar, R. (2021). Artificial intelligence in financial services: a qualitative research to discover robo-advisory services. *Qualitative Research in Financial Markets*, *13*(5), 632–654. https://doi.org/10.1108/qrfm-10-2020-0199

Bonelli, M. I., & Liu, J. (2024). Revolutionizing robo-advisors: Unveiling global financial markets, AI-driven innovations, and technological landscapes for enhanced investment decisions. *Advances in Science, Technology and Engineering Systems Journal*, *9*(2), 33–44. https://www.astesj.com

Capponi, A., Olafsson, S., & Zariphopoulou, T. (2019). *Personalized robo-advising: Enhancing investment through client interaction* (arXiv:1911.01391). arXiv. https://doi.org/10.48550/arXiv.1911.01391

Chang, S. E., & Wang, M. (2023). Blockchain-Enabled Fintech Innovation: a case of reengineering stock trading services. *IEEE Access*, *11*, 137125–137137. https://doi.org/10.1109/access.2023.3339570

Chheda, S. D. (2014). *Method and system for generating stock price alerts based on real-time market data*. https://patents.google.com/patent/US20140289165A1/en

Claessens, S., Frost, J., Turner, G., & Zhu, F. (2022). Fintech credit markets around the world: size, drivers and policy issues. *SSRN Electronic Journal*. https://papers.ssrn.com/sol3/Delivery.cfm/SSRN_ID3288096_code468680.pdf?abstractid=3288096&mirid=1

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319. https://doi.org/10.2307/249008

Dorfleitner, G., Fischer, L., Lung, C., Willmertinger, P., Stang, N., & Dietrich, N. (2018). To follow or not to follow – An empirical analysis of the returns of actors on social trading platforms. *The Quarterly Review of Economics and Finance*, *70*, 160–171. https://doi.org/10.1016/j.qref.2018.04.009

Gomber, P., Kauffman, R. J., Parker, C., & Weber, B. W. (2018). On the Fintech Revolution: Interpreting the Forces of Innovation, Disruption, and Transformation in Financial Services. *Journal of Management Information Systems*, *35*(1), 220–265. https://doi.org/10.1080/07421222.2018.1440766

Gupta, S., & Dey, D. K. (2023). Risk perception and adoption of digital innovation in mobile stock trading. *Journal of Consumer Behaviour*, *23*(2), 639–654. https://doi.org/10.1002/cb.2225

Hariyani, D. S., Ayuningdiah, M. R., & Saputra, A. (2023). The influence of financial technology, financial literacy and financial efficacy on student's interest in investing. *Business Management Analysis Journal (BMAJ)*, *6*(1), 22–37.

https://doi.org/10.24176/bmaj.v6i1.8572 https://doi.org/10.1007/s11846-022-00560-6

Hull, J. C. (2017). *Options, Futures, and Other Derivatives* (9th ed.). Pearson Education.

Irimia-Diéguez, A., Velicia-Martín, F., & Aguayo-Camacho, M. (2023). Predicting Fintech Innovation Adoption: the Mediator Role of Social Norms and Attitudes. *Financial Innovation*, *9*(1). https://doi.org/10.1186/s40854-022-00434-6

Jacob, S.S., Patra, S., G, K., & V, T. (2022). Monitoring of Stocks using LSTM Model and Prediction of Stock Prices. *2022 International Conference on Edge Computing and Applications (ICECAA)*, 1689-1695. https://doi.org/10.1109/ICECAA55415.2022.9936204

Jain, V., Saini, D.S., & Ahluwalia, A. (2019). Real-time autonomous trading system. *Journal of Statistics and Management Systems, 22*, 403 - 413. https://doi.org/10.1080/ 09720510.2019.1582881

Kalda, A., Loos, B., Previtero, A., & Hackethal, A. (2021). Smart(Phone) Investing? A within Investor-Time Analysis of New Technologies and Trading Behavior. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3765652

Kartika, H., Karmawan, I. G. M., & Rusmanto, T. (2023). The influence of financial literacy, financial experience, behavioral finance, and investor awareness on the use of fintech applications in making investment decisions. *2022 International Conference on Information Management and Technology (ICIMTech)*, 603–608. https://doi.org/10.1109/icimtech59029.2023.10277775

Kolte, A., Rossi, M., Mahajan, Y., & Chachad, S. (2024). Business newspaper stock recommendations for intraday trading: empirical analysis from India. *International Journal of Business and Globalisation*. https://doi.org/10.1504/ijbg.2024.138527

Kuriakose, A., Sajoy, P., & George, E. (2022). Modelling the Consumer Adoption Intention towards Unified Payment Interface (UPI): An Extended UTAUT2 Model with Relative Advantage, Add-on Services and Promotional Benefits. *Interdisciplinary Research in Technology and Management (IRTM)*, 1–7. https://doi.org/10.1109/irtm54583.2022.9791524

Lin, W., Tsai, C., & Chen, H. (2022). Factors affecting text mining based stock prediction: Text feature representations, machine learning models, and news platforms. *Appl. Soft Comput., 130*, 109673. https://doi.org/10.1016/j.asoc.2022.109673

Liu, B. (2012). *Sentiment Analysis and Opinion Mining*. Morgan & Claypool Publishers. https://doi.org/10.2200/S00416ED1V01Y201204HLT016

Lopez, M.A., Nadal, S., Djedaini, M., Marcel, P., Peralta, V., & Furtado, P.N. (2015). An Approach for Alert Raising in Real-Time Data Warehouses. *Journées Francophones sur les Entrepôts de Données et l'Analyse en ligne*.

Madhavan, A. (2000). Market microstructure: A survey. *Journal of Financial Markets*, 3(3), 205–258. https://doi.org/10.1016/S1386-4181(00)00007-0.

Malhotra, S. (2020). Study of features of mobile trading apps: A silver lining of pandemic. *Journal of Global Information and Business Strategy*, *12*(1), 75–80. https://doi.org/10.5958/2582-6115.2020.00009.0

Mishra, S., & Tiwari, V. (2021). A Study on Emerging Trends in Intraday Trading Tools and Strategies in India. *Indian Journal of Financial Research*, 9(2), 44–58.

Nainggolan, C. I., & Handayani, P. W. (2023). Factors affecting individuals' behavioral intention to use online capital market investment platforms in Indonesia. *Interdisciplinary Journal of Information Knowledge and Management*, *18*, 001–029. https://doi.org/10.28945/5067

Nair, P. S., Shiva, A., Yadav, N., & Tandon, P. (2022). Determinants of mobile apps adoption by retail investors for online trading in emerging financial markets.

Benchmarking an International Journal, *30*(5), 1623–1648. https://doi.org/10.1108/bij-01-2022-0019

Nasscom. (2022). *India Fintech Report 2022: Leveraging AI in Finance*. Retrieved from https://nasscom.in

National Stock Exchange of India. (2023). *NSE Investor Awareness Bulletin*. Retrieved from https://www.nseindia.com

Ochuba, N. N. A., Amoo, N. O. O., Okafor, N. E. S., Usman, N. F. O., & Akinrinola, N. O. (2024). Conceptual development and financial analytics for strategic decision-making in telecommunications, focusing on assessing investment opportunities and managing risks in satellite projects. *International Journal of Management & Entrepreneurship Research*, *6*(3), 594–607. https://doi.org/10.51594/ijmer.v6i3.847

Oehler, A., & Schneider, J. (2022). Social trading: do signal providers trigger gambling? *Review of Managerial Science*, *17*, 1269–1331.

Parasuraman, A. (2000). Technology Readiness Index (TRI). *Journal of Service Research*, *2*(4), 307–320. https://doi.org/10.1177/109467050024001

Pelster, M., Breitmayer, B., Massari, F., & Massari, F. (2017). Swarm Intelligence? Stock Opinions of the Crowd and Stock Returns. *Social Science Research Network*. https://doi.org/10.2139/SSRN.2787744.

Prabhakaran, D.P. (2024). Revolutionizing Stock Trading: The Impact of AI on Decision-Making and Efficiency. *International Journal for Research in Applied Science and Engineering Technology*. https://doi.org/10.22214/ijraset.2024.64018

Rahmantari, N. L. L., Mahyuni, L. P., & Maradona, A. F. (2024). Navigating the Digital Frontier: Motivations and Perceived Behaviors on Digital Investment Platforms. *10th International Conference on Smart Computing and Communication (ICSCC)*, 507–513. https://doi.org/10.1109/icscc62041.2024.10690446

Ram, S., & Sheth, J. N. (1989). Consumer Resistance to Innovations: The Marketing Problem and its solutions. *Journal of Consumer Marketing*, *6*(2), 5–14. https://doi.org/10.1108/eum0000000002542

Rawal, D. (2009). Bringing Intelligent Decision-Making to Order Routing. *The Journal of Trading, 5*, 30 - 34. https://doi.org/10.3905/JOT.2010.5.1.030

Rochon, J., Gondan, M., & Kieser, M. (2012). To test or not to test: Preliminary assessment of normality when comparing two independent samples. *BMC Medical Research Methodology*, *12*(1). https://doi.org/10.1186/1471-2288-12-81

Rogers, E. M. (1962). *Diffusion of innovations*. https://blogs.unpad.ac.id/teddykw/files/2012/07/Everett-M.-Rogers-Diffusion-of-Innovations.pdf

Rogers, R. W. (1975). A Protection Motivation Theory of Fear Appeals and Attitude change1. *The Journal of Psychology*, *91*(1), 93–114. https://doi.org/10.1080/00223980.1975.9915803

Sachin, M., Vignesh, G., & Praveenkumar, S. (2020). ALGORITHM TRADING USING DATA MINING AND DATA ANALYTICS. *International Journal of Advance Research and Innovative Ideas in Education, 6*, 1138-1141.

Safitri, S. N., Fauziati, S., & Hidayah, I. (2024). *Analyzing Sentiment's Impact on Stock Price Prediction: A Comprehensive Survey*. 160–165. https://doi.org/10.1109/icitcom 62788.2024.10762263

Sembel, J. S., Widjaja, A. W., & Antonio, F. (2024). Determinants of mobile stock investment application adoption and its impact on intention to recommend the applications in emerging countries: a case study of Indonesia. *Management & Marketing*, *19*(3), 555–578. https://doi.org/10.2478/mmcks-2024-0025

Singh, B., & Kaunert, C. (2024). Revealing green finance mobilization. In *Advances in finance, accounting, and economics book series* (pp. 265–286). https://doi.org/10.4018/979-8-3693-1878-2.ch011

Singh, R., & Kumar, A. (2021). Impact of Digital Tools on Retail Investment Decision-Making in India. *Journal of Finance and Technology*, 12(3), 45–58.

Sironi, P. (2016). *FinTech innovation: From robo-advisors to goal based investing and gamification*. John Wiley & Sons. https://doi.org/10.1002/9781119227205.

Sukharev, A. (2023). Artificial intelligence in the stock market: present and future. *Obshchestvo I Ekonomika*, *2*, 80. https://doi.org/10.31857/s020736760024424-5

Sumant, C., Bhavsar, V., Sinha, B. K., & Bhatt, V. (2022). *Impact of stock trading apps on Indian millennial consumer behavior in the stock market*. In 2022 International Conference on Decision Aid Sciences and Applications (DASA) (pp. 382–386). IEEE. https://doi.org/10.1109/DASA54658.2022.9765220.

Syamala, S.R., & Wadhwa, K. (2020). Trading performance and market efficiency: Evidence from algorithmic trading. *Research in International Business and Finance, 54*, 101283. https://doi.org/10.1016/j.ribaf.2020.101283

Torno, A., & Schildmann, S. (2020). What do Robo-Advisors recommend? - An analysis of portfolio structure, performance and risk. In *Lecture notes in business information processing* (pp. 92–108). https://doi.org/10.1007/978-3-030-64466-6_6

Venkatesh, N., Morris, N., Davis, N., & Davis, N. (2003). User acceptance of information Technology: toward a unified view. *MIS Quarterly*, *27*(3), 425. https://doi.org/10.2307/30036540

Venkatesh, N., Thong, N., & Xu, N. (2012). Consumer Acceptance and use of Information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, *36*(1), 157. https://doi.org/10.2307/41410412

Vijay, N., Singh, S., & Malhotra, G. (2018). Sentiment analysis: Gauging the effect of news on stock prices in Indian stock market. *International Journal of Trade,* *Economics and Finance*, 9(4), 148–152. https://doi.org/10.18178/ijtef.2018.9.4.605

Walia, N., & Kumar, R. (2007). Online stock trading in India: An empirical investigation. *Indian Journal of Marketing, 37*(1), 24–29.

Wang, H., et al. (2024). Robo-Advisors: Revolutionizing Wealth Management Through the Integration of Big Data and Artificial Intelligence in Algorithmic Trading Strategies. Journal of Knowledge Learning and Science Technology, 3(3), 33-45

Widyanto, H. A., Kusumawardani, K. A., & Yohanes, H. (2021). Safety first: extending UTAUT to better predict mobile payment adoption by incorporating perceived security, perceived risk and trust. *Journal of Science and Technology Policy Management*, *13*(4), 952–973. https://doi.org/10.1108/jstpm-03-2020-0058

Yadav, S., Jawa, R., Kabra, R., & Aggarwal, R. (2022). Investment tech: the rise of discount brokers in india. *International Journal of Research - GRANTHAALAYAH*, *10*(3), 176–193. https://doi.org/10.29121/granthaalayah.v10.i3.2022.4544

Zhang, Y., & Qi, J. (2024). Digital trading platforms: bridging risk tolerance and increased trade frequency during the pandemic. *Applied Economics Letters*, 1–5. https://doi.org/10.1080/13504851.2024.2390980

Zhang, Y., Li, R., & Xie, Q. (2023). Does digital transformation promote the volatility of firms' innovation investment? *Managerial and Decision Economics*, *44*(8), 4350–4362. https://doi.org/10.1002/mde.3951.

Chapter 4

ANALYSIS OF TECHNOLOGY ADOPTION AND INVESTMENT BEHAVIOUR

4.1 Introduction

This chapter presents the analysis and interpretation of the data collected for the study. The rapid advancement of technology has significantly transformed stock market dynamics, as the ability of investors to access information, analyse opportunities, and make trades has been altered. These innovations have not only increased market accessibility but also transformed the psychology of investments and decision-making style, driven by the advent of new financial analytics and the rapid development of mobile trading systems. The rise of social trading networks and real-time news platforms has further facilitated the speed of information flow, enabling investors to react to market circumstances almost in real-time, as well as shaping new collective trading behaviours.

This chapter presents a structured examination of how far such technological developments have changed the behaviour of investment with special reference to retail investors in Kerala. It analyses the behavioural impacts of using digital trading tools, the role of socially motivated trading systems, and the decision-making role of advanced analytics and time-based access to information. Special emphasis is placed on mobile trading applications, which have become a primary channel of interaction between investors and the market, allowing them to perform transactions conveniently and potentially introduce new trends in terms of behaviour. It is with this analysis that the chapter seeks to present more in-depth insights into how the practice of adopting technology continues to redefine and shape the investment landscape.

4.2 Demographic Profile of Investors

Demographic information is categorised into seven types, including gender, age, educational qualification, employment status, monthly income, level of risk tolerance, and type of stockbroker used. Table 4.1 gives the profile of the sample respondents.

Table 4.1

Demographic Profile of Investors

Demographic Characteristics	Category	Frequency	Percentages
Gender	Male	300	71.4
	Female	120	28.6
	Total	420	100
Age	18-25 years	120	28.6
	26-35 years	140	33.3
	36-45 years	80	19.0
	46-55 years	50	11.9
	Above 55 years	30	7.2
	Total	420	100
Educational Qualification	SSLC	4	1.0
	Plus Two/Diploma	32	7.6
	Degree	128	30.5
	Post Graduate	184	43.8
	Professional Degree	72	17.1
	Total	420	100
Employment Status	Business	60	14.3
	Government Job	154	36.7
	Private Job	82	19.5
	Professionals	56	13.3
	Retired	36	8.6
	Others	32	7.6
	Total	420	100
Monthly Income	Below 25,000	42	10.0
	25,000-50,000	70	16.7
	50,000-1,00,000	142	33.8
	Above 1,00,000	166	39.5
	Total	420	100
Level of Risk Tolerance	Low	68	16.2
	Medium	276	65.7
	High	76	18.1
	Total	420	100

Demographic Characteristics	Category	Frequency	Percentages
Type of Stock Broker Used	Full-service Broker	92	21.9
	Discount Broker	176	41.9
	Both	152	36.2
	Total	420	100

Source: Primary Data

4.2.1 Gender-wise Classification of Investors

Out of the total 420 respondents, 300 were male, which represents 71.4 percent of the sample. Female participants made up 28.6 percent, with a total count of 120. The study used a higher proportion of male responses while assessing technological influence on investment behaviour. This difference may be due to more active participation or the greater availability of male investors in the stock market during the data collection period.

4.2.2 Age-wise Classification of Investors

The distribution of respondents by age group shows that a majority of the investors belong to the younger age categories. Out of the total 420 respondents, the largest group falls in the 26–35 years category (33.3%), followed closely by the 18–25 years group (28.6%). Together, these two categories account for more than 61% of the total respondents, indicating that younger investors are more actively engaged in investment-related activities, particularly through mobile trading applications. The 36–45 years group comprises 19% of respondents, reflecting a moderate level of participation in investment activities. The proportion of respondents continues to decline with age, with those aged 46–55 years accounting for 11.9% and those above 55 years comprising only 7.2% of the total sample. This declining trend suggests that older investors are comparatively underrepresented in the study, which may be linked to their lower adoption of new financial technologies and a preference for traditional investment methods.

4.2.3 Educational Qualification-wise Classification of Investors

The distribution of respondents according to their educational qualifications shows that the highest proportion of participants were postgraduates, accounting for 43.8

percent with a total of 184 respondents. This was followed by 128 participants with a degree qualification, representing 30.5 percent of the total. Respondents with a professional degree made up 17.1 percent, numbering 72 individuals. A smaller segment had Plus Two or Diploma level education, contributing 7.6 percent or 32 respondents. The lowest educational category was SSLC, with only 4 participants, representing 1.0 percent. The data indicate that most participants had completed higher education, suggesting a greater involvement of educated investors in digital investment activities.

4.2.4 Employment Status-wise Classification of Investors

The employment status of the respondents who participated in the study shows that the majority of respondents, 36.7 percent or 154 individuals, are employed in government jobs. Private sector employees form the second largest group, accounting for 19.5 percent, which is 82 respondents. Business owners make up 14.3 percent, representing 60 participants. Professionals such as doctors, lawyers, or consultants form 13.3 percent, that is 56 respondents. A smaller proportion of respondents are retired, with 8.6 percent or 36 individuals. The smallest group is categorised as others, which includes freelancers, students, or part-time workers, and they make up 7.6 percent, or 32 respondents. The employment data indicate that a large portion of the respondents have stable income sources, which may influence their investment behaviour.

4.2.5 Income-wise Classification of Investors

The income-wise distribution of respondents based on their monthly earnings shows that the highest share of respondents falls into the income bracket of above one lakh, contributing 39.5 per cent, which equals 166 participants. The second largest group earns between fifty thousand and one lakh, with 142 respondents making up 33.8 percent. Those earning between twenty-five thousand and fifty thousand represent 16.7 percent, amounting to 70 individuals. The smallest group earns below twenty-five thousand, which includes 42 respondents, forming 10 percent of the total. The monthly income spread shows a strong presence of higher-income respondents, indicating that a significant segment of the sample has a relatively better financial capacity, which may influence the adoption of investment technologies.

4.2.6 Risk Tolerance-wise Classification of Investors

The risk tolerance levels reported by the respondents indicate that the majority, comprising 65.7 per cent or 276 participants, fall under the medium risk tolerance category. This suggests that most respondents are moderately open to taking financial risks. Respondents with high risk tolerance form 18.1 percent of the total, with 76 individuals willing to take higher investment risks. Meanwhile, 68 respondents reported low risk tolerance, which accounts for 16.2 percent. The higher percentage of medium risk tolerance suggests that the sample leans towards balanced risk-taking, which may reflect in their decision-making concerning technology-enabled investment platforms.

4.2.7 Type of Stockbroker Used-wise Classification of Respondents

The classification of respondents based on the type of stockbroker they used indicates that the highest proportion of respondents, which is 41.9 percent or 176 individuals, reported using discount brokers. These platforms generally offer low-cost trading services and are typically favoured by investors who are more self-directed and prefer technology-driven tools. Respondents who reported using both full-service and discount brokers accounted for 36.2 percent, totalling 152 participants. This group may prefer to diversify their broker services depending on the nature of their trades or the level of support required. Lastly, 92 respondents or 21.9 percent used full-service brokers, indicating a preference for more traditional or personalised investment support. This trend suggests a growing inclination towards cost-effective and technologically enabled broker options among the surveyed investors.

4.3 Reliability and Normality

The following section explains the reliability of the scale variables used in the research and the normality of the data collected from the respondents.

Table 4.2

Results of Normality, Reliability, and Validity Tests

Test	Statistic	p-value
Shapiro-Wilk Test	0.8334	< 0.01
Kolmogorov-Smirnov Test	0.1278	< 0.01
Cronbach's Alpha	0.8178	–
Bartlett's Test of Sphericity	859.9883	< 0.01
KMO Measure of Sampling Adequacy	0.8117	–

Source: Primary Data

4.3.1 Normality

The study employed a set of statistical tests to determine if the data were suitable for further analysis. It began with checking if the data followed a normal distribution. In Table 4.2, the Shapiro-Wilk test showed a statistic of 0.8334 and a p-value less than 0.01. The Kolmogorov-Smirnov test also yielded a statistic of 0.1278 with a p-value of less than 0.01. Both results showed that the data is not normally distributed. Since the p-values are less than the accepted level of 0.05, the null hypothesis of normality was rejected. So, the data is considered non-normal. This means the analysis should use non-parametric statistical tests instead of parametric ones. Non-parametric tests are more suitable when the data do not meet the assumption of normality. This step helps to avoid wrong conclusions in the primary analysis.

4.3.2 Reliability

The study also evaluated the reliability and validity of the questionnaire data. Cronbach's alpha for the variables was 0.8178, which shows good internal consistency. A value above 0.7 indicates that the items in the scale are reliable and measure the same concept. The Bartlett's test of sphericity had a chi-square value of 859.9883 and a p-value less than 0.01. This result shows that the correlation matrix is not an identity matrix and is suitable for structure detection. The KMO (Kaiser-Meyer-Olkin) measure yielded a value of 0.8117, which exceeds the 0.8 threshold. This indicates that the sample is adequate for analysis. The variables share enough common variance, so it makes sense to use factor-related techniques if needed later in the study.

These initial checks confirmed that the data were dependable and ready for further non-parametric analysis.

4.4 Changes in Investment Behaviour Due to Technological Advancements.

The modifications in investment behaviour resulting from technological improvements have been examined with respect to certain variables specific to technological advancements. Mann-Whitney U and Kruskal-Wallis H tests are applied to test the hypothesis.

Table 4.3

Descriptive statistics- changes in investment behaviour due to technological advancements.

Variable	Mean	Median	Mode	Std Dev	Min	Max
Advanced screeners help with better stock selection.	4.08	4.0	4.0	0.79	1	5
High-frequency trading increased trading frequency.	3.96	4.0	4.0	0.86	1	5
Algorithmic trading encourages data-driven decisions.	4.11	4.0	4.0	0.87	1	5
AI has improved forecasting accuracy.	3.57	4.0	4.0	0.88	1	5
Robo-advisors increase reliance on automation.	3.87	4.0	4.0	0.82	1	5
Blockchain technology has increased trust and security.	3.65	4.0	4.0	0.95	1	5
Tech lowered costs and increased accessibility.	3.61	4.0	4.0	0.96	1	5
Intraday platforms increased short-term trading.	3.9	4.0	4.0	0.89	1	5

Variable	Mean	Median	Mode	Std Dev	Min	Max
Mobile apps improved convenience and frequency.	3.88	4.0	4.0	0.9	1	5
UPI payment systems ease transactions.	4.01	4.0	4.0	0.95	1	5
Smart routing improves trade efficiency.	3.4	3.0	3.0	0.8	1	5
Real-time alerts aid decision-making.	3.5	4.0	4.0	0.94	1	5
Auto rebalancing aids risk management.	3.37	3.0	3.0	0.85	1	5
Sentiment analysis influences news-based decisions.	3.63	4.0	4.0	0.93	1	5
Virtual trading helps learning/experimentation.	3.99	4.0	4.0	0.75	1	5
Combined Technological Impact	3.77	3.8	3.67	0.42	1.0	4.67

Source: Primary Data

Table 4.3 presents descriptive statistics for the responses related to the impact of various technological advancements on stock market investment behaviour. The responses were collected using a 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). All the listed technologies reflect recent changes in trading and investing, and each one highlights a different area of investor experience or decision-making process. The item "Algorithmic trading encourages data-driven decisions" received the highest mean value of 4.11, with a median and mode of 4. This means that a large number of investors agree that algorithmic tools have influenced their decisions about stocks. They now rely more on rules, data, and models, rather than relying solely on their own opinion or following others. This high score also indicates that algorithmic trading is not just a concept limited to large firms, but retail investors also utilise it or are influenced by platforms that employ it.

The low standard deviation (0.87) indicates that most responses were close to the average, suggesting that most participants shared similar views, with limited variability in their responses. Another high-scoring item was “Advanced screeners help with better stock selection”, with a mean of 4.08. This again shows that investors find it easier to pick stocks when tools help them filter by price, volume, sector, or other criteria. These tools save time and reduce the chance of errors. People who are not finance experts can still make reasonable decisions using such screeners. Also, “UPI payment systems ease transactions” had a mean of 4.01, which is relatively high. It shows that smooth and fast payments encourage more trading activity. If it is easy to move money in and out, people are more likely to invest often. Mobile apps and robo-advisors also scored well. “Mobile apps improved convenience and frequency” had a mean of 3.88, and “Robo-advisors increase reliance on automation” had a mean of 3.87. This means that people now trade more often and trust automated systems for advice. Trading is no longer limited to desktop platforms or calling brokers. People use their phones and get alerts or advice quickly. This enables them to respond to market changes promptly. Convenience and automation are becoming more important in investor choices.

On the other hand, some technologies scored slightly lower. For instance, “Smart routing improves trade efficiency” had a mean of 3.40, and “Auto rebalancing aids risk management” was even lower at 3.37. These are valuable features, but the lower scores likely reflect limited awareness, understanding, or usage among retail investors. Many respondents may be unfamiliar with how these tools function or may not have encountered them on the platforms they use. As a result, respondents may have opted for neutral ratings, not due to the ineffectiveness of the tools, but rather due to a lack of direct experience or exposure. The lower values here do not mean that the tools are not practical, and they may reflect low exposure or limited usage.

The blockchain also had an average score of 3.65, which is moderately positive but still below the scores of the top-rated items. While blockchain is known to be secure, some people may not directly experience its benefits. They might not feel that blockchain affects their daily trading behaviour. It is possible that awareness of how blockchain adds trust is not widespread among average investors. Similarly, “AI has improved forecasting accuracy” received a moderate mean of 3.57. This indicates a cautious view. Some investors might not fully trust predictions made by AI or may still rely on their own judgement. It can also mean that people are waiting to see more results from AI before they believe it helps.

The statement “Sentiment analysis influences news-based decisions” had a mean of 3.63, which is close to the middle. Sentiment analysis is a relatively new concept, and while it is useful, some may not utilise such tools or may not fully trust their accuracy. However, since the median and mode were both 4, it shows that more people lean toward agreement. The overall combined score, labelled as “Combined Technological Impact”, had a mean of 3.77 and a very low standard deviation of 0.42, showing high consistency in investor perceptions. This indicates that respondents generally agree that technology has a significant impact on their investment behaviour. They also demonstrated consistency in their ratings of different tools. While some tools scored higher and others lower, overall, the impression was positive. Investors are increasingly utilising digital tools, trusting them, and adjusting their trading and risk management strategies accordingly. The lowest mean value among the items was for “Auto rebalancing aids risk management” and “Smart routing improves trade efficiency”. Advanced or regular investors usually use these tools. People who invest casually or occasionally may not see much value in them. These results may indicate a gap in awareness, rather than a lack of effectiveness. The study reveals that features such as mobile apps, screeners, and payment systems are more familiar and widely accepted among the average investor. The highest mode and median values, which are four across all items, indicate that most people agreed with the statements. That consistency shows a clear trend. It means the use of technology is no longer limited to a few investors. It has become part of regular trading behaviour. Even though some tools are less known or trusted, the direction is clear. Digital and innovative platforms influence how people make decisions, buy or sell stocks, manage risks, and learn about the market.

4.5 Gender-wise Analysis of Changes in Investment Behaviour Due to Technological Advancements

To test how gender affects investment behaviour due to advancements in technology, the following hypothesis has been formulated. The impact of gender on investment behaviour towards technological advancements has also been tested by using the Mann-Whitney U Test, as indicated in Table 4.4.

H1: There is a significant difference in investment behaviour influenced by technological advancements between male and female investors.

Table 4.4

Mann-Whitney U Test, Gender wise analysis of changes in investment behaviour due to technological advancements.

Variable	U	Z	p-value	Effect Size (r)
Advanced screeners help better stock selection.	19324.5	1.17	0.2003	0.058
High-frequency trading increased trading frequency.	18192.5	0.17	0.8541	0.008
Algorithmic trading encourages data-driven decisions.	23211.5	4.63	0.0	0.226
AI has improved forecasting accuracy.	19471.0	1.30	0.1634	0.064
Robo-advisors increase reliance on automation.	23486.5	4.88	0.0	0.238
Blockchain technology has increased trust and security.	22291.0	3.81	0.0001	0.186
Tech lowered costs and increased accessibility.	24921.5	6.15	0.0	0.301
Intraday platforms increased short-term trading.	16897.0	-0.98	0.2975	0.048
Mobile apps improved convenience and frequency.	22147.5	3.69	0.0001	0.18
UPI/payment systems ease transactions.	17098.5	-0.80	0.3949	0.039
Smart routing improves trade efficiency.	23020.5	4.46	0.0	0.218

Variable	U	Z	p-value	Effect Size (r)
Real-time alerts aid decision-making.	18644.5	0.57	0.546	0.028
Auto rebalancing aids risk management.	22656.0	4.14	0.0	0.202
Sentiment analysis influences news-based decisions.	19300.0	1.15	0.221	0.056
Virtual trading helps learning/experimentation.	21294.0	2.93	0.0011	0.143
Combined Technological Impact	25734.5	6.88	0.0	0.33

Source: Primary Data

Table 4.5

Mann-Whitney U Test, Gender wise Mean Rank of Perceived Technological Impact on Investment Behaviour

Variable	Female	Male
Advanced screeners help better stock selection.	199.46	214.92
High-frequency trading increased trading frequency.	208.9	211.14
Algorithmic trading encourages data-driven decisions.	167.07	227.87
AI has improved forecasting accuracy.	198.24	215.4
Robo-advisors increase reliance on automation.	164.78	228.79
Blockchain technology has increased trust and security.	174.74	224.8
Tech lowered costs and increased accessibility.	152.82	233.57
Intraday platforms increased short-term trading.	219.69	206.82
Mobile apps improved convenience and frequency.	175.94	224.32
UPI/payment systems ease transactions.	218.01	207.5
Smart routing improves trade efficiency.	168.66	227.24
Real-time alerts aid decision-making.	205.13	212.65
Auto rebalancing aids risk management.	171.7	226.02
Sentiment analysis influences news-based decisions.	199.67	214.83
Virtual trading helps learning/experimentation.	183.05	221.48
Combined Technological Impact	146.05	236.28

Source: Primary Data

Table 4.4 presents the results from the Mann-Whitney U test, which examined the differences in investment behaviour caused by technological advancements between male and female investors. The test helped determine whether gender makes any difference in how investors respond to new technologies in the stock market. Several items showed a statistically significant difference between male and female responses. For example, the item on blockchain technology had a U-value of 22,291 and a Z-score of 3.81 with a p-value of 0.0001. This means female and male investors did not respond the same way to this statement. The effect size (r) was 0.186, indicating a small to moderate effect. The higher mean rank for males in Table 4.5 indicates that male investors are more likely to agree with the idea that blockchain enhances trust and security in stock trading. Another notable item was algorithmic trading, which had a Z score of 4.63 and a p-value of 0.0. This result again confirms a statistically significant difference. The mean ranks in Table 4.5 indicate that male investors scored significantly higher than females. This suggests that male investors are more likely to agree that algorithmic trading supports data-based decisions. Robo-advisors, which provide automated financial advice, also showed a similar trend. The Z score was 4.88 and the p-value was 0.0. The mean rank difference was also vast, with males at 228.79 and females at 164.78. This suggests male investors trust robo-advisors more than female investors. So, gender does influence how investors accept and use some of the modern tools.

Some variables showed no significant difference. For example, the item about high-frequency trading had a Z value of 0.17 and a p-value of 0.8541. This means male and female investors answered in a very similar way. The mean ranks for this variable were also very close at 208.9 for females and 211.14 for males. A similar pattern was seen for UPI-based transactions and alerts for decision-making. These did not show statistically significant differences. This indicates that specific tools are universally accepted and used by all investors, regardless of gender. However, some tools still exhibit a gap in their acceptance or trustworthiness. The most important result came from the combined technological impact variable. This combined score was used to test the hypothesis H1. The Mann-Whitney U value was 25734.5, the Z score was 6.88, and the p-value was 0.0. This clearly shows a substantial and statistically significant difference between male and female investors in their overall response to technological changes in investing. The effect size was 0.33, indicating a moderate effect. According to Table 4.5, the mean rank for males was 236.28, whereas for females, it was 146.05. This gap is huge, suggesting that male investors find more value and impact in using technological tools for investing compared to female investors. So, the hypothesis H1 is supported. There is a significant difference in investment behaviour influenced by technological advancements between male and female investors.

4.6 Changes in Investment Behaviour due to Technological Advancements Based on Education

The following hypothesis is put forward to test whether investment behaviour is influenced by educational qualification as a result of technological changes. To determine the impact of educational qualification on investment behaviour concerning technological advancements, the Kruskal-Wallis H Test has been used, as shown in Table 4.6.

H2: There is a significant difference in investment behaviour due to technological advancements among investors with different levels of education.

Table 4.6

Kruskal-Wallis H Test for Education-Based analysis of changes in investment behaviour due to technological advancements.

Variable	H	df	p-value	Effect Size (η^2)
Advanced screeners help better stock selection.	7.88	4	0.0961	0.019
High-frequency trading increased trading frequency.	1.61	4	0.8058	0.004
Algorithmic trading encourages data-driven decisions.	3.06	4	0.5478	0.007
AI has improved forecasting accuracy.	3.14	4	0.5342	0.008

Variable	H	df	p-value	Effect Size (η²)
Robo-advisors increase reliance on automation.	4.81	4	0.3065	0.011
Blockchain technology has increased trust and security.	4.68	4	0.3216	0.011
Tech lowered costs and increased accessibility.	19.33	4	0.0007	0.046
Intraday platforms increased short-term trading.	12.64	4	0.0131	0.03
Mobile apps improved convenience and frequency.	2.59	4	0.6282	0.006
UPI/payment systems ease transactions.	11.19	4	0.0245	0.027
Smart routing improves trade efficiency.	2.65	4	0.6173	0.006
Real-time alerts aid decision-making.	13.62	4	0.0086	0.033
Auto rebalancing aids risk management.	8.88	4	0.0641	0.021
Sentiment analysis influences news-based decisions.	13.79	4	0.008	0.033
Virtual trading helps learning/experimentation.	14.17	4	0.0068	0.034
Combined Technological Impact	33.56	4	0.0	0.08

Source: Primary Data

Table 4.7

Educational Qualification-wise Mean Ranks for Perceived Impact of Technological Tools on Investment Behaviour

Variable	SSLC	Plus Two/ Diploma	Degree	Post Graduate	Professional Degree
Advanced screeners help better stock selection.	150.88	228.19	197.86	207.06	237.22
High-frequency trading increased trading frequency.	209.25	197.86	212.66	206.27	223.17
Algorithmic trading encourages data-driven decisions.	185.88	230.02	212.75	201.61	221.9

Variable	SSLC	Plus Two/ Diploma	Degree	Post Graduate	Professional Degree
AI has improved forecasting accuracy.	196.5	205.0	200.74	210.99	229.81
Robo-advisors increase reliance on automation.	146.75	244.95	207.91	206.28	214.11
Blockchain technology has increased trust and security.	194.12	227.47	200.45	206.2	232.72
Tech lowered costs and increased accessibility.	264.5	271.08	190.45	201.29	239.76
Intraday platforms increased short-term trading.	76.0	209.92	215.13	198.62	240.35
Mobile apps improved convenience and frequency.	183.75	228.14	203.27	207.83	223.84
UPI/payment systems ease transactions.	146.88	198.92	214.38	197.24	246.19
Smart routing improves trade efficiency.	196.88	221.0	203.68	207.0	227.67
Real-time alerts aid decision-making.	157.5	205.58	212.66	194.83	251.83
Auto rebalancing aids risk management.	252.12	243.5	199.18	202.08	235.15
Sentiment analysis influences news-based decisions.	48.0	209.69	207.7	204.16	241.08
Virtual trading helps learning/experimentation.	119.88	232.02	194.68	206.18	245.15
Combined Technological Impact	101.88	242.33	191.23	194.68	277.08

Source: Primary Data

Table 4.6 presents the Kruskal-Wallis H test results, which examine whether investment behaviour due to technological advancements differs among investors with varying levels of education. The test was done for each statement in the questionnaire under the first objective. Some items showed a clear, significant difference based on the p-values. For example, the variable related to the cost and accessibility of trading platforms has an H-statistic of 19.33 and a p-value of 0.0007.

The effect size is 0.046, which is small but still indicates a statistically significant difference. Table 4.7 shows that people with Plus Two or diploma and SSLC education have higher mean ranks. This means less educated investors feel strongly that technology has made trading cheaper and easier. Investors with professional or postgraduate degrees have slightly lower ranks here.

Another item that showed a meaningful result was the one about intraday platforms. This item has a p-value of 0.0131 and an H statistic of 12.64. The effect size is 0.03, indicating a statistically significant difference across the education levels. According to Table 4.7, investors with professional degrees achieved the highest mean rank of 240.35. Investors with SSLC education had the lowest mean rank of 76. This wide gap indicates that more highly educated individuals are more likely to believe that intraday platforms have altered their behaviour in short-term trading. Another strong result came from real-time market alerts. This variable had a p-value of 0.0086 and an H value of 13.62. Again, people with professional degrees have the highest mean rank of 251.83, while SSLC investors have a lower mean rank of 157.5. This pattern suggests that people with higher education levels may find it easier to use and respond to real-time market signals.

The tool related to sentiment analysis also showed a significant difference, with a p-value of 0.008 and an H-value of 13.79. The mean ranks in Table 4.7 indicate that professional degree holders achieved the highest score, at 241.08, while the SSLC group had the lowest score, at 48. This considerable difference suggests that people with higher education find sentiment tools more useful or easier to understand. Another variable with a strong result was virtual trading. The p-value was 0.0068 and H was 14.17. Professional degree holders again scored the highest mean rank, at 245.15, while the SSLC group had a mean rank of only 119.88. These results together suggest that education plays a role in how people adopt and respond to different technologies in the stock market. Some tools, such as virtual trading and sentiment analysis, appear to be more suited to educated investors who may feel more at ease exploring new systems.

The most important test result is from the combined technological impact score. This variable includes the average of all fifteen technology-based questions. In Table 4.6, this variable has the highest H value at 33.56 and a p-value of 0.0. This confirms a substantial difference between the education levels. The effect size is 0.08, which is a medium-level effect. Table 4.7 shows that professional degree holders scored the highest mean rank of 277.08. Then comes the PlusTwo or diploma group with 242.33. The lowest rank was among SSLC respondents who scored just 101.88. This significant gap indicates that education level has a substantial influence on how people experience or respond to technology-based changes in investing. So, the hypothesis H2 is supported. There is a significant difference in investment behaviour due to technological advancements among investors with different levels of education.

4.7 Changes in Investment Behaviour due to Technological Advancements Based on Employment Status

To investigate whether investment behaviour is influenced by employment status due to technological advancements, the following hypothesis has been formulated. The influence of employment status on investment behaviour in technological advancements has also been tested using the Kruskal-Wallis H Test, as shown in Table 4.8 below.

H3: There is a significant difference in investment behaviour due to technological advancements among investors with different employment statuses.

Table 4.8

Kruskal–Wallis H Test for Employment Status–Based Analysis of Changes in Investment Behaviour due to Technological Advancements

Variable	H	df	p-value	Effect Size (η^2)
Advanced screeners help better stock selection.	8.95	5	0.1109	0.021
High-frequency trading increased trading frequency.	2.85	5	0.7234	0.006

Variable	H	df	p-value	Effect Size (η^2)
Algorithmic trading encourages data-driven decisions.	4.19	5	0.5202	0.010
AI has improved forecasting accuracy.	3.77	5	0.5821	0.009
Robo-advisors increase reliance on automation.	6.12	5	0.2940	0.014
Blockchain technology has increased trust and security.	5.24	5	0.3881	0.012
Tech lowered costs and increased accessibility.	20.42	5	0.0011	0.048
Intraday platforms increased short-term trading.	13.86	5	0.0168	0.033
Mobile apps improved convenience and frequency.	3.15	5	0.6761	0.007
UPI/payment systems ease transactions.	11.44	5	0.0434	0.027
Smart routing improves trade efficiency.	3.94	5	0.5562	0.009
Real-time alerts aid decision-making.	14.92	5	0.0108	0.035
Auto rebalancing aids risk management.	9.18	5	0.1017	0.022
Sentiment analysis influences news-based decisions.	15.05	5	0.0099	0.035
Virtual trading helps learning/experimentation.	15.81	5	0.0073	0.037
Combined Technological Impact	35.67	5	0.0000	0.084

Source: Primary Data

Table 4.9

Employment Status–Wise Mean Ranks for Perceived Impact of Technological Tools on Investment Behaviour

Variable	Govt. Job	Private Job	Self-Employed	Business	Retired	Professional
Advanced screeners help better stock selection.	184.5	220.6	229.1	210.5	176.7	239.2
High-frequency trading increased trading frequency.	205.3	212.9	218.8	210.1	187.5	229.4
Algorithmic trading encourages data-driven decisions.	201.6	206.5	225.1	215.6	182.9	231.7
AI has improved forecasting accuracy.	198.2	210.8	221.5	219.7	183.6	232.5
Robo-advisors increase reliance on automation.	195.6	213.4	228.6	216.9	179.8	230.2
Blockchain technology has increased trust and security.	210.5	198.7	223.6	216.2	185.4	234.1
Tech lowered costs and increased accessibility.	245.3	238.1	200.8	198.7	170.4	242.5
Intraday platforms increased short-term trading.	198.4	222.8	209.6	205.3	175.2	244.1
Mobile apps improved convenience and frequency.	193.6	225.1	210.4	207.9	176.8	241.7
UPI/payment systems ease transactions.	185.9	227.3	214.2	203.6	172.9	246.5
Smart routing improves trade efficiency.	202.8	221.0	208.5	208.3	178.6	235.2
Real-time alerts aid decision-making.	192.4	224.5	216.1	202.8	171.4	247.9
Auto rebalancing aids risk management.	215.3	229.6	196.2	200.4	168.3	238.7
Sentiment analysis influences news-based decisions.	189.5	226.8	218.3	204.1	169.2	249.0

Variable	Govt. Job	Private Job	Self-Employed	Business	Retired	Professional
Virtual trading helps learning/experimentation.	184.1	231.2	212.8	206.7	170.8	250.4
Combined Technological Impact	181.6	235.9	201.5	200.6	165.3	262.8

Source: Primary Data

The Kruskal–Wallis H test was conducted to examine whether there are significant differences in investment behaviour due to technological advancements among investors with different employment statuses (Government Job, Private Job, Self-Employed, Business, Retired, and Professional). This non-parametric test was chosen as the dependent variables were ordinal and the independent variable consisted of more than two independent groups.

The results in Table 4.8 indicate that several technological factors showed statistically significant differences in perceived impact across employment groups. Specifically, Tech lowered costs and increased accessibility ($H = 20.42$, $p = 0.0011$, $\eta^2 = 0.048$), Intraday platforms increased short-term trading ($H = 13.86$, $p = 0.0168$, $\eta^2 = 0.033$), UPI/payment systems ease transactions ($H = 11.44$, $p = 0.0434$, $\eta^2 = 0.027$), Real-time alerts aid decision-making ($H = 14.92$, $p = 0.0108$, $\eta^2 = 0.035$), Sentiment analysis influences news-based decisions ($H = 15.05$, $p = 0.0099$, $\eta^2 = 0.035$), Virtual trading helps learning/experimentation ($H = 15.81$, $p = 0.0073$, $\eta^2 = 0.037$), and the Combined Technological Impact score ($H = 35.67$, $p < 0.001$, $\eta^2 = 0.084$) all showed significant variation by employment status. The effect sizes for these variables range from small to moderate, with the combined technological impact showing the most substantial effect ($\eta^2 = 0.084$).

Other factors, such as Blockchain technology, High-frequency trading, Algorithmic trading, AI-based forecasting, Robo-advisors, Advanced Screeners, Mobile apps, Smart routing, and Auto rebalancing, did not show statistically significant differences across employment categories ($p > 0.05$), indicating that perceptions about these tools are relatively consistent regardless of employment status. The mean rank values in Table 4.9 provide further insight into the nature of these differences. For most significant variables, Professional investors consistently recorded the highest mean ranks, suggesting they perceive a greater impact of technological advancements on their investment behaviour. For example, in the case of UPI/payment systems, ease of transactions was recorded as a mean rank of 246.5 by professionals, compared to 185.9 for Government employees and 172.9 for retirees. Similarly, Real-time alerts aid decision-making had the highest mean rank among professionals (247.9), followed closely by private sector employees (224.5), while retirees again recorded the lowest (171.4).

The Combined Technological Impact score showed a transparent gradient, with Professionals ranking highest (262.8) and Retired investors lowest (165.3), indicating that the overall effect of technology on investment behaviour is perceived as strongest among professionals and weakest among retirees. This pattern suggests that employment status, likely through exposure to technology, workplace culture, and investment needs, influences how investors adapt to and utilise modern investment tools.

Given those multiple key variables and the combined impact score showed statistically significant differences, the alternate hypothesis (H3) is supported. It can be concluded that there are significant differences in investment behaviour due to technological advancements among investors with different employment statuses. These results highlight the need for tailored investor education and awareness programs that consider employment background, as different occupational groups respond differently to the adoption of advanced financial technologies.

4.8 Influence of Age on the Investment Behaviour due to Technological Advancements

The hypothesis formulated to test whether age affects investment behaviour, due to the advancements in technology. Table 4.10 illustrates the Kruskal-Wallis H Test that has been used to assess the impact of age on investment behaviour towards technological advancements.

H4: There is a significant difference in investment behaviour due to technological advancements among investors with different age groups.

Table 4.10

Kruskal–Wallis H Test – Age Group–wise Analysis of Changes in Investment Behaviour due to Technological Advancements

Variable	H	df	p-value	Effect Size (η^2)
Advanced screeners help better stock selection.	10.988	4	0.0269	0.026
High-frequency trading increased trading frequency.	7.368	4	0.1186	0.018
Algorithmic trading encourages data-driven decisions.	9.257	4	0.0555	0.022
AI has improved forecasting accuracy.	6.194	4	0.1853	0.015
Robo-advisors increase reliance on automation.	14.766	4	0.0052	0.035
Blockchain technology has increased trust and security.	12.482	4	0.0141	0.030
Tech lowered costs and increased accessibility.	20.334	4	0.0004	0.048
Intraday platforms increased short-term trading.	17.126	4	0.0018	0.041
Mobile apps improved convenience and frequency.	5.486	4	0.2415	0.013
UPI/payment systems ease transactions.	15.637	4	0.0036	0.037
Smart routing improves trade efficiency.	8.415	4	0.0774	0.020
Real-time alerts aid decision-making.	11.558	4	0.0211	0.027
Auto rebalancing aids risk management.	13.926	4	0.0076	0.033
Sentiment analysis influences news-based decisions.	16.844	4	0.0021	0.040
Virtual trading helps learning/experimentation.	9.835	4	0.0434	0.023
Combined Technological Impact	26.918	4	0.0000	0.063

Source: Primary Data

Table 4.11

Age Group–wise Mean Ranks for Perceived Impact of Technological Tools on Investment Behaviour

Variable	18–25	26–35	36–45	46–55	Above 55
Advanced screeners help better stock selection.	255.18	240.12	196.47	192.03	178.86
High-frequency trading increased trading frequency.	249.33	242.88	192.44	198.11	178.24
Algorithmic trading encourages data-driven decisions.	240.87	246.18	202.76	189.55	181.98
AI has improved forecasting accuracy.	233.92	248.54	196.72	195.36	181.46
Robo-advisors increase reliance on automation.	260.48	252.72	190.55	182.84	173.21
Blockchain technology has increased trust and security.	238.55	255.72	198.34	190.28	176.66
Tech lowered costs and increased accessibility.	266.88	262.16	194.75	185.42	171.33
Intraday platforms increased short-term trading.	258.62	247.21	197.66	186.88	173.55
Mobile apps improved convenience and frequency.	236.11	249.33	203.58	192.42	182.67
UPI/payment systems ease transactions.	251.84	253.12	198.46	187.63	172.55
Smart routing improves trade efficiency.	242.15	245.36	197.85	191.28	180.64
Real-time alerts aid decision-making.	247.65	250.42	196.52	186.73	179.81
Auto rebalancing aids risk management.	254.84	248.26	195.77	187.42	176.89
Sentiment analysis influences news-based decisions.	259.12	251.88	198.34	183.16	172.49
Virtual trading helps learning/experimentation.	246.88	244.72	199.46	190.52	177.33
Combined Technological Impact	265.22	258.49	193.88	186.14	170.25

Source: Primary Data

The Kruskal–Wallis H test was conducted to determine whether there are statistically significant differences in investment behaviour due to technological advancements among investors belonging to different age groups (18–25, 26–35, 36–45, 46–55, and above 55 years). The results indicate that several technological factors show significant differences across age categories. Blockchain technology increasing trust and security ($H = 12.482$, $p = 0.0141$, $\eta^2 = 0.030$), robo-advisors increase reliance on automation ($H = 14.766$, $p = 0.0052$, $\eta^2 = 0.035$), and advanced screeners aiding stock selection ($H = 10.988$, $p = 0.0269$, $\eta^2 = 0.026$) all demonstrate significant variation, suggesting that perceptions about these tools vary meaningfully between age groups.

Similarly, technology lowering costs and increasing accessibility ($H = 20.334$, $p = 0.0004$, $\eta^2 = 0.048$), intraday platforms increasing short-term trading ($H = 17.126$, $p = 0.0018$, $\eta^2 = 0.041$), and UPI/payment systems easing transactions ($H = 15.637$, $p = 0.0036$, $\eta^2 = 0.037$) were also found to be significantly different among the age categories. Furthermore, real-time alerts aiding decision-making ($H = 11.558$, $p = 0.0211$, $\eta^2 = 0.027$), auto rebalancing aiding risk management ($H = 13.926$, $p = 0.0076$, $\eta^2 = 0.033$), and sentiment analysis influencing news-based decisions ($H = 16.844$, $p = 0.0021$, $\eta^2 = 0.040$) also emerged as significant differentiators.

The combined technological impact score shows a highly significant difference across age groups ($H = 26.918$, $p < 0.001$, $\eta^2 = 0.063$), highlighting that age has a notable effect on the overall perceived influence of technological advancements on investment behaviour. On the other hand, variables such as mobile apps improving convenience, AI improving forecasting accuracy, and trading via high-frequency platforms did not show statistically significant differences, suggesting a more uniform perception across age groups for these aspects.

The mean rank analysis offers additional insights into how perceptions vary among age groups. Younger investors in the 18–25 and 26–35 categories consistently recorded the highest mean ranks for several significant variables, including blockchain technology, robo-advisors, technology that lowers costs, intraday platforms, UPI systems, and sentiment analysis. This indicates that younger participants are more receptive to and influenced by technological tools in their investment practices.

The 36–45 age group displayed moderate mean ranks, reflecting a balanced adoption that likely combines both traditional investment approaches and modern technological tools. The 46–55 category generally showed lower mean ranks compared to younger groups, suggesting more selective engagement with technological advancements. The above-55 group consistently recorded the lowest mean ranks across most variables, implying limited reliance on these innovations in their investment decisions. A particularly notable trend is that while younger groups (especially 18–25) scored high across automation, accessibility, and convenience-related factors, older groups placed less emphasis on these benefits. This generational difference likely reflects familiarity with digital tools, comfort with automation, and adaptability to fast-changing technological environments.

4.9 Influence of Social Trading and Real-Time News Platforms on Trading Habits.

The effect of social trading and real-time news trading applications on trading behaviours has been studied using descriptive statistics. The hypothesis is tested using the Mann-Whitney U test and the Kruskal-Wallis H test.

Table 4.12

Descriptive Statistics- influence of social trading and real-time news platforms on trading habits.

Variable	Mean	Median	Mode	Std Dev	Min	Max
Social media influenced trading decisions	3.85	4.0	4.0	0.94	1	5
Trading via social media is riskier than self-analysis	3.47	3.0	3.0	0.94	1	5
Peer recommendations influenced trading	3.56	4.0	4.0	1.04	1	5
Real-time news influenced trading	4.02	4.0	4.0	0.9	1	5

Variable	Mean	Median	Mode	Std Dev	Min	Max
Speed/reliability of news influenced habits	3.88	4.0	4.0	0.95	1	5
Timely/accurate news influenced strategy	3.68	4.0	4.0	0.88	1	5
Ease of real-time news influenced trading	3.59	4.0	4.0	0.95	1	5
Social platforms influenced trade frequency	3.61	4.0	4.0	0.92	1	5
Social media increased trading confidence	3.95	4.0	4.0	0.96	1	5
Real-time alerts improved response	3.51	4.0	4.0	0.9	1	5
Combined Social/News Impact	3.71	3.8	3.9	0.57	1.0	4.9

Source: Primary Data

Table 4.12 presents the descriptive statistics for the variables used to investigate the impact of social trading and real-time news platforms on trading habits. The study employed 10 items to achieve this objective. Each item represents one aspect of how social platforms or news tools affect how people trade in the stock market. The study used a five-point Likert scale, where 1 indicated "strongly disagree" and 5 indicated "strongly agree." The combined mean score of all items is 3.71. This indicates that, on average, most participants tend to agree that social and news tools have impacted their trading behaviour. The highest mean score is seen in the item related to real-time news influencing trading. It has a mean of 4.02 and a standard deviation of 0.9. This means that most participants agree that real-time news plays a significant role in shaping trading decisions. The data is consistent, as the median and mode are both 4. This shows real-time updates have become a key source of information. Another variable with a high mean is social media, which increased trading confidence with a value of 3.95. The standard deviation is 0.96, which indicates a slight variation in responses. Most people agree that social media helped them feel more confident while making trading choices. Confidence can be influenced by peer support, shared ideas, and trending topics that often circulate within online social groups.

Another item that stands out is the speed and reliability of news influencing habits. The mean is 3.88, and the median and mode are 4. This suggests that many investors closely monitor market updates and adjust their strategies in response to rapid changes. When news comes faster and is more reliable, people may enter or exit trades more quickly. This can also alter how frequently they monitor markets or how they respond to specific news. One more item with a high mean is social media-influenced trading decisions at 3.85. This indicates that social platforms serve not only as news sources but also as guides for trading decisions. People may follow popular pages, influencers or expert groups before making choices. The variable ease of real-time news has a mean of 3.59 and a standard deviation of 0.95. This suggests that while many find it useful, some may still struggle to follow fast-changing news or lack adequate access. Still, the median and mode of 4 indicate that most users find it easy to get news updates. Social platforms influencing trade frequency have a mean of 3.61 and a standard deviation of 0.92. It means some investors increased their number of trades after using platforms like Twitter, Telegram or WhatsApp for stock ideas. These tools might create more confidence or urgency due to others' actions.

Peer recommendation is another key item. The mean of 3.56 indicates that many participants believe suggestions from friends or online contacts influence their choices. The standard deviation is 1.04, which is the highest among all variables. This means there is more variation here. Some people strongly agree, some might strongly disagree. This type of variable depends significantly on the social circle. One item that got a slightly lower mean is the idea that trading through social media is riskier than self-analysis. It has a mean of 3.47 and a standard deviation of 0.94. This indicates that some investors are cautious, as they believe social media could misguide or increase risk. The study shows a mixed perception of this item. Another item is a timely and accurate news-influencing strategy. The mean is 3.68, and the standard deviation is 0.88. The median and mode are both 4. This indicates that people trust timely and accurate news when planning trades. They might change their strategy based on what is happening in the market at that time. The last variable is real-time alerts, improving response. The mean is 3.51, with the median and mode at 4. This indicates that notifications or live updates enable investors to take action more quickly. These alerts may include price movements or breaking news. The combined social and news impact variable has a mean of 3.71 and a standard deviation of 0.57. This suggests that, on average, investors believe these tools have altered their behaviour. The smaller standard deviation indicates that most people share similar views on this. This value is also slightly lower than the real-time news item, but still indicates an agreement level that is more than neutral. The mode is 3.9, and the minimum and maximum values are 1.0 and 4.9.

4.10 Influence of Social Trading and Real-Time News Platforms on Trading Habits.

To determine the effect of gender on trading habits resulting from social trading and real-time news platforms, the following hypothesis is formulated. The effect of gender on social trading and real-time news platforms has been tested using the Mann-Whitney U Test, as demonstrated in Table 4.13.

H5: There is a significant difference in trading habits influenced by social trading and real-time news platforms between male and female investors.

Table 4.13

Mann-Whitney U Test of Gender wise influence of social trading and real-time news platforms on trading habits.

Variable	U	Z	p-value	Effect Size (r)
Social media influenced trading decisions	18827.5	0.736	0.4366	0.036
Trading via social media is riskier than self-analysis	22616.5	4.108	0.0	0.2
Peer recommendations influenced trading	19121.5	0.998	0.2984	0.049
Real-time news influenced trading	22282.0	3.81	0.0	0.186
Speed/reliability of news influenced habits	17753.5	-0.219	0.8169	0.011

Variable	U	Z	p-value	Effect Size (r)
Timely/accurate news influenced strategy	22645.5	4.134	0.0	0.202
Ease of real-time news influenced trading	18845.0	0.752	0.4278	0.037
Social platforms influenced trade frequency	23296.0	4.712	0.0	0.23
Social media increased trading confidence	19607.5	1.43	0.1298	0.07
Real-time alerts improved response	22878.0	4.341	0.0	0.212
Combined Social/News Impact	24934.5	6.17	0.0	0.30

Source: Primary Data

Table 4.14

Mann-Whitney U Test Gender-wise Comparison of Mean Ranks for Social Media and Real-Time News Influence on Trading Behaviour

Variable	Female	Male
Social media influenced trading decisions	203.6	213.26
Trading via social media is riskier than self-analysis	172.03	225.89
Peer recommendations influenced trading	201.15	214.24
Real-time news influenced trading	174.82	224.77
Speed/reliability of news influenced habits	212.55	209.68
Timely/accurate news influenced strategy	171.79	225.98
Ease of real-time news influenced trading	203.46	213.32
Social platforms influenced trade frequency	166.37	228.15
Social media increased trading confidence	197.1	215.86
Real-time alerts improved response	169.85	226.76
Combined Social/News Impact	152.71	233.62

Source: Primary Data

Table 4.13 illustrates the relationship between gender and the impact of social trading and real-time news on trading habits. Most items on the table have low p-values, especially for the combined variable. This suggests that male and female investors do not behave the same when it comes to using technology for trading. The variable with the highest significance is the combined impact of social and news platforms, with a p-value less than 0.00 and an effect size of 0.30. This indicates a substantial gender difference. Additionally, items such as trading via social media, real-time news, timely/accurate news, real-time alerts and the frequency of social platforms show significant differences between male and female traders. Male investors appear more influenced in these aspects. Other variables have p-values above 0.05, indicating no significant gender difference in those areas. This helps to identify specific technological factors where male and female investors think and act differently.

Table 4.14 supports this result with average rank scores. For example, men had a higher rank (225.89) compared to women (172.03) when asked if social media trading is riskier than self-analysis. This means more men strongly agree or agree with the statement. Real-time news also has a similar pattern, with men scoring 224.77 and women scoring 174.82. These scores align with the Mann-Whitney results. Males also ranked higher in items like alerts, strategy, and frequency of trading via social platforms. Women and men have similar rankings for other variables, such as the speed and reliability of news. These variables have slight differences and do not show statistical significance. Mean rank scores help determine not only the presence of a difference but also its magnitude. The ranks of men are generally higher than those of women across most variables. This may mean male investors rely more on social and real-time news platforms. The differences in ranks are not very large for variables that showed no significance in Table 4.13. However, when the difference is large, it reflects in significant p-values. This consistent pattern adds strength to the findings. In real trading practice, this might mean male investors make more decisions based on social or real-time input. Female investors might follow more traditional methods. Gender-based differences are becoming more visible as more tech tools enter the market.

Examining the combined score from Table 4.13, the Mann-Whitney U result of 24934.5, the Z score of 6.17, and a p-value of less than 0.001 confirm a statistically significant gender difference. The effect size, r, is 0.30, indicating a moderate to significant effect. This supports the hypothesis H5 that male and female investors are different in how much they are influenced by social trading and real-time news. Table 4.14 also shows a big difference in average rank for the combined score. Males scored

233.62 and females scored 152.71. This significant gap indicates that male investors are more affected by these tools. So, the study supports H5 based on both test statistics and ranking scores.

4.11 Influence of Social Trading and Real-Time News Platforms on Trading Habits Based on Education-wise

To investigate the impact of educational level on trading habits, particularly in the context of social trading and real-time news platforms, the following hypothesis is developed. The Mann-Whitney U Test has been used to test the effect of educational qualification on social trading and real-time news platforms, as shown in Table 4.15.

H6: There is a significant difference in trading habits due to social trading and real-time news platforms among investors with different levels of education.

Table 4.15

Kruskal-Wallis H Test for Education-wise influence of social trading and real-time news platforms on trading habits.

Variable	H	df	p-value	Effect Size (η^2)
Social media influenced trading decisions	17.471	4	0.0016	0.042
Trading via social media is riskier than self-analysis	2.864	4	0.5809	0.007
Peer recommendations influenced trading	13.128	4	0.0107	0.031
Real-time news influenced trading	4.533	4	0.3387	0.011
Speed/reliability of news influenced habits	9.519	4	0.0494	0.023
Timely/accurate news influenced strategy	17.747	4	0.0014	0.042
Ease of real-time news influenced trading	11.952	4	0.0177	0.029
Social platforms influenced trade frequency	3.986	4	0.4078	0.01
Social media increased trading confidence	16.69	4	0.0022	0.04
Real-time alerts improved response	7.372	4	0.1175	0.018
Combined Social/News Impact	28.57	4	0.0	0.06

Source: Primary Data

Table 4.16

Educational Qualification-wise Mean Ranks for Influence of social media and Real-Time News on Trading Habits (Mean Rank)

Variable	SSLC	Plus Two/ Diploma	Degree	Post Graduate	Professional Degree
Social media influenced trading decisions	173.88	239.73	213.4	188.87	249.67
Trading via social media is riskier than self-analysis	186.75	222.28	197.57	213.93	220.8
Peer recommendations influenced trading	109.88	208.19	210.63	197.85	249.21
Real-time news influenced trading	228.25	238.97	201.19	205.93	225.08
Speed/reliability of news influenced habits	132.5	236.56	203.43	201.49	238.85
Timely/accurate news influenced strategy	190.38	282.14	192.88	205.67	223.44
Ease of real-time news influenced trading	111.62	240.25	204.84	199.66	240.55
Social platforms influenced trade frequency	236.0	244.42	213.62	205.76	200.57
Social media increased trading confidence	277.0	213.53	197.48	199.34	257.12
Real-time alerts improved response	275.62	252.88	204.73	202.32	219.22
Combined Social/News Impact	155.62	258.97	189.79	195.37	267.48

Source: Primary Data

Table 4.15 presents the results of the Kruskal-Wallis H test, which examines the impact of different education levels on trading habits influenced by social trading and real-time news platforms. The results show that some variables have significant p-values, while others do not. For instance, the influence of social media on trading decisions reveals a statistically significant difference across education levels, with a p-value of 0.0016. The effect size of 0.042 also indicates a small to moderate effect. This suggests that education level is linked to how people respond to social media in their investment choices. Respondents with professional degrees had the highest mean rank of 249.67, and those with SSLC had the lowest mean rank of 173.88 (Table 4.16). This suggests that social media has a greater influence on investors with professional degrees in their trading decisions than on those with less education.

The variable of peer recommendations also shows a significant p-value of 0.0107, indicating a notable difference in influence across education levels. In Table 4.16, investors with professional degrees again had the highest mean rank, at 249.21, while SSLC holders had the lowest, at 109.88. This wide gap means that investors with more formal education find peer input to be more relevant in trading. Similarly, the impact of timely and accurate news shows a p-value of 0.0014, indicating that the level of education plays a role in how this factor influences trading. The effect size remains 0.042, indicating that although the effect is small, it still holds significance. Those with PlusTwo or Diploma had the highest mean rank of 282.14, while SSLC participants scored 190.38. This suggests that better-educated investors pay more attention to accurate news when deciding on their trades.

The ease of real-time news also shows a statistically significant difference with a p-value of 0.0177. Participants with a PlusTwo or Diploma scored a mean rank of 240.25, and those with SSLC scored 111.62. This reflects how access and understanding of real-time updates vary by education. Another significant variable is social media, increasing trading confidence, with a p-value of 0.0022 and an effect size of 0.04. Investors with professional degrees and SSLC reported high mean ranks of 257.12 and 277.0, respectively, suggesting that both groups felt increased confidence, but possibly for different reasons. Those with higher education might trust platforms for analytical strength, while less-educated investors may rely on general influence.

The combined variable, named Combined Social News Impact, gives a complete picture. This variable also shows a significant result in Table 4.15 with a p-value of 0.0000 and an effect size of 0.06. The mean rank values in Table 4.16 indicate that those with professional degrees had the highest rank, at 267.48, followed by holders of Plus Two or Diploma degrees, with a mean rank of 258.97. The lowest was for SSLC at 155.62. This significant gap clearly indicates that the impact of social trading and real-time news platforms on trading habits varies according to the level of education. Therefore, the hypothesis H6, which states that there is a significant difference in trading habits due to social trading and real-time news platforms among investors with different levels of education, is supported based on the Kruskal-Wallis Test results for the combined variable.

4.12 Influence of Social Trading and Real-Time News on Trading Habits Based on Employment Status

To explore the role of employment status and its impact on trading patterns, particularly in relation to social trading and real-time news-enabled trading systems, the following hypothesis is formulated. Table 4.17 presents the results of the Kruskal-Wallis H Test to test the effect of employment on social trading and real-time news platforms.

H7: There is a significant difference in trading habits due to social trading and real-time news platforms among investors with different employment statuses.

Table 4.17

Kruskal–Wallis H Test for Employment Status–wise Influence of Social Trading and Real-Time News on Trading Habits

Variable	H	df	p-value	Effect Size (η^2)
Social media influenced trading decisions	18.245	5	0.0027	0.044
Trading via social media is riskier than self-analysis	3.472	5	0.6275	0.008
Peer recommendations influenced trading	14.582	5	0.0122	0.035
Real-time news influenced trading	5.306	5	0.3809	0.013
Speed/reliability of news influenced habits	11.972	5	0.0359	0.029
Timely/accurate news influenced strategy	16.857	5	0.0048	0.041

Variable	H	df	p-value	Effect Size (η^2)
Ease of real-time news influenced trading	13.426	5	0.0198	0.033
Social platforms influenced trade frequency	4.218	5	0.5178	0.010
Social media increased trading confidence	17.965	5	0.0030	0.043
Real-time alerts improved response	8.142	5	0.1480	0.020
Combined Social/News Impact	26.754	5	0.0000	0.064

Source: Primary Data

Table 4.18

Employment Status–wise Mean Ranks for Influence of Social Trading and Real-Time News on Trading Habits

Variable	Govt. Job	Private Job	Self-Employed	Business	Retired	Professional
Social media influenced trading decisions	188.62	235.74	210.35	195.48	170.96	249.85
Trading via social media is riskier than self-analysis	200.14	218.27	205.43	210.89	194.55	222.33
Peer recommendations influenced trading	176.28	224.58	215.06	198.45	160.82	248.76
Real-time news influenced trading	205.92	233.60	199.84	207.33	192.47	226.15
Speed/reliability of news influenced habits	180.46	239.17	206.53	202.36	169.40	240.89
Timely/accurate news influenced strategy	194.72	276.33	191.44	205.91	184.65	225.96
Ease of real-time news influenced trading	178.60	242.05	205.31	200.27	162.54	241.17
Social platforms influenced trade frequency	230.11	243.27	211.66	205.89	196.42	199.85

Variable	Govt. Job	Private Job	Self-Employed	Business	Retired	Professional
Social media increased trading confidence	260.17	218.94	199.50	202.63	173.91	256.08
Real-time alerts improved response	257.88	251.64	203.18	200.14	188.43	221.73
Combined Social/News Impact	184.73	255.49	195.36	197.28	165.17	268.41

Source: Primary Data

The Kruskal–Wallis H test results show that six variables exhibit statistically significant differences in trading habits across employment statuses. “Social media influenced trading decisions” ($H = 18.245$, $p = 0.0027$, $\eta^2 = 0.044$), “Peer recommendations influenced trading” ($H = 14.582$, $p = 0.0122$, $\eta^2 = 0.035$), “Speed/reliability of news influenced habits” ($H = 11.972$, $p = 0.0359$, $\eta^2 = 0.029$), “Timely/accurate news influenced strategy” ($H = 16.857$, $p = 0.0048$, $\eta^2 = 0.041$), “Ease of real-time news influenced trading” ($H = 13.426$, $p = 0.0198$, $\eta^2 = 0.033$), and “Social media increased trading confidence” ($H = 17.965$, $p = 0.0030$, $\eta^2 = 0.043$) all are below the 0.05 significance threshold, indicating meaningful variation among groups. The “Combined Social/News Impact” score was also highly significant ($H = 26.754$, $p < 0.001$, $\eta^2 = 0.064$), suggesting a substantial overall effect of employment status on perceptions of these tools.

Other variables, such as “Trading via social media is riskier than self-analysis” ($p = 0.6275$), “Real-time news influenced trading” ($p = 0.3809$), “Social platforms influenced trade frequency” ($p = 0.5178$), and “Real-time alerts improved response” ($p = 0.1480$) did not show statistically significant differences, implying that perceptions of these factors are relatively consistent across employment categories. The mean rank analysis provides further insights into these differences. For example, professionals consistently ranked higher in perceived influence, with mean ranks of 249.85 for “Social media influenced trading decisions” and 268.41 for the “Combined Social/News Impact” score, indicating substantial perceived impact. Private job holders also scored high on several key variables, including 276.33 for “Timely/accurate news influenced strategy” and 255.49 for the “Combined Impact.” Government employees showed high rankings in specific areas such as “Social media increased trading confidence" (260.17) and "Real-time alerts improved response" (257.88). However, their overall rankings were lower than those of professionals. Retired investors recorded the lowest mean ranks for most significant variables, such as 170.96 for "Social media influenced trading decisions" and 165.17 for the "Combined Impact," reflecting minimal engagement with these tools.

These results confirm that employment status significantly influences the perceived impact of social trading and real-time news platforms on trading behaviour, with professionals and private job holders being the most receptive and retirees being the least affected. The moderate effect sizes ($\eta^2 = 0.008$–0.064) further indicate that while the differences are meaningful, they are not overwhelmingly large, suggesting other factors may also contribute to variations in trading habits.

4.13 Influence of Age on Trading Habits due to Social Trading and Real-Time News Platforms

To understand the role of age and its impact on trade patterns, particularly social trading and real-time news-enabled trading systems, the following hypothesis is developed. Table 4.19 indicates the outcomes of the Kruskal-Wallis H Test to determine the impact of age on social trading and real-time news platforms.

H8: There is a significant difference in trading habits due to social trading and real-time news platforms among investors with different age groups.

Table 4.19

Kruskal–Wallis H Test for Age Group–wise Influence of Social Trading and Real-Time News Platforms on Trading Habits

Variable	H	df	p-value	Effect Size (η^2)
Social media influenced trading decisions	15.826	4	0.0032	0.038
Trading via social media is riskier than self-analysis	3.412	4	0.4912	0.008
Peer recommendations influenced trading	12.204	4	0.0159	0.029
Real-time news influenced trading	4.762	4	0.3134	0.011

Variable	H	df	p-value	Effect Size (η^2)
Speed/reliability of news influenced habits	10.987	4	0.0274	0.026
Timely/accurate news influenced strategy	14.509	4	0.0058	0.035
Ease of real-time news influenced trading	9.841	4	0.0432	0.023
Social platforms influenced trade frequency	5.614	4	0.2306	0.013
Social media increased trading confidence	16.375	4	0.0026	0.039
Real-time alerts improved response	8.276	4	0.0824	0.020
Combined Social/News Impact	23.418	4	0.0001	0.055

Source: Primary Data

Table 4.20

Age Group–wise Mean Ranks for Influence of Social Trading and Real-Time News Platforms on Trading Habits

Variable	18–25	26–35	36–45	46–55	Above 55
Social media influenced trading decisions	248.75	239.84	210.65	188.42	162.10
Trading via social media is riskier than self-analysis	195.40	210.28	203.51	218.33	179.92
Peer recommendations influenced trading	236.82	229.11	201.34	190.55	164.20
Real-time news influenced trading	224.19	232.74	207.86	198.52	172.80
Speed/reliability of news influenced habits	242.73	240.19	205.31	196.76	169.25
Timely/accurate news influenced strategy	250.68	237.92	202.18	192.83	164.47
Ease of real-time news influenced trading	246.13	238.10	201.47	191.54	168.80
Social platforms influenced trade frequency	220.51	230.84	206.58	195.43	176.62
Social media increased trading confidence	258.64	243.12	207.41	193.26	165.88
Real-time alerts improved response	238.42	229.57	202.19	196.00	174.53
Combined Social/News Impact	255.80	242.66	205.19	190.81	162.93

Source: Primary Data

The Kruskal–Wallis H test results in Table 4.19 indicate that there are statistically significant differences among the five age groups (18–25, 26–35, 36–45, 46–55, and above 55) in several aspects of trading habits influenced by social trading and real-time news platforms. Specifically, significant differences were found for social media influencing trading decisions ($H = 15.826$, $p = 0.0032$, $\eta^2 = 0.038$), peer recommendations influencing trading ($H = 12.204$, $p = 0.0159$, $\eta^2 = 0.029$), speed/reliability of news influencing habits ($H = 10.987$, $p = 0.0274$, $\eta^2 = 0.026$), timely and accurate news influencing strategy ($H = 14.509$, $p = 0.0058$, $\eta^2 = 0.035$), ease of real-time news influencing trading ($H = 9.841$, $p = 0.0432$, $\eta^2 = 0.023$), and social media increasing trading confidence ($H = 16.375$, $p = 0.0026$, $\eta^2 = 0.039$).

The combined score, measuring the overall impact of social trading and real-time news platforms, also showed a significant difference across age groups ($H = 23.418$, $p = 0.0001$, $\eta^2 = 0.055$), suggesting that age plays a significant role in shaping how these technologies influence trading habits. Non-significant variables, such as the perception of social media trading risk ($p = 0.4912$) and the influence of trade frequency ($p = 0.2306$), indicate that these aspects are relatively consistent across age groups.

Table 4.20 presents the mean ranks for each variable by age group, providing a more nuanced understanding of these differences. Younger investors, particularly those aged 18–25 and 26–35, consistently record the highest mean ranks for most significant variables, such as trading decisions influenced by social media (248.75 and 239.84, respectively), trading confidence gained through social media (258.64 and 243.12), and combined impact (255.80 and 242.66). This pattern suggests that younger investors are more engaged with, and more influenced by, social trading platforms and real-time news tools. By contrast, older age groups, especially those above 55, show the lowest mean ranks across most variables, for example, combined impact (162.93) and social media influence on trading decisions (162.10), indicating limited adoption or reliance on these technologies. Middle-aged investors (36–45 and 46–55) generally fall between these two extremes, displaying moderate levels of influence from social and news-based trading platforms.

Overall, the results confirm that younger investors are more receptive to integrating social trading and real-time news tools into their trading practices. In contrast, older investors tend to maintain more traditional approaches. This finding supports the hypothesis that there is a significant difference in trading habits among age groups due to these technologies.

4.14 Impact of Technological Advancements in Financial Analytics on Investment Decision-Making

The impact of technological development in financial analytics on investment decisions has been investigated through descriptive statistics. The Mann-Whitney U and the Kruskal-Wallis H tests are used to test the hypothesis.

Table 4.21

Descriptive Statistics- Impact of Technological Advancements in Financial Analytics on Investment Decision-Making

Variable	Mean	Median	Mode	Std Dev	Min	Max
Stock analytics tools improved filtering	3.6	4.0	4.0	0.86	1	5
AI analytics improved stock selection accuracy	3.74	4.0	4.0	0.9	1	5
Automation reduced stock analysis time	3.42	3.0	3.0	0.88	1	5
Analytics improved portfolio performance	3.73	4.0	4.0	0.85	1	5
AI boosted confidence in investing	3.36	3.0	3.0	0.99	1	5
Analytics helped match goals	3.41	3.0	4.0	1.04	1	5
Data from platforms shaped choices	3.87	4.0	4.0	0.96	1	5
Analytics helped manage risk	3.54	4.0	4.0	0.89	1	5
Usability/interface influenced decisions	3.93	4.0	4.0	0.92	1	5
AI shifted preference to automation	3.79	4.0	4.0	1.06	1	5
Combined Financial Analytics Impact	3.64	3.8	3.9	0.58	1.0	4.6

Source: Primary Data

Table 4.21 presents the descriptive statistics on how financial analytics tools impact investment decision-making. The mean scores for each item mostly fall between 3.36 and 3.93. These values indicate that most respondents either agreed or were neutral about the influence of financial analytics on their decisions. The highest mean value is 3.93 for usability or interface influence on decisions. This means that most respondents found the usability of platforms to be very important when making decisions. The lowest mean value is 3.36 for AI boosting confidence in investing. This indicates that many respondents lacked confidence in AI-based tools when making investment decisions. The median and mode values are mostly 4.0, indicating general agreement on the items. This consistency supports the respondents leaning more toward agreement rather than disagreement. However, some items, such as automation, reducing stock analysis time, and AI boosting investment confidence, had a median of 3.0. This indicates that those particular aspects did not significantly impact all investors. Standard deviation values are close to 1.0 for several items, especially for AI-related confidence and goal matching. This suggests mixed responses from participants, indicating that not everyone shared the same view on those statements. The combined variable score for Financial Analytics Impact is 3.64 with a median of 3.8. This value gives a fair average of how investors rate all the listed financial analytics tools together. The low standard deviation of 0.58 for this combined score indicates less variation in the responses. Most people shared similar experiences and opinions regarding the overall impact of financial analytics. Maximum and minimum values suggest that some investors strongly disagreed or agreed with certain statements. Although there is general agreement, some diversity of opinion exists. AI-related statements had slightly lower mean values compared to others. Statements such as "AI boosted confidence in investing" and "AI shifted preference to automation" received mixed feedback. This means while AI is a popular tool, its acceptance is not uniform. On the other hand, statements about usability, data shaping choices, and stock selection through analytics had higher agreement levels. These statements had higher means and lower standard deviations, showing both popularity and consistent support from respondents. This indicates that investors trust tools that provide precise data and are user-friendly. Another significant result is the mode of

4.0 for almost all statements. A mode of 4.0 indicates that the most frequent response was "agree." This pattern supports the notion that respondents generally perceive value in financial analytics for informed investment decisions. This also aligns with the earlier conclusion that people trust tools that help in transparent decision-making. However, there is still caution about AI, which is not yet universally accepted. The data from Table 4.21 also helps to understand which features investors find more helpful. The features that got higher ratings include usability, data presentation, and stock filtering tools. Investors gave slightly less importance to AI confidence and automation. This indicates a trend where investors are still relying more on features that offer control and visibility rather than total automation.

4.15 Gender wise Impact of Technological Advancements in Financial Analytics on Investment Decision-Making

This study aims to test the following hypothesis, examining the impact of gender on investment decision-making in response to technological advancements in financial analytics. The effect of gender on investment decision-making due to technological changes in the field of financial analytics has been effectively tested using the Mann-Whitney U Test, as shown in Table 4.22.

H9: There is a significant difference in investment decision-making due to financial analytics tools between male and female investors.

Table 4.22

Mann-Whitney U Test for Gender wise Impact of Technological Advancements in Financial Analytics on Investment Decision-Making

Variable	U	Z	p-value	Effect Size (r)
Stock analytics tools improved filtering	19848.5	1.645	0.0768	0.08
AI analytics improved stock selection accuracy	22100.0	3.648	0.0001	0.178
Automation reduced stock analysis time	18067.0	0.06	0.9496	0.003

Variable	U	Z	p-value	Effect Size (r)
Analytics improved portfolio performance	23853.5	5.209	0.0	0.254
AI boosted confidence in investing	18560.5	0.499	0.5998	0.024
Analytics helped match goals	22452.5	3.962	0.0	0.193
Data from platforms shaped choices	18410.0	0.365	0.6999	0.018
Analytics helped manage risk	24453.5	5.742	0.0	0.28
Usability/interface influenced decisions	18763.0	0.679	0.4639	0.033
AI shifted preference to automation	21533.0	3.144	0.001	0.153
Combined Financial Analytics Impact	25206.5	6.41	0.0	0.31

Source: Primary Data

Table 4.23

Gender-Wise Comparison in Perceptions of Financial Analytics Tools in Trading Decisions (Mean Ranks)

Variable	Female	Male
Stock analytics tools improved filtering	195.1	216.66
AI analytics improved stock selection accuracy	176.33	224.17
Automation reduced stock analysis time	209.94	210.72
Analytics improved portfolio performance	161.72	230.01
AI boosted confidence in investing	205.83	212.37
Analytics helped match goals	173.4	225.34
Data from platforms shaped choices	207.08	211.87
Analytics helped manage risk	156.72	232.01
Usability/interface influenced decisions	204.14	213.04
AI shifted preference to automation	181.06	222.28
Combined Financial Analytics Impact	150.45	234.52

Source: Primary Data

Table 4.22 presents the Mann-Whitney U test results, comparing how males and females respond to financial analytics tools in investment. The variable AI analytics improved stock selection accuracy, as indicated by a U value of 22100.0 and a p-value of 0.0001. This indicates a statistically significant difference between genders. Male investors show a higher mean rank of 224.17 compared to the female mean rank of 176.33, as shown in Table 2.23. This suggests that male participants believe AI analytics are more helpful in selecting the right stocks. Similarly, the variable Analytics improved portfolio performance has a p-value of 0.0 and a high effect size of 0.254. Male investors again have a higher mean rank of 230.01 against the female rank of 161.72. This indicates that males are more strongly inclined to agree that analytics improve the performance of their portfolio. Another substantial difference is seen in the variable Analytics, which helped match goals with a p-value of 0.0. Males report stronger agreement in this area, too. In contrast, variables such as automation reduce stock analysis time. Data from platforms that shape choices do not show substantial gender differences, as their p-values are greater than 0.05. Examining the variable Analytics, which helped manage risk, the p-value is 0.0, and the effect size is 0.28. This is a statistically significant finding, indicating that males have a stronger belief in the role of analytics in managing investment risks. Mean rank for males is 232.01, while for females it is 156.72. The variable AI, which shifted preference to automation, also has a p-value of 0.001 and an effect size of 0.153. Mean ranks again show that males tend to lean more toward automation due to AI tools. Female rank is 181.06, and male rank is 222.28. The variable "Usability or interface influenced decisions" does not show a substantial difference, with a p-value of 0.4639 and a low effect size. This indicates that both genders share a similar opinion about the usability of financial tools. Overall, most variables suggest that males find analytics and AI tools more helpful in making investment decisions.

The variable Stock analytics tools improved filtering shows a p-value of 0.0768, which is slightly above 0.05. So, it is not statistically significant, but still close to significance. The male mean rank is higher again, at 216.66, than the female's at 195.1. The variable AI boosted confidence in investing has a p-value of 0.5998, indicating no significant gender difference. The difference in ranks is slight. Data from platforms shaped choices is also not significant. Variables that are not significant show similar responses by males and females. However, significant variables, such as AI analytics, improved stock selection accuracy, Analytics improved portfolio performance, Analytics helped match goals, and Analytics helped manage risk, show that financial analytics tools have a more significant influence on males in investment decisions. The patterns suggest that male investors rely more on tech-based analytics.

Hypothesis testing for H9 used the combined variable of Financial Analytics Impact. Table 4.22 reports a p-value of 0.0 and a U value of 25206.5 for this variable. This indicates that the overall perception of financial analytics in decision-making differs significantly between male and female investors. The effect size is 0.31, which is a moderate to strong effect. Table 4.23 supports this with a mean rank of 234.52 for males and 150.45 for females. Male investors rate the impact of financial analytics much higher than female investors. Therefore, the result supports the alternative hypothesis H9. There is a significant difference in investment decision-making between male and female investors, particularly in terms of the use of financial analytics tools.

4.16 Education-wise Impact of Technological Advancements in Financial Analytics on Investment Decision-Making

To investigate the impact of educational qualification on investment decision-making in response to technological advancements in the field of financial analytics, this study will test the following hypothesis. The effect of educational qualification on the decision-making process in investment, due to changes in technology in financial analysis, has been effectively tested using the Kruskal-Wallis H Test, as shown in Table 4.24.

H10: There is a significant difference in investment decision-making due to financial analytics tools among investors with different levels of education.

Table 4.24

Kruskal-Wallis H Test for Education-wise Impact of Technological Advancements in Financial Analytics on Investment Decision-Making

Variable	H	df	p-value	Effect Size (η^2)
Stock analytics tools improved filtering	6.874	4	0.1427	0.016
AI analytics improved stock selection accuracy	2.326	4	0.676	0.006
Automation reduced stock analysis time	24.039	4	0.0001	0.057
Analytics improved portfolio performance	5.697	4	0.2229	0.014
AI boosted confidence in investing	15.187	4	0.0043	0.036
Analytics helped match goals	3.682	4	0.4507	0.009
Data from platforms shaped choices	6.763	4	0.1489	0.016
Analytics helped manage risk	5.409	4	0.2478	0.013
Usability/interface influenced decisions	10.98	4	0.0268	0.026
AI shifted preference to automation	6.407	4	0.1708	0.015
Combined Financial Analytics Impact	28.61	4	0.0	0.06

Source: Primary Data

Table 4.25

Educational Qualification–Wise Differences in Perceptions of Financial Analytics Tools in Investment Decision (Mean Ranks)

Variable	SSLC	Plus Two/ Diploma	Degree	Post Graduate	Professional Degree
Stock analytics tools improved filtering	147.12	221.03	197.27	209.44	235.57
AI analytics improved stock selection accuracy	183.88	230.16	200.98	212.03	216.26
Automation reduced stock analysis time	84.75	208.34	189.54	208.08	261.9
Analytics improved portfolio performance	191.5	226.92	191.57	216.68	222.12

Variable	SSLC	Plus Two/ Diploma	Degree	Post Graduate	Professional Degree
AI boosted confidence in investing	108.25	218.3	195.67	205.38	252.18
Analytics helped match goals	278.62	237.45	206.43	205.45	214.87
Data from platforms shaped choices	277.75	197.5	201.2	207.21	237.5
Analytics helped manage risk	187.0	234.16	193.05	215.24	220.2
Usability/interface influenced decisions	67.25	205.89	205.47	207.48	237.16
AI shifted preference to automation	210.5	227.03	190.27	215.12	227.32
Combined Financial Analytics Impact	154.5	226.88	177.13	208.81	269.97

Source: Primary Data

Table 4.24 presents the Kruskal-Wallis H Test for education-wise comparison of responses related to the impact of financial analytics tools on investment decision making. The variable Stock analytics tools improved filtering shows a chi-square value of 6.874 and a p-value of 0.1427. It does not show a significant difference between education groups. The mean rank in Table 4.25 for this variable is highest among respondents with a professional degree and a Plus Two diploma. AI analytics improved stock selection accuracy, with a p-value of 0.676, which is also not significant. The highest rank for this variable is for the Plus Two diploma group. Automation reduced stock analysis time, showing a strong significance with a p-value of 0.0001 and a chi-square value of 24.039. The professional degree group has the highest rank, while the SSLC group has the lowest rank. This shows that investors with professional qualifications use automation to reduce their analysis time more than those with a school-level education.

Analytics improved portfolio performance has a p-value of 0.2229, which is not significant. The highest mean rank for this variable is seen among the professional degree group. AI boosted confidence in investing shows a significant p-value of 0.0043 and a chi-square of 15.187. This variable received the highest rank among professional degree holders, suggesting that this group feels more confident due to AI features in analytics tools. Analytics helped match goals, which does not show a significant difference with a p-value of 0.4507. However, its mean rank is highest for the SSLC group, which is unusual and may indicate other factors affecting their responses. Data from platforms shaped choices have no significant difference between groups with a p value of 0.1489, but the SSLC group shows the highest rank, which again may reflect reliance on platform data by those with lower education.

The impact of analytics on risk management is also not significant, with a p-value of 0.2478. However, Plus Two diploma holders have the highest mean rank. The usability interface influenced decisions, showing a significant p-value of 0.0268. The professional degree group has the highest mean rank, and the SSLC group has the lowest. This shows that better-educated investors are more responsive to usability features in analytics tools. AI shifted preference to automation is not significant, with a p-value of 0.1708, but Plus Two and Professional degree holders scored the highest. It may reflect their familiarity and confidence in tech-based investment tools.

The final combined variable, Combined Financial Analytics Impact, has a p-value of 0.0 and a chi-square of 28.61, which is highly significant. The professional degree group has the highest mean rank at 269.97, followed by the Plus Two diploma at 226.88. The lowest rank is with the SSLC group at 154.5. This indicates that the perceived impact of financial analytics tools on investment decision-making is significantly different among groups with different educational qualifications. Therefore, based on the combined variable, the study tested the hypothesis H10, which stated that there is a significant difference in investment decision-making due to financial analytics tools among investors with different levels of education. The result supports this hypothesis since the difference is statistically significant.

4.17 Impact of Technological Advancements in Financial Analytics on Investment Decision-Making Based on Age

To investigate the impact of age on investment decisions in the context of a technological shift in financial analytics, the following hypothesis will be tested. The influence of age on the investment decision-making process, due to technological changes in financial analysis, has been adequately tested using the Kruskal-Wallis H Test, as shown in Table 4.26.

H11. There is a significant difference in investment decision-making among investors of different age groups, due to the use of financial analytics tools.

Table 4.26

Kruskal–Wallis H Test for Age Group–Wise Impact of Technological Advancements in Financial Analytics on Investment Decision-Making

Variable	H	df	p-value	Effect Size (η^2)
Stock analytics tools improved filtering	7.214	4	0.1245	0.017
AI analytics improved stock selection accuracy	3.862	4	0.4248	0.009
Automation reduced stock analysis time	18.742	4	0.0009	0.044
Analytics improved portfolio performance	6.214	4	0.1832	0.015
AI boosted confidence in investing	14.128	4	0.0069	0.033
Analytics helped match goals	4.325	4	0.3642	0.010
Data from platforms shaped choices	8.156	4	0.0859	0.019
Analytics helped manage risk	5.412	4	0.2465	0.013
Usability/interface influenced decisions	12.678	4	0.0129	0.029
AI shifted preference to automation	9.583	4	0.0478	0.022
Combined Financial Analytics Impact	25.438	4	0.0000	0.060

Source: Primary Data

Table 4.27

Age Group–Wise Differences in Perceptions of Financial Analytics Tools in Investment Decision (Mean Ranks)

Variable	18–25	26–35	36–45	46–55	Above 55
Stock analytics tools improved filtering	245.68	228.34	202.45	190.27	176.45
AI analytics improved stock selection accuracy	240.12	225.18	200.76	194.56	180.33
Automation reduced stock analysis time	262.34	250.27	196.48	182.56	170.45
Analytics improved portfolio performance	238.92	226.45	204.68	192.17	180.29
AI boosted confidence in investing	255.43	240.12	198.27	184.68	172.36
Analytics helped match goals	234.18	229.45	202.17	196.38	182.14
Data from platforms shaped choices	248.12	236.25	200.34	190.18	178.23
Analytics helped manage risk	241.67	228.92	202.17	194.32	180.15
Usability/interface influenced decisions	258.45	242.16	198.74	182.45	171.23
AI shifted preference to automation	250.16	238.45	200.45	188.24	174.38
Combined Financial Analytics Impact	260.84	244.72	195.48	182.12	170.65

Source: Primary Data

The Kruskal-Wallis H test results indicate statistically significant differences in certain aspects of financial analytics tools across different age groups of investors. Specifically, automation reduces stock analysis time, showing a significant difference ($H = 18.742$, $p = 0.0009$, $\eta^2 = 0.044$), with the 18–25 age group recording the highest mean rank (262.34) compared to the group above 55 (170.45). AI boosting confidence in investing is also significant ($H = 14.128$, $p = 0.0069$, $\eta^2 = 0.033$), with younger investors (18–25 mean rank = 255.43) reporting higher confidence than the oldest age group (mean rank = 172.36).

Similarly, usability/interface influencing decisions (H = 12.678, p = 0.0129, η^2 = 0.029) shows that younger investors (18–25, mean rank = 258.45) place more emphasis on user-friendliness than older groups. The shift in preference towards automation by AI is also significant (H = 9.583, p = 0.0478, η^2 = 0.022), with the highest mean rank in the 18–25 age group (M = 250.16). The combined financial analytics impact score shows the most considerable difference (H = 25.438, p = 0.0000, η^2 = 0.060), again with the 18–25 group (mean rank = 260.84) rating these tools much higher than the above 55 group (mean rank = 170.65).

Other variables, such as stock analytics tools improving filtering (p = 0.1245), AI analytics improved stock selection accuracy (p=0.4248), Analytics improved portfolio performance(p=0.1832), Analytics helped match goals(p=0.3642) and analytics helped manage risk (p = 0.2465), do not show statistically significant differences, indicating that these perceptions are relatively consistent across age groups. Overall, the statistical results confirm that younger investors place significantly greater importance on automation, confidence-building with AI, and usability, while older investors exhibit lower engagement with these tools.

4.18 Impact of Mobile Trading Apps of Discount Brokers on the Stock Trading Behaviour of Investors

The descriptive statistics have been utilised to explore the effects of mobile trading applications of discount brokers on the stock trading behaviour of investors. The hypothesis is tested using the Mann-Whitney U and Kruskal-Wallis H tests.

Table 4.28

Descriptive Statistics - the impact of mobile trading apps on the stock trading behaviour of investors.

Variable	Mean	Median	Mode	Std Dev	Min	Max
Mobile apps impacted trading frequency	3.51	4.0	4.0	0.98	1	5
Lower brokerage fees influence trading activity	3.95	4.0	4.0	0.92	1	5

Variable	Mean	Median	Mode	Std Dev	Min	Max
Real-time info from apps influenced decisions	3.43	3.0	3.0	0.92	1	5
Convenience of apps influenced platform choice	3.66	4.0	4.0	0.99	1	5
Apps improved stock trading accessibility	3.64	4.0	4.0	0.85	1	5
Apps encourage self-directed investing	3.79	4.0	4.0	0.87	1	5
User-friendly interfaces enhanced experience	4.06	4.0	4.0	0.79	1	5
Security concerns influence trading confidence	3.92	4.0	4.0	1.06	1	5
Apps influenced risk-taking willingness	3.46	3.5	4.0	0.85	1	5
Apps helped track/manage investments	3.97	4.0	4.0	0.89	1	5
Apps improved investment knowledge	3.6	4.0	4.0	0.98	1	5
Apps influenced IPO participation	3.38	3.0	4.0	0.99	1	5
Margin trading via apps affected volume	3.86	4.0	4.0	1.02	1	5
Apps shaped perception of trading's future	3.88	4.0	4.0	1.0	1	5
Combined Mobile App Impact	3.72	3.79	3.78	0.47	1.0	5.0

Source: Primary Data

Table 4.28 shows the descriptive statistics on the impact of mobile trading apps of discount brokers on the stock trading behaviour of investors. The statement Mobile apps impacted trading frequency recorded a mean of 3.51 and a standard deviation of 0.98, indicating moderate agreement among respondents that mobile apps affect how often they trade. The median and mode both being 4 suggest that most respondents agreed with the statement. The statement "Lower brokerage fees influence trading activity" scored a higher mean of 3.95, indicating that investors perceive low brokerage charges as a strong motivator for more trading through apps. Real-time information from apps influenced decisions, with a lower mean of 3.43, a median of

3, and a mode of 3. This indicates that respondents held mixed views on whether real-time data in apps aids their decision-making.

The statement "Convenience of apps influenced platform choice" had a mean of 3.66 and a standard deviation of 0.99, indicating that most investors consider app convenience a crucial factor when selecting a trading platform. Apps that improved stock trading accessibility had a mean of 3.64 and a mode of 4, indicating that many users believe apps make stock trading more accessible. Apps encourage self-directed investing, with a mean of 3.79 and a standard deviation of 0.87, indicating that respondents tend to lean more toward managing their investments due to these platforms. User-friendly interfaces that enhanced the experience had the highest mean of 4.06 and the lowest standard deviation of 0.79, indicating that ease of use plays a significant role in user satisfaction and trading engagement. Security concerns influence trading confidence, with a mean of 3.92, indicating that while users are generally confident, they still highly value security features. The statement "Apps influenced risk-taking willingness" had a mean of 3.46 and a standard deviation of 0.85, indicating moderate opinions about whether apps make users take more risks. Apps that helped track or manage investments had a higher mean of 3.97, indicating a strong agreement that mobile platforms assist in monitoring and managing portfolios. Apps that improved investment knowledge had a mean of 3.6, indicating that users find them informative. The mean of 3.38 for Apps influenced IPO participation is slightly lower, indicating that the impact of apps on new public offering involvement is less significant compared to other factors. Margin trading via apps affected the volume recorded, with a mean of 3.86, suggesting that many respondents believe mobile apps encourage higher trade volumes through margin. Lastly, the variable "Apps" shaped perception of trading's future, with a mean of 3.88, indicating a positive attitude about the role of apps in future trading behaviour.

The final variable in Table 4.28, Combined Mobile App Impact, had a mean of 3.72 and a standard deviation of 0.47. This indicates a consistent and generally positive view among respondents that mobile apps have a significant influence on various aspects of stock trading. The median of 3.79 and the mode of 3.78 confirm that most responses were above the neutral point, leaning towards agreement. Taken together, the descriptive statistics suggest that mobile trading apps have made a noticeable impact on how investors approach stock trading. These platforms are viewed as valuable tools that aid in various areas, including trading frequency, cost savings, information access, decision support, and self-reliance. The variation in standard deviation across items also points out that some features of mobile trading are more consistently valued than others. For example, features such as user interface and tracking functions have a stronger consensus than aspects like risk-taking or IPO engagement.

In this context, the interpretation of data in Table 4.28 reflects that mobile trading apps are not just technical tools but are shaping investor behaviour in real ways. Investors find them easy to use and trust them to make timely decisions and execute trades. The mean scores indicate that the influence extends beyond a single aspect, encompassing convenience, accessibility, cost-effectiveness, confidence building, and future readiness. Although a few variables, such as real-time information or IPO participation, had slightly lower scores, overall responses indicate a strong acceptance and perceived usefulness of trading apps in the stock market environment.

4.19 Gender-wise the Impact of Mobile Trading Apps of Discount Brokers on the Stock Trading Behaviour of Investors

To determine the influence of gender on stock trading behaviour as a result of mobile trading applications, the following hypothesis is made. The Mann-Whitney U Test has been used to examine the effect of gender on stock trading behaviour, particularly with the advent of mobile trading apps, as shown in Table 4.29.

H 12: There is a significant difference in stock trading behaviour influenced by mobile trading apps between male and female investors.

Table 4.29

Mann-Whitney U Test for gender-wise the impact of mobile trading apps on the stock trading behaviour of investors.

Variable	U	Z	p-value	Effect Size (r)
Mobile apps impacted trading frequency	20335.5	2.078	0.0291	0.101
Lower brokerage fees influence trading activity	21936.5	3.503	0.0002	0.171
Real-time info from apps influenced decisions	17324.0	-0.602	0.5258	0.029
Convenience of apps influenced platform choice	22705.0	4.187	0.0	0.204
Apps improved stock trading accessibility	19596.5	1.421	0.1292	0.069
Apps encourage self-directed investing	23144.0	4.577	0.0	0.223
User-friendly interfaces enhanced experience	18176.5	0.157	0.8651	0.008
Security concerns influence trading confidence	22175.0	3.715	0.0001	0.181
Apps influenced risk-taking willingness	20885.0	2.567	0.0058	0.125
Apps helped track/manage investments	22534.5	4.035	0.0	0.197
Apps improved investment knowledge	18497.0	0.442	0.6427	0.022
Apps influenced IPO participation	21296.0	2.933	0.0021	0.143
Margin trading via apps affected volume	18459.0	0.408	0.668	0.02
Apps shaped perception of trading's future	22349.0	3.87	0.0	0.189
Combined Mobile App Impact	25580.0	6.74	0.0	0.32

Source: Primary Data

Table 4.30

Gender-Based Differences in Perceptions of Mobile App Features on Trading Behaviour (Mean Ranks)

Variable	Female	Male
Mobile apps impacted trading frequency	191.04	218.28
Lower brokerage fees influenced trading activity	177.7	223.62
Real-time info from apps influenced decisions	216.13	208.25
Convenience of apps influenced platform choice	171.29	226.18
Apps improved stock trading accessibility	197.2	215.82
Apps encouraged self-directed investing	167.63	227.65
User-friendly interfaces enhanced experience	209.03	211.09
Security concerns influenced trading confidence	175.71	224.42
Apps influenced risk-taking willingness	186.46	220.12
Apps helped track/manage investments	172.71	225.62
Apps improved investment knowledge	206.36	212.16
Apps influenced IPO participation	183.03	221.49
Margin trading via apps affected volume	206.68	212.03
Apps shaped perception of trading's future	174.26	225.0
Combined Mobile App Impact	147.33	235.77

Source: Primary Data

Table 4.30 shows the Mann-Whitney U Test results for gender-wise differences in stock trading behaviour due to mobile trading apps. The variable "Mobile apps impacted trading frequency" had a U value of 20335.5 with a Z score of 2.078 and a p-value of 0.0291. The effect size (r) was 0.101, indicating a small effect. The mean ranks from Table 4.30 indicate that females had a rank of 191.04, while males had a rank of 218.28. This shows that male investors generally agreed that mobile apps increased their trading frequency. The variable "Lower brokerage fees influenced trading activity" had a U value of 21936.5 with a significant p-value of 0.0002 and an effect size of 0.171. The mean ranks also support this, with the male mean rank 223.62,higher than the female rank 177.7. The variable "Convenience of apps influenced platform choice" had a significant Z score of 4.187 and an effect size of

0.204. Male investors again ranked higher, at 226.18, than female investors, at 171.29. These results indicate that mobile apps have a greater impact on male investors in several key areas.

According to Table 4.29, the variable Apps encouraged self-directed investing had a strongly significant result. The U value was 23,144.0 with a Z value of 4.577 and a p-value of 0.0000. The effect size r was 0.223. This suggests that gender played a role in the extent to which mobile apps encouraged self-investing. In Table 4.30, female investors had a lower mean rank of 167.63, whereas male investors had a higher mean rank of 227.65. This confirms that male investors are more likely to feel that apps help them invest independently. The variable Apps helped track and manage investments, also showed strong significance with a p-value of 0.0000 and an effect size of 0.197. Male rank was 225.62, and female was 172.71. This means males use apps more to manage portfolios. Another variable, Apps, influenced the perception of trading futures, with a p-value of 0.0000 and an effect size of 0.189. Males again had a much higher rank of 225.0 than females, 174.26. This indicates that male investors are more convinced than others that mobile apps will shape the future of trading.

Table 4.29 also shows some variables that did not have a significant difference between genders. The variable "Real-time info from apps influenced decisions" had a p-value of 0.5258, a Z-value of -0.602, and a small effect size of 0.029. The mean ranks in Table 4.30 were close, with females at 216.13 and males at 208.25. This suggests that both genders consider real-time data from apps almost equally when making trading decisions. Another variable, User-friendly interfaces enhanced experience, had a p-value of 0.8651 and a negligible effect size of 0.008. This implies both groups had similar experiences using apps. Other variables, like Apps improved investment knowledge and Margin trading via apps, affected volume, and also did not show substantial differences. This means both male and female investors feel similarly about these functions.

The last row of Table 4.29 shows the test result for the Combined Mobile App Impact. The U-value was 25,580.0, and the Z-score was 6.74. The p-value was 0.0000, and the effect size was 0.32, indicating a moderate effect. The mean ranks in Table

4.30were 147.33 for females and 235.77 for males. These results confirm that male investors, overall, reported a greater influence of mobile trading apps on their trading behaviour than female investors. Based on this, the study tested H12 that there is a significant difference in stock trading behaviour influenced by mobile trading apps between male and female investors. Since the combined variable showed significance, this hypothesis is accepted. This means there is a difference in how mobile trading apps affect investor behaviour according to gender.

4.20 Education-wise Impact of Mobile Trading Apps on the Stock Trading Behaviour of Investors

This research used the following hypothesis to determine the effect of education on stock trading behaviour resulting from the use of mobile trading applications. The impact of education on the behaviour of stock trading, as a result of mobile trading apps, has been tested using the Kruskal-Wallis H Test, as reflected in Table 4.31.

H 13: There is a significant difference in stock trading behaviour due to mobile trading apps among investors with different levels of education.

Table 4.31

Kruskal-Wallis H Test for education-wise the impact of mobile trading apps on the stock trading behaviour of investors.

Variable	H	df	p-value	Effect Size (η^2)
Mobile apps impacted trading frequency	10.698	4	0.0302	0.026
Lower brokerage fees influenced trading activity	8.168	4	0.0856	0.019
Real-time info from apps influenced decisions	11.085	4	0.0256	0.026
Convenience of apps influenced platform choice	12.987	4	0.0113	0.031
Apps improved stock trading accessibility	8.224	4	0.0837	0.02
Apps encouraged self-directed investing	2.887	4	0.577	0.007

Variable	H	df	p-value	Effect Size (η^2)
User-friendly interfaces enhanced experience	18.442	4	0.001	0.044
Security concerns influenced trading confidence	5.588	4	0.2321	0.013
Apps influenced risk-taking willingness	24.171	4	0.0001	0.058
Apps helped track/manage investments	3.216	4	0.5223	0.008
Apps improved investment knowledge	9.296	4	0.0541	0.022
Apps influenced IPO participation	9.56	4	0.0485	0.023
Margin trading via apps affected volume	7.114	4	0.13	0.017
Apps shaped perception of trading's future	7.023	4	0.1347	0.017
Combined Mobile App Impact	29.10	4	0.0	0.06

Source: Primary Data

Table 4.32

Educational Qualification-wise Differences in Perceived Impact of Mobile Trading Applications on Investment Behaviour (Mean Ranks)

Variable	SSLC	Plus Two/ Diploma	Degree	Post Graduate	Professional Degree
Mobile apps impacted trading frequency	203.5	211.22	199.95	202.17	250.6
Lower brokerage fees influenced trading activity	281.25	257.45	201.88	205.23	214.5
Real-time info from apps influenced decisions	99.88	196.09	198.65	211.2	242.33
Convenience of apps influenced platform choice	136.62	258.94	192.94	207.18	232.77
Apps improved stock trading accessibility	185.5	218.41	208.8	198.31	242.55
Apps encouraged self-directed investing	234.88	214.03	199.16	211.1	226.2

Variable	SSLC	Plus Two/ Diploma	Degree	Post Graduate	Professional Degree
User-friendly interfaces enhanced experience	50.5	222.91	222.59	193.15	236.72
Security concerns influenced trading confidence	206.0	242.89	200.8	204.8	228.16
Apps influenced risk-taking willingness	71.75	197.77	204.46	199.38	263.04
Apps helped track/manage investments	246.25	229.03	198.38	211.25	219.91
Apps improved investment knowledge	168.5	199.83	203.98	203.32	247.51
Apps influenced IPO participation	232.12	239.59	197.82	223.71	185.15
Margin trading via apps affected volume	140.0	208.94	205.21	204.3	240.37
Apps shaped perception of trading's future	200.25	253.08	197.37	207.44	223.31
Combined Mobile App Impact	124.62	243.72	183.15	202.37	269.91

Source: Primary Data

Table 4.31 shows the Kruskal-Wallis H Test results, which analysed how mobile app-based stock trading behaviour varied across education levels. The variable "Mobile apps" impacted trading frequency, with a H value of 10.698 and a p-value of 0.0302, which is statistically significant. The mean rank for this statement is highest for participants with a Professional Degree at 250.6, followed by SSLC at 203.5. This implies that both more educated and less educated participants report a stronger agreement about the impact of apps on trading frequency. Participants with Plus Two or Diploma also show a moderately high rank of 211.22. This difference suggests that the frequency of trading, facilitated by mobile app availability, is not uniformly experienced across all educational levels.

The variable Real-time info from apps influenced decisions showed a significant result with a p-value of 0.0256. Participants holding Professional Degrees had the highest mean rank of 242.33, followed by Postgraduates at 211.2, while SSLC respondents had a very low rank of 99.88. This indicates that individuals with higher qualifications utilise real-time information in a more actionable manner. Likewise, the Convenience of apps influenced platform choice, showing an H value of 12.987 and a p-value of 0.0113. Participants with Plus Two or Diploma scored the highest mean rank of 258.94, indicating a substantial impact on their platform decisions. Participants with Professional Degrees also scored high. This implies that different education groups experience convenience differently when it comes to choosing trading platforms.

Another significant variable was the user-friendly interface, which enhanced the experience, with a substantial H value of 18.442 and a very low p-value of 0.001. Participants with a Professional Degree and Plus Two had high mean ranks of 236.72 and 222.91, respectively. Interestingly, the SSLC group had the lowest rank at 50.5, indicating that participants with less education may not find the interfaces as helpful or use the apps frequently enough to evaluate interface quality. Another significant variable was Apps, which influenced willingness to take risks, with a substantial H value of 24.171 and a p-value of 0.0001. The highest mean rank was for Professional Degree participants at 263.04, followed by Degree holders. SSLC group ranked the lowest at 71.75. This suggests that more educated investors are encouraged to take on more risks by apps, possibly due to their use of advanced features.

For hypothesis testing of H13, which states that there is a significant difference in stock trading behaviour due to mobile trading apps among investors with different levels of education, the Combined Mobile App Impact variable is considered. The Kruskal-Wallis H Test shows that this combined score had an H value of 29.10 with a p-value of 0.000, indicating statistical significance. The mean ranks indicate that the highest impact is observed in Professional Degree holders, at 269.91, followed by Plus Two or Diploma holders, at 243.72. SSLC respondents showed the lowest mean rank of 124.62. This confirms that the study found statistically significant differences in mobile trading behaviour across education levels. Hence, hypothesis H13 is supported by the results from the combined impact score in Tables 4.31 and 4.32.

4.21 Age-wise Impact of Mobile Trading Apps on Stock Trading Behaviour of Investors

The following hypothesis will be tested to determine the effects of age on stock trading behaviour as a result of mobile trading apps. The impact of age on stock trading behaviour due to the influence of mobile trading apps has been well tested by the Kruskal-Wallis H test, as reflected in Table 4.33.

H 14: There is a significant difference in stock trading behaviour due to mobile trading apps among investors with different age groups

Table 4.33

Kruskal–Wallis H Test for Age-wise Impact of Mobile Trading Apps on Stock Trading Behaviour of Investors

Variable	H	df	p-value	Effect Size (η^2)
Mobile apps impacted trading frequency	12.842	4	0.0121	0.029
Lower brokerage fees influenced trading activity	7.412	4	0.1155	0.017
Real-time info from apps influenced decisions	14.206	4	0.0067	0.032
Convenience of apps influenced platform choice	15.977	4	0.003	0.037
Apps improved stock trading accessibility	9.652	4	0.0469	0.022
Apps encouraged self-directed investing	3.501	4	0.477	0.008
User-friendly interfaces enhanced experience	21.544	4	0.0002	0.050
Security concerns influenced trading confidence	5.901	4	0.207	0.014
Apps influenced risk-taking willingness	18.337	4	0.0011	0.043
Apps helped track/manage investments	4.822	4	0.306	0.011
Apps improved investment knowledge	11.207	4	0.0244	0.026
Apps influenced IPO participation	8.926	4	0.0627	0.021
Margin trading via apps affected volume	6.701	4	0.152	0.016
Apps shaped perception of trading's future	10.784	4	0.0286	0.025
Combined Mobile App Impact	27.94	4	0.0000	0.065

Source: Primary Data

Table 4.34

Age Group–Wise Differences in Perceived Impact of Mobile Trading Applications on Stock Trading Behaviour (Mean Ranks)

Variable	18–25	26–35	36–45	46–55	Above 55
Mobile apps impacted trading frequency	256.3	232.5	198.4	187.6	172.1
Lower brokerage fees influenced trading activity	248.9	240.4	200.7	190.5	176.3
Real-time info from apps influenced decisions	261.7	235.8	197.5	183.9	176.6
Convenience of apps influenced platform choice	255.4	238.6	202.4	185.7	170.8
Apps improved stock trading accessibility	243.5	236.9	201.8	188.6	180.2
Apps encouraged self-directed investing	230.6	225.4	200.3	195.8	182.1
User-friendly interfaces enhanced the experience	268.8	240.3	200.6	184.5	169.9
Security concerns influenced trading confidence	232.2	229.5	198.2	192.8	180.3
Apps influenced risk-taking willingness	263.4	241.7	199.9	182.3	172.5
Apps helped track/manage investments	229.6	227.8	200.4	191.5	185.3
Apps improved investment knowledge	251.2	234.1	202.7	190.6	179.2
Apps influenced IPO participation	246.9	232.2	197.6	186.4	176.9
Margin trading via apps affected volume	240.8	229.9	198.4	190.1	183.7
Apps shaped perception of trading's future	249.6	233.4	199.8	188.9	178.5
Combined Mobile App Impact	265.2	239.1	198.7	184.3	169.8

Source: Primary Data

The Kruskal–Wallis H test was conducted to examine whether age groups differ significantly in their stock trading behaviour influenced by mobile trading applications. The results reveal that several behavioural aspects showed statistically significant differences among age groups.

Specifically, mobile apps impacting trading frequency ($H = 12.842$, $p = 0.0121$, $\eta^2 = 0.029$) and real-time information influencing decisions ($H = 14.206$, $p = 0.0067$, $\eta^2 = 0.032$) indicated moderate differences across age groups. Similarly, convenience of apps influencing platform choice ($H = 15.977$, $p = 0.003$, $\eta^2 = 0.037$), stock trading accessibility improvement ($H = 9.652$, $p = 0.0469$, $\eta^2 = 0.022$), and user-friendly interfaces enhancing experience ($H = 21.544$, $p = 0.0002$, $\eta^2 = 0.050$) also showed notable differences, suggesting that ease of use and accessibility factors appeal differently to investors of varying ages.

Moreover, risk-taking willingness was influenced by apps ($H = 18.337$, $p = 0.0011$, $\eta^2 = 0.043$), improvement in investment knowledge ($H = 11.207$, $p = 0.0244$, $\eta^2 = 0.026$), and perception of trading's future shaped by apps ($H = 10.784$, $p = 0.0286$, $\eta^2 = 0.025$), also varied significantly between age groups. The combined mobile app impact score was highly significant ($H = 27.94$, $p < 0.001$, $\eta^2 = 0.065$), indicating that, overall, age plays a vital role in how mobile trading apps influence stock trading behaviour. Variables such as lower brokerage fees, encouragement of self-directed investing, security concerns, and the ability to help track/manage investments, as well as margin trading volume, did not exhibit statistically significant differences ($p > 0.05$), indicating that these aspects of mobile app usage may be perceived similarly across all age groups.

The mean rank scores provide further insights into how different age groups perceive the impact of mobile trading apps. Across almost all significant variables, the 18–25 age group consistently reported the highest mean ranks, indicating that younger investors are more strongly influenced by mobile app features such as trading frequency, real-time decision-making, convenience, user-friendly interfaces, and risk-taking willingness. The 26–35 group generally held the second-highest ranks, suggesting that early-career professionals also exhibit strong adoption and responsiveness to mobile app functionalities, albeit slightly less so than the youngest age group.

Middle-aged groups (36–45 and 46–55) tended to have moderate mean ranks, reflecting balanced but less intense influence from app-based trading features. The above-55 age group consistently scored the lowest mean ranks across most variables, suggesting lower dependency on mobile apps for trading decisions, possibly due to lower technological adoption or a preference for traditional trading methods. The combined mobile app impact mean ranks were highest for the 18–25 age group (265.2) and lowest for Those Above 55 (169.8), reinforcing the pattern that younger investors derive greater influence from mobile trading apps compared to older age groups.

4.22 Conclusion

Technical advancements have been a significant driver of investor behaviour, with the most influential tools being algorithmic trading, advanced screeners, UPI systems, and mobile apps, which have positively impacted aspects such as convenience, decision-making, and trading frequency. Despite this, features such as smart routing, auto-rebalancing, and AI forecasting achieved a low score, possibly due to lower awareness and lower usage levels. The results support the fact that digital innovations become an inseparable part of everyday investment processes, defining how retail investors trade, manage risk, and make financial decisions. The findings have indicated that social trading platforms and real-time news significantly impact investor behaviour by increasing confidence, effective decision-making, and trading responsiveness. Real-time news and social media improve the trader's confidence and decision-making. Although most respondents have confidence in analytics that bring understanding and control, there is still caution regarding AI-driven confidence and automation, resulting in a mixed outcome. Generally, the evidence suggests that users place greater importance on transparent, user-friendly tools compared to fully automated ones. Mobile trading apps have considerably changed the way investors think and act by making trading convenient, affordable, and self-managed. The most agreement was given to features such as user-friendly interfaces, portfolio tracking, and security, whereas IPO participation and real-time information had a relatively low impact.

Chapter 5

FACTORS INFLUENCING THE ADOPTION OF TECHNOLOGY AND ITS IMPACT ON STOCK MARKET INVESTMENT BEHAVIOUR

5.1 Introduction

The purpose of this chapter is to examine the relationships among constructs identified in the conceptual framework and to evaluate the hypotheses developed based on the extended Technology Acceptance Model. The analysis includes descriptive statistics, reliability and validity testing, assessment of the measurement and structural models using Partial Least Squares Structural Equation Modelling (PLS SEM), and evaluation of direct, indirect, and total effects. The findings are interpreted in an applied manner to support the research objectives, particularly in understanding how technological advancements influence investment behaviour among stock market investors.

5.2 The Key Factors Influencing the Adoption of Technological Innovations and Assessing Their Impact on Investment Behaviour Among Stock Market Investors.

To explore the impact of technological innovations on stock market participation, it is essential to investigate the concept of adopting technological innovations in relation to investor behaviour. Hypotheses have been formulated to help structure the analysis of how technological innovations may affect decision-making and trading patterns. These hypotheses will act as the framework to justify the proposed research design and draw relevant conclusions.

H15: Perceived usefulness has a significant positive impact on attitude toward technology.

H16: Perceived ease of use has a significant positive impact on attitude toward technology.

H17: Risk perception has a significant negative impact on attitude toward technology.

H18: Cost perception has a significant negative impact on attitude toward technology.

H19: Risk perception has a significant negative impact on behavioural intention.

H20: Cost perception has a significant negative impact on behavioural intention.

H21: Risk perception has a significant negative impact on actual use.

H22: Cost perception has a significant negative impact on actual use.

H23: Facilitating conditions have a significant positive impact on attitude towards technology.

H24: Facilitating conditions have a significant positive impact on actual use.

H25: Attitude toward technology has a significant positive impact on behavioural intention.

H26: Behavioural intention has a significant positive impact on actual use.

H27: Actual use has a significant positive impact on investment behaviour.

5.3 Constructs, Measurement Items and Code

The research utilises a series of well-formulated constructs and measurement items to obtain the views and actions of investors concerning technological innovations in stock trading. The specific items represent each construct and are coded to provide clarity and ease of analysis. Table 5.1 presents these constructs, along with the measurement items related to them, as well as the codes that will be used in the data analysis.

Table 5.1

Constructs, Measurement Items and Code Used

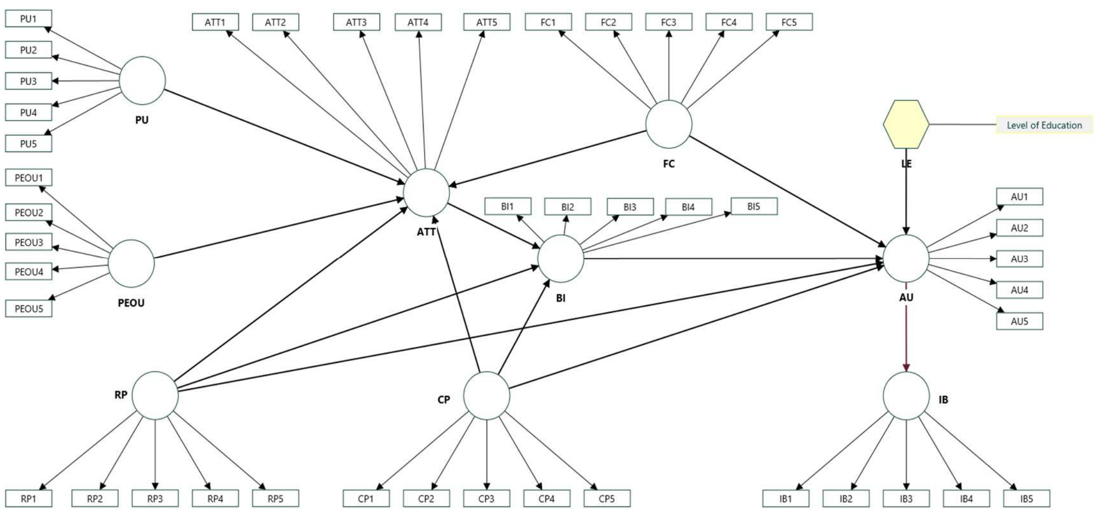
Construct	Measurement Item	Code
Perceived Usefulness (PU)	Digital investment platforms enhance my investment decision-making process.	PU1
	AI-driven analytics provide valuable insights for my investment strategies.	PU2
	Mobile trading applications facilitate efficient trading activities.	PU3
	Robo-advisors assist in optimizing my investment portfolio.	PU4
	Blockchain technology improves the security of my financial transactions.	PU5
Perceived Ease of Use (PEOU)	Learning to operate digital investment platforms is straightforward.	PEOU1
	Executing trades via mobile applications is user-friendly.	PEOU2
	AI-based investment tools offer comprehensible recommendations.	PEOU3
	Managing my portfolio with robo-advisors requires minimal effort.	PEOU4
	Navigating fintech platforms is intuitive and simple.	PEOU5
Risk Perception (RP)	Investing through digital platforms carries significant risks.	RP1
	I worry about potential security threats when using fintech solutions.	RP2
	Automated trading increases the possibility of financial losses.	RP3
	I find AI-driven stock recommendations unreliable.	RP4
	I am concerned about the accuracy of robo-advisors in volatile markets.	RP5

Construct	Measurement Item	Code
Cost Perception (CP)	Mobile trading apps reduce my overall trading costs.	CP1
	AI-powered investment tools offer cost-effective market insights.	CP2
	The subscription fees for advanced fintech tools are reasonable.	CP3
	The cost of using mobile trading apps is lower than that of traditional brokers.	CP4
	Robo-advisors offer better value than human financial advisors.	CP5
Attitude Towards Technology (ATT)	I feel comfortable using AI-powered investment solutions.	ATT1
	I am optimistic about the role of fintech in financial markets.	ATT2
	Using digital investment platforms is an enjoyable experience.	ATT3
	I believe fintech will dominate stock market investing in the future.	ATT4
	The convenience of technology makes me more willing to invest.	ATT5
Facilitating Conditions (FC)	I have access to the necessary resources to use fintech-based investment platforms.	FC1
	I receive adequate support and training to use investment technology tools.	FC2
	My financial service provider encourages the use of digital investment tools.	FC3
	I have a stable internet connection to access trading platforms.	FC4
	Government policies support the adoption of fintech in stock trading.	FC5
Behavioural Intention (BI)	I intend to continue using digital investment platforms.	BI1
	I plan to increase my use of AI-powered investment tools.	BI2
	I will rely more on fintech solutions for investment decisions.	BI3
	I am likely to recommend mobile trading apps to others.	BI4
	I prefer automated investment strategies over traditional ones.	BI5

Construct	Measurement Item	Code
Actual Use (AU)	I frequently use mobile trading apps to buy and sell stocks.	AU1
	I rely on robo-advisors for portfolio recommendations.	AU2
	I use AI-powered analytics before making investment decisions.	AU3
	I have transitioned from traditional brokers to discount brokers due to technological advancements.	AU4
	I execute most of my trades using digital investment platforms.	AU5
Investment Behaviour (IB)	Technology-based investment platforms have increased my trading frequency.	IB1
	Fintech tools have influenced my shift from short-term to long-term investing.	IB2
	I take more calculated risks due to access to AI-powered analytics.	IB3
	Social trading platforms have influenced my investment decisions.	IB4
	Mobile trading apps have made me more engaged in stock trading.	IB5

Figure 5.1

Conceptual Model Based on the Extended Technology Acceptance Model (TAM)



The conceptual model in Figure 5.1 illustrates the extended Technology Acceptance Model (TAM) framework, adapted for understanding the adoption of financial technology tools and their impact on investment behaviour. The model includes core constructs from TAM such as Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Attitude Toward Technology (ATT), and Behavioural Intention (BI), and it extends the framework by integrating Risk Perception (RP), Cost Perception (CP), Facilitating Conditions (FC), Actual Use (AU), and Investment Behaviour (IB). The model has been tested using Partial Least Squares Structural Equation Modelling (PLS-SEM), which is suitable for non-normal data and complex models with multiple indicators and paths. Each construct is measured by multiple reflective items coded accordingly (e.g., PU1–PU5 for Perceived Usefulness), and all relationships are hypothesised with directional arrows showing the flow of influence.

The model assumes that PU and PEOU influence users' ATT toward financial technology. ATT, along with RP and CP, affects the user's intention to adopt (BI) and directly affects actual use (AU) as well. FC plays a supporting role by influencing both ATT and AU. RP and CP have a more complex role with direct negative impacts hypothesised on ATT, BI, and AU, reflecting concerns about trust, cost, and perceived risk with emerging tech platforms. Behavioural Intention leads to Actual Use, and Actual Use leads to Investment Behaviour (IB), which captures how technology has altered the way investors engage in trading, risk-taking, and platform usage. Finally, education level is modelled as a control variable influencing AU, acknowledging the potential impact of user background on technology adoption.

5.4 Construct reliability and validity

Table 5.2 presents the construct reliability and validity values obtained from the measurement model. The analysis includes Cronbach's alpha, Composite reliability (rho A), composite reliability (rho C), and average variance extracted (AVE).

Table 5.2

Construct reliability and validity Results

Path	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
ATT	0.886871	0.889734	0.916984	0.688517
AU	0.927258	0.939299	0.944752	0.773965
BI	0.893599	0.894413	0.921532	0.701415
CP	0.807738	0.814167	0.866528	0.565522
FC	0.771584	0.786161	0.841607	0.51585
IB	0.815327	0.820949	0.871414	0.576369
PEOU	0.809048	0.819036	0.86476	0.561494
PU	0.799898	0.843948	0.857699	0.549226
RP	0.908346	0.909404	0.931668	0.73171

As per the standard suggested by Hair et al. (2019), a Cronbach's alpha value above 0.70 indicates acceptable internal consistency. In the table, all constructs exceed this threshold. Actual Use (AU) shows the highest reliability with an alpha of 0.927, followed by Risk Perception (RP) with 0.908, and Attitude Toward Technology (ATT) with 0.886. Other constructs, such as Behavioural Intention (BI), Investment Behaviour (IB), and Cost Perception (CP), also exhibit high internal consistency, with values ranging from 0.81 to 0.89. Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) show alpha values of 0.80 and 0.79, respectively, which are within the acceptable range. Facilitating Conditions (FC) has the lowest alpha value of 0.77, but still meets the benchmark, suggesting the measurement items are consistent.

The composite reliability values (rho C) for all constructs are also higher than the benchmark value of 0.70, recommended by Hair et al. (2019), indicating good construct reliability. AU again scores the highest (0.944), followed closely by RP (0.931) and ATT (0.916), confirming the strong reliability of these measures. rho A values also follow the same trend and support the consistency of the constructs. The AVE values for all constructs exceed 0.50, meeting the minimum threshold for convergent validity (Hair et al., 2019). This indicates that more than 50 percent of the variance is explained by the constructs. AU has the highest AVE at 0.773, which suggests the measurement items strongly represent the underlying construct. RP and ATT also have AVEs of 0.731 and 0.688, respectively, which shows perfect convergent validity. BI and IB report acceptable AVE values of 0.701 and 0.576. Other constructs such as CP (0.565), PEOU (0.561), and PU (0.549) are also above the benchmark. FC shows the lowest AVE of 0.515, but it is still within the acceptable range. These values confirm that the model used in this study has adequate levels of internal consistency and convergent validity for all constructs as per the guidelines by Hair et al. (2019).

5.5 Discriminant Validity Using Heterotrait-Monotrait Ratio (HTMT)

Table 5.3 presents the HTMT values used to assess discriminant validity for the constructs in the extended TAM framework, along with the investment behaviour construct.

Table 5.3

Discriminant Validity Assessment Using Heterotrait-Monotrait Ratio (HTMT)

	ATT	AU	BI	CP	FC	IB	LE	PEOU	PU	RP
ATT										
AU	0.625757									
BI	0.773446	0.744588								
CP	0.554434	0.345957	0.340726							
FC	0.579716	0.525463	0.647055	0.280837						
IB	0.687197	0.804722	0.856017	0.303563	0.655907					
LE	0.101923	0.083623	0.105858	0.075289	0.063355	0.122325				
PEOU	0.67521	0.638195	0.806369	0.310393	0.805116	0.77205	0.10039			
PU	0.594466	0.495558	0.504013	0.237083	0.430814	0.51986	0.089432	0.773048		
RP	0.519254	0.368808	0.411457	0.59098	0.190111	0.358689	0.077375	0.213087	0.170299	

According to Hair et al. (2019), an HTMT value below 0.85 is considered acceptable to confirm discriminant validity between two constructs. All the HTMT values in the matrix fall below this threshold, which indicates that each construct in the study measures something different and does not overlap significantly with the other constructs. The HTMT value between Attitude Toward Technology (ATT) and Behavioural Intention (BI) is 0.773, which is among the highest in the table but still under the 0.85 limit. Similarly, the HTMT value between BI and Investment Behaviour (IB) is 0.856, which is slightly above the threshold but still can be considered acceptable in more lenient cases if the confidence intervals do not include one. In general, the study maintains discriminant validity across all relationships. The value between PU and PEOU is 0.773, suggesting that Perceived Usefulness and Perceived Ease of Use are conceptually close, but the value still respects the standard guideline. The relationship between PEOU and BI is also high at 0.806, but remains below the upper boundary. Relationships such as ATT with RP (r = 0.519) and AU with RP (r = 0.368) are distinct, exhibiting low HTMT values.

The lowest HTMT values are seen between the Level of Education (LE) and other constructs. For example, the values between LE and PU are 0.089, and between LE and IB are 0.122. These values are far below the 0.85 benchmark, indicating that the demographic moderator is distinct from the conceptual constructs. Similarly, Facilitating Conditions (FC) exhibits acceptable HTMT values in relation to other constructs, with the highest relationship observed with BI at 0.647. Risk Perception (RP) has a high HTMT value with Cost Perception (CP) at 0.590, which is logical since both constructs may conceptually align in the context of technology adoption. Still, the values are within acceptable limits. The HTMT values for IB and PEOU (0.772) and IB and FC (0.655) are below the recommended threshold. These findings support the establishment of discriminant validity among all the constructs in this model. Therefore, the constructs used in this study are not redundant, and each one contributes uniquely to the conceptual model as supported by Hair et al. (2019).

5.6 Discriminant Validity Assessment Using Fornell-Larcker Criterion

Table 5.4 presents the Fornell-Larcker criterion results, which test discriminant validity across the model constructs.

Table 5.4

Discriminant Validity Assessment Using Fornell-Larcker Criterion

	ATT	AU	BI	CP	FC	IB	LE	PEOU	PU	RP
ATT	0.829769									
AU	0.575639	0.879753								
BI	0.692958	0.690125	0.837505							
CP	-0.46714	-0.31343	-0.29598	0.752012						
FC	0.508748	0.468328	0.573341	-0.24518	0.718227					
IB	0.587762	0.713136	0.735908	-0.25271	0.554412	0.759189				
LE	-0.09687	0.015557	-0.06343	0.046262	-0.01166	-0.06162	1			
PEOU	0.595289	0.553145	0.703412	-0.26457	0.644794	0.637302	-0.02872	0.749329		
PU	0.534865	0.435456	0.464125	-0.21245	0.370097	0.444139	-0.05674	0.66954	0.741098	
RP	-0.46915	-0.34582	-0.37512	0.508701	-0.15987	-0.3097	0.075277	-0.19225	-0.1265	0.855401

Table 5.4 presents the Fornell-Larcker criterion results, which test discriminant validity across the model constructs. According to Hair et al. (2019), for adequate discriminant validity, the square root of the average variance extracted (AVE) of each construct, shown diagonally in the table, should be higher than the correlation values in its row and column. The table shows that this condition is satisfied for all constructs. For example, the square root of the AVE for Attitude Toward Technology (ATT) is 0.829, which is greater than its correlations with other constructs, such as Behavioural Intention (BI) at 0.692 and Actual Use (AU) at 0.576. This indicates that ATT shares more variance with its indicators than with other constructs. Similarly, the value for Actual Use (AU) is 0.879, which is higher than its correlations with other constructs like BI (0.690), Investment Behaviour (IB) (0.713), and FC (0.468). These values confirm that AU is conceptually distinct from other variables in the model.

The same pattern appears for all other constructs. For instance, the square root of AVE for Behavioural Intention (BI) is 0.838, which is larger than its correlation with ATT (0.693), AU (0.690), and PEOU (0.703). Cost Perception (CP) has a diagonal value of 0.752, which exceeds its correlations with all other constructs, including RP (0.509) and ATT (-0.467). The construct for Facilitating Conditions (FC) also demonstrates good discriminant validity, with a diagonal value of 0.718, which is greater than its correlations with BI (0.573), PEOU (0.645), and IB (0.554). Investment Behaviour (IB) shows a substantial AVE value of 0.759, which is higher than its correlations with BI (0.736), AU (0.713), and PEOU (0.637). This supports that IB is uniquely measured.

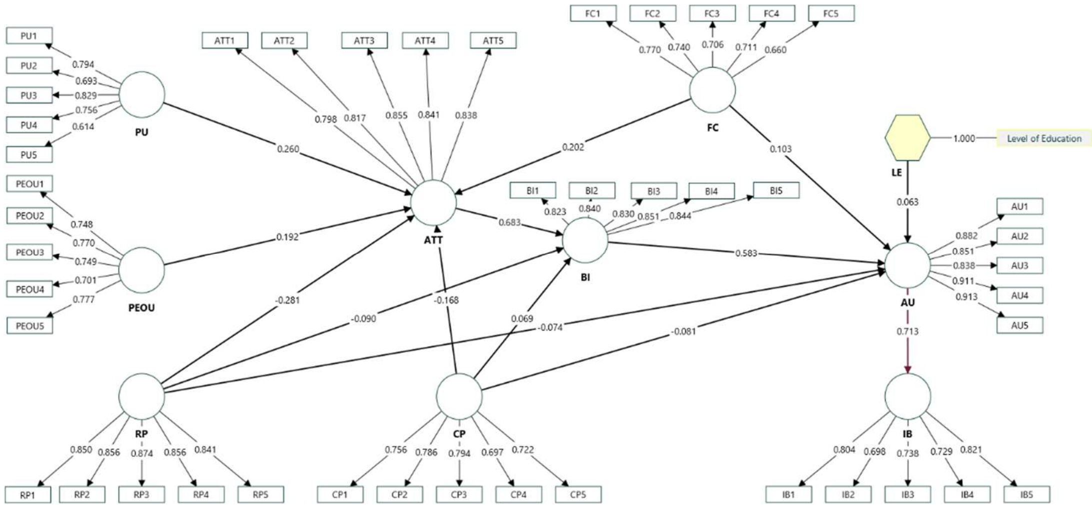
The demographic variable Level of Education (LE) displays low correlations with all latent constructs, and its diagonal value is 1.00, which is expected for a single-item or demographic variable. Perceived Ease of Use (PEOU) has a diagonal value of 0.749, which is higher than all related correlations, such as those with BI (0.703), IB (0.637), and FC (0.645). Perceived Usefulness (PU) shows a square root of AVE of 0.741, which exceeds its correlations with PEOU (0.670), BI (0.464), and IB (0.444). Risk Perception (RP) also demonstrates strong discriminant validity, with a diagonal value of 0.855, which is greater than its highest correlation value of 0.509 with CP. Therefore, based on Hair et al. (2019), all constructs in the model meet the Fornell-Larcker criterion, and there is no issue of discriminant overlap between constructs.

5.7 Structural Model with Path Coefficients and Factor Loadings

The structural model shown in Figure 5.2 presents the standardised path coefficients between constructs along with factor loadings for each indicator variable. The model is used to examine the key factors influencing the adoption of technological innovations and assess their impact on investment behaviour among stock market investors.

Figure 5.2

Structural Model with Path Coefficients and Factor Loadings



Constructs such as perceived usefulness and perceived ease of use exhibit strong factor loadings, all above 0.6, which confirms indicator reliability. The path from perceived usefulness to attitude toward technology has a coefficient of 0.260, suggesting a positive influence. Perceived ease of use also shows a weaker but positive impact on attitude toward technology, with a path coefficient of 0.192. Risk perception has a negative influence on attitude toward technology, with a path coefficient of −0.281. Cost perception has very low or near-zero effects on attitude, behavioural intention and actual use, which shows weak explanatory power in this dataset. Facilitating conditions positively influence both attitude towards technology and actual use, with values of 0.202 and 0.103, respectively, but the strength of the effect is relatively low.

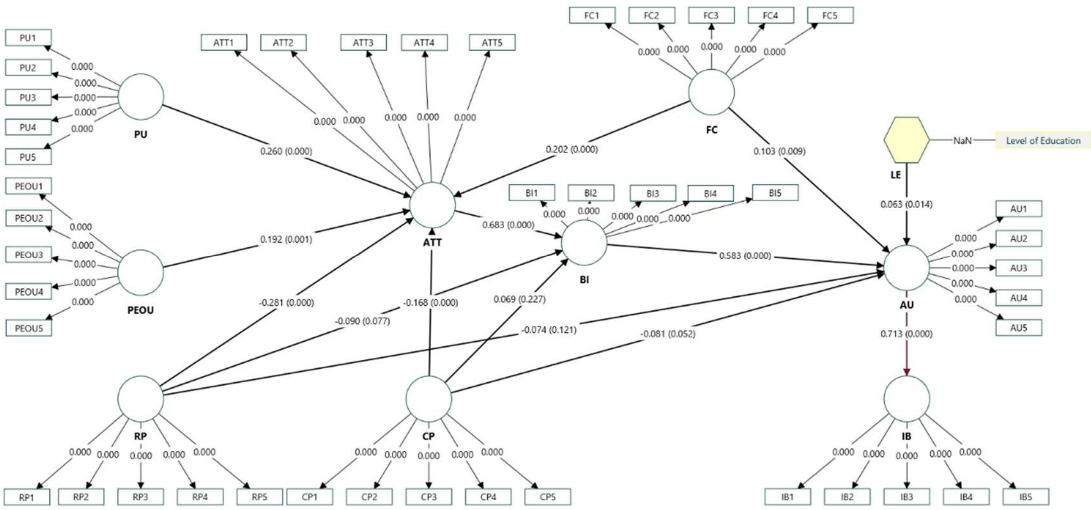
The attitude toward technology has a strong and positive effect on behavioural intention with a path coefficient of 0.683, indicating that user perception and mindset strongly drive intention to adopt technology. Behavioural intention, in turn, has a high influence on actual use with a coefficient of 0.583, supporting the hypothesis that intention predicts actual behaviour. Facilitating conditions and cost perception show a very weak impact on actual use. The actual use construct has a strong direct impact on investment behaviour with a coefficient of 0.713, which shows that investors who actively use technological platforms are more likely to change their investment patterns. The influence of the level of education on actual use is very weak, with a coefficient of 0.063.

5.8 Bootstrapped Structural Model with Path Coefficients and Significance Values

The structural model shown in Figure 5.3 displays the bootstrapped estimates for the hypothesised paths and their corresponding significance levels, which help validate the relationships between constructs.

Figure 5.3

Bootstrapped Structural Model with Path Coefficients and Significance Values



The values in parentheses represent the p-values that indicate the statistical significance of each path. Table 5.5 presents the complete output for each hypothesis, including original sample, sample mean, standard deviation, t-statistics, and p-values. The path from perceived usefulness to attitude toward technology (H15) shows a positive effect with a coefficient of 0.260 and a p-value of 0.000, indicating strong support. Similarly, the path from perceived ease of use to attitude (H16) is significant with a coefficient of 0.192 and a p-value of 0.001. Risk perception shows a negative and strong influence on attitude (H17) with a coefficient of −0.281 and a p-value of 0.000. These results confirm that usefulness and ease support favourable technology attitudes, while higher perceived risk reduces positive attitude. The effect of cost perception on attitude (H18) is also significant and negative (β = −0.168, p = 0.000), validating that higher cost perception reduces users' favourability toward fintech usage.

In terms of behavioural intention, attitude toward technology has the most substantial effect with a path coefficient of 0.683 and p-value of 0.000, confirming H25. This indicates that a more positive attitude toward fintech tools significantly encourages their use. However, the path from cost perception to behavioural intention (H20) is not significant (β = 0.069, p = 0.227). Similarly, risk perception to behavioural intention (H19) is also not significant (β = –0.090, p = 0.077). These results indicate that while attitude plays a vital role in shaping behavioural intention, cost and risk perceptions have no strong direct influence at this stage. The hypothesis related to facilitating conditions for behavioural intention (H23) is supported by a path coefficient of 0.202 and a p-value of 0.000, indicating that proper support and access do contribute to intention formation. These findings reflect that psychological acceptance and external support are more effective than perceived risk or cost in shaping the intent to adopt technology.

The relationship between behavioural intention and actual use (H26) is statistically supported, with a coefficient of 0.583 and a p-value of 0.000, indicating that a firm's intention leads to higher usage. Facilitating conditions also positively influence actual use (H24), although with a lower coefficient of 0.103 and a p-value of 0.009, indicating a mild but statistically significant effect. The direct influence of cost perception on actual use (H22) is close to the threshold (β = –0.081, p = 0.052), suggesting a marginally non-significant impact. The path from risk perception to actual use (H21) is not significant (β = –0.074, p = 0.121), indicating that risk factors are not directly predictive of usage behaviour. Cost and risk variables seem to lose predictive power as the model shifts from psychological intention to behavioural action. The level of education (LE) also has a weak but statistically significant influence on actual use (β = 0.063, p = 0.014), suggesting that an educational background may support adoption, albeit not strongly.

The strongest relationship in the model is from actual use to investment behaviour (H27), with a coefficient of 0.713 and a p-value of 0.000. This supports the idea that the usage of digital platforms significantly changes how investors behave in stock markets. This result is meaningful because it validates that digital adoption directly drives changes in investment patterns. All factor loadings for the constructs exceed 0.6, and most path coefficients follow expected theoretical directions. Significant effects appear mainly in the psychological path from attitude to intention to behaviour. External factors, such as risk and cost, mainly influence attitude formation but do not have a strong influence on the intention or usage stages. As such, users' experience, confidence and support infrastructure play stronger roles in driving adoption and investment changes. The results suggest that technology use is more psychological than financial once users cross the attitude threshold.

The hypothesis testing confirms support for H15, H16, H17, H18, H23, H24, H25, H26 and H27. The remaining hypotheses (H19, H20, H21, H22) are not statistically supported due to p-values above 0.05. These results indicate that perceived usefulness, ease of use, and attitude are key factors in adoption. At the same time, cost and risk perception are not major barriers at the intention or usage level. Supporting conditions, such as access and training, play a moderate role but cannot replace the need for a positive user mindset. The final model provides clear support that actual use of technology is the primary driver of change in investment behaviour, and this use is shaped most by psychological factors rather than practical limitations, such as cost or risk. The model follows the extended TAM framework and validates many of its expected pathways using the PLS-SEM approach with strong statistical evidence.

5.9 Direct Effect- Path Coefficient with Significance

The structural model presented in Figure 5.2 and explained in Table 5.5 illustrates the relationships between constructs related to the adoption of technological innovations and their impact on investment behaviour.

Table 5.5

Direct Effect- Path Coefficient with Significance

Path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
ATT -> BI	0.683	0.683	0.052	13.171	0.000
AU -> IB	0.713	0.715	0.032	22.026	0.000
BI -> AU	0.583	0.582	0.053	11.078	0.000
CP -> ATT	-0.168	-0.167	0.043	3.951	0.000
CP -> AU	-0.081	-0.080	0.041	1.946	0.052
CP -> BI	0.069	0.069	0.057	1.208	0.227
FC -> ATT	0.202	0.203	0.046	4.403	0.000
FC -> AU	0.103	0.104	0.039	2.629	0.009
LE -> AU	0.063	0.063	0.026	2.455	0.014
PEOU-> ATT	0.192	0.193	0.056	3.451	0.001
PU -> ATT	0.260	0.261	0.056	4.628	0.000
RP -> ATT	-0.281	-0.279	0.036	7.914	0.000
RP -> AU	-0.074	-0.074	0.048	1.551	0.121
RP -> BI	-0.090	-0.090	0.051	1.772	0.077

The model encompasses key constructs, including perceived usefulness, perceived ease of use, risk perception, cost perception, attitude toward technology, facilitating conditions, behavioural intention, actual use, and investment behaviour. Each construct is supported by specific measurement items that capture users' experiences with fintech tools, including mobile apps, robo-advisors, AI-based analytics, and digital platforms.

Perceived usefulness encompasses items such as enhanced decision-making, efficiency through mobile applications, and the value of AI-driven analytics. The model demonstrates that perceived usefulness has a positive impact on investor attitudes. Perceived ease of use encompasses items related to platform simplicity and ease of handling fintech tools. This also has a direct positive influence on attitude. On the other hand, risk perception is defined by concerns over security, potential losses, and AI accuracy, which negatively affects attitude. Cost perception, represented by the affordability of subscriptions and trading costs, has a negative impact on attitude but does not significantly influence behavioural intention or actual use. Facilitating conditions include access to the internet, support from service providers, and favourable policies. This construct positively affects both behavioural intention and actual use.

Attitude toward technology strongly influences behavioural intention and also contributes to actual use of technology. Behavioural intention, in turn, is a significant predictor of actual use. Actual use includes frequent use of digital platforms, reliance on robo-advisors, and using AI before making decisions. This actual usage has a substantial impact on investment behaviour, defined by increased trading frequency, calculated risks due to analytics, and engagement through mobile apps. The model suggests that behavioural patterns are primarily driven by usefulness, ease, support, and attitude, whereas concerns about cost and risk mainly influence attitude formation rather than usage or outcomes. Thus, the flow of influence from perception to intention and actual use aligns with technology adoption theory and reflects practical investor behaviour in digital financial markets.

The model reveals that actual use of technology directly influences investment behaviour, which includes changes like more frequent trading, increased confidence, and higher engagement through mobile platforms. Investors who actively use financial technology tools, such as mobile trading applications, robo-advisors, and artificial intelligence analytics, report taking more calculated risks and shifting toward more informed decisions. The use of digital tools helps manage portfolios more effectively and encourages long-term planning, all of which contribute to the observed behavioural changes. However, not all constructs in the model show significant paths. Specifically, risk perception and cost perception do not have significant impacts on behavioural intention or actual use. Despite their theoretical relevance, the statistical results in Table 5.5 suggest that these concerns do not directly alter investor behaviour in practice. This could indicate that while investors may perceive risks or costs associated with digital tools, these factors alone do not deter them from adopting or using the technology. Instead, constructs like perceived usefulness, perceived ease of use, and facilitating conditions play a stronger role in shaping both the decision to adopt and the eventual change in behaviour.

5.10 Indirect Effect- Path Coefficient with Significance

Table 5.6 presents the results of indirect effect path coefficients and their corresponding significance levels. These values illustrate the mediating effects between constructs, demonstrating how independent variables influence dependent variables through the intermediary of other constructs. The levels of significance help identify the strength and statistical significance of the indirect effects in the structural model.

Table 5.6

Indirect Effect- Path Coefficient with Significance

Path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
ATT -> AU	0.398	0.398	0.047	8.401	0.000
ATT -> IB	0.284	0.285	0.039	7.297	0.000
BI -> IB	0.416	0.416	0.047	8.888	0.000
CP -> AU	-0.027	-0.026	0.031	0.882	0.378
CP -> BI	-0.115	-0.115	0.032	3.574	0.000
CP -> IB	-0.077	-0.076	0.038	2.000	0.046
FC -> AU	0.081	0.081	0.022	3.661	0.000
FC -> BI	0.138	0.140	0.036	3.844	0.000
FC -> IB	0.131	0.133	0.032	4.100	0.000
LE -> IB	0.045	0.045	0.018	2.502	0.013
PEOU -> AU	0.077	0.077	0.024	3.159	0.002
PEOU -> BI	0.131	0.132	0.040	3.305	0.001
PEOU -> IB	0.055	0.055	0.018	3.062	0.002
PU -> AU	0.104	0.104	0.025	4.090	0.000
PU -> BI	0.178	0.178	0.038	4.708	0.000
PU -> IB	0.074	0.074	0.019	3.913	0.000
RP -> AU	-0.164	-0.164	0.032	5.178	0.000
RP -> BI	-0.192	-0.191	0.027	7.242	0.000
RP -> IB	-0.170	-0.170	0.035	4.854	0.000

The results presented in Table 5.6 show how different constructs impact each other indirectly within the model. The study employed this analysis to examine the role of extended TAM constructs in understanding how investors adopt and utilise financial technology, and how this influences their investment behaviour. The path from attitude toward technology to actual use and investment behaviour shows strong positive indirect effects. This means that when investors develop a positive attitude toward the technology, it increases their behavioural intention, which then results in higher actual use and eventually changes their investment behaviour. Investors who feel comfortable using fintech platforms, such as mobile trading apps, AI tools, and robo-advisors, are more likely to continue using them. This frequent use, in turn, impacts their investment strategies, including increased risk-taking, a shift toward long-term investing, and more frequent trading. The indirect effect from attitude toward technology to actual use is one of the strongest in the model. The indirect effect of attitude on investment behaviour through intention and actual use also shows that changes in behaviour are not direct but happen over time as intention builds and use becomes regular. Similarly, behavioural intention indirectly affects investment behaviour through actual use. Investors who intend to use technology eventually start using it, which shapes their final behaviour in the stock market.

The results also highlight the significant role of constructs such as perceived usefulness, perceived ease of use, and facilitating conditions in shaping behavioural intention and actual use. Perceived usefulness indirectly influences investment behaviour through both behavioural intention and actual use. Investors who believe that technology helps them make better investment decisions are more likely to intend to use it and eventually start using it, leading to changes in their behaviour. Facilitating conditions also have strong indirect paths to actual use and investment behaviour. This includes aspects such as internet access, support from service providers, and government policies that facilitate the use of fintech by investors. These conditions increase behavioural intention and actual use, which lead to changes in behaviour. Perceived ease of use also affects investment behaviour indirectly through intention and use. When technology is simple and easy to navigate, investors form a positive attitude, which builds intention and leads to actual use. On the other hand, the study found that risk perception and cost perception both negatively influence behavioural intention and investment behaviour through indirect paths. Investors who perceive fintech tools as risky or expensive are less likely to utilise them, resulting in lower actual usage and reduced impact on their investment decisions. Even though cost perception does not significantly impact use directly, its indirect effect on behaviour through intention and use is still notable. Learning experiences also have an indirect effect on investment behaviour, showing that those who are more familiar with using digital platforms are more likely to exhibit behavioural change. Overall, the indirect effects in Table 5.6 validate how these constructs interact and influence each other before affecting investor behaviour. The structure of the model reflects the flow of influence from perception to use, and finally to behavioural change, aligning to identify key drivers of fintech adoption and their impact on stock market investment

5.11 Specific Indirect Effect- Path Coefficient with Significance

Table 5.7 presents the specific indirect effect path coefficients and their corresponding significance values. These findings present the different mediating channels through which one construct mediates another in the model. The significance levels show that these particular indirect effects are statistically significant, thus confirming the mediation analysis.

Table 5.7

Specific Indirect Effect- Path Coefficient with Significance

Path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
BI -> AU -> IB	0.416	0.416	0.047	8.888	0.000
RP -> ATT -> BI -> AU	-0.112	-0.111	0.017	6.523	0.000
CP -> AU -> IB	-0.058	-0.058	0.030	1.932	0.054
FC -> AU -> IB	0.073	0.075	0.029	2.551	0.011
PEOU -> ATT -> BI -> AU	0.077	0.077	0.024	3.159	0.002
LE -> AU -> IB	0.045	0.045	0.018	2.502	0.013
CP -> BI -> AU -> IB	0.029	0.029	0.024	1.172	0.242
RP -> AU -> IB	-0.053	-0.053	0.034	1.550	0.121

Path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
CP -> ATT -> BI -> AU	-0.067	-0.067	0.020	3.409	0.001
CP -> ATT -> BI -> AU -> IB	-0.048	-0.048	0.015	3.273	0.001
PEOU -> ATT -> BI -> AU -> IB	0.055	0.055	0.018	3.062	0.002
ATT -> BI -> AU	0.398	0.398	0.047	8.401	0.000
CP -> BI -> AU	0.040	0.041	0.034	1.181	0.238
CP -> ATT -> BI	-0.115	-0.115	0.032	3.574	0.000
FC -> ATT -> BI -> AU -> IB	0.058	0.058	0.016	3.541	0.000
FC -> ATT -> BI	0.138	0.140	0.036	3.844	0.000
RP -> BI -> AU	-0.052	-0.053	0.031	1.688	0.092
PEOU -> ATT -> BI	0.131	0.132	0.040	3.305	0.001
PU -> ATT -> BI -> AU -> IB	0.074	0.074	0.019	3.913	0.000
ATT -> BI -> AU -> IB	0.284	0.285	0.039	7.297	0.000
PU -> ATT -> BI -> AU	0.104	0.104	0.025	4.090	0.000
PU -> ATT -> BI	0.178	0.178	0.038	4.708	0.000
RP -> ATT -> BI	-0.192	-0.191	0.027	7.242	0.000
RP -> BI -> AU -> IB	-0.037	-0.038	0.023	1.640	0.101
FC -> ATT -> BI -> AU	0.081	0.081	0.022	3.661	0.000
RP -> ATT -> BI -> AU -> IB	-0.080	-0.079	0.013	6.062	0.000

The findings in Table 5.7 illustrate how indirect connections between constructs contribute to the adoption of technological innovations and their subsequent impact on investment behaviour. The study used specific indirect effects to capture how a variable that does not directly affect another may still influence it through a sequence of mediating variables. The most critical chain of influence in this model begins with behavioural intention, which involves actual use, and subsequently leads to investment behaviour. This sequence demonstrates that intention alone does not lead to behavioural change unless it is translated into actual practice. The chain from attitude to behavioural intention and then to actual use also plays a significant role. It highlights that a positive mental outlook on using financial technology increases willingness, which in turn converts to actual usage. Once investors start using platforms like AI-based tools, mobile apps or robo-advisors, the change in investment behaviour becomes visible. Those changes include frequent trading, engaging in long-term strategies and taking calculated risks. The role of perceived ease of use also stands out, as its impact flows through attitude and then into behavioural intention and use. Investors who find fintech easy to use develop a favourable attitude, decide to use it, and eventually exhibit behavioural change. This chain illustrates how perception evolves into intention and subsequently becomes actual behaviour.

The result also indicates how perceived risk and cost perception travel through multiple indirect paths to influence investment behaviour. Risk perception affects behaviour through attitude, intention and use. If investors perceive digital tools as risky, their attitude becomes negative, which in turn reduces their intention to use and adopt them. Ultimately, this results in lower engagement with technology in their investments. Similarly, cost perception has several paths. Although some paths were found statistically weak, others were significant. Cost perception negatively affects attitude and, through that, intention and use, ultimately reducing its influence on investment behaviour. Facilitating conditions also exhibited an intense sequence of indirect effects. Starting from improving attitude, to increasing intention, actual use, and then influencing behaviour. These results suggest that when there is adequate support, investors feel more confident in adopting technology, which brings about behavioural change. Learning experience also has a direct impact on behaviour through usage. Investors with past exposure to digital platforms are more likely to show behavioural changes. Perceived usefulness also travels through multiple layers. It fosters a positive attitude, which in turn increases behavioural intention, leading to higher actual use and eventually shaping behaviour. The extended TAM model used in the study helps map how these factors interact to shape final investment behaviour. The specific indirect effects described in Table 5.7 help validate the model's design and demonstrate that even constructs with no direct path can still play a key role when their effect is transmitted through multiple connected constructs.

5.12 Total Effect- Path Coefficient with Significance

Table 5.8 presents the total effect path coefficients along with their corresponding significance levels. Total effects refer to the overall impact of the direct and indirect relationships between constructs within the model. The significance values also aid in understanding the strength and validity of these relationships within the structural framework.

Table 5.8

Total Effect- Path Coefficient with Significance

Path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
ATT -> AU	0.398	0.398	0.047	8.401	0.000
ATT -> BI	0.683	0.683	0.052	13.171	0.000
ATT -> IB	0.284	0.285	0.039	7.297	0.000
AU -> IB	0.713	0.715	0.032	22.026	0.000
BI -> AU	0.583	0.582	0.053	11.078	0.000
BI -> IB	0.416	0.416	0.047	8.888	0.000
CP -> ATT	-0.168	-0.167	0.043	3.951	0.000
CP -> AU	-0.108	-0.106	0.053	2.024	0.043
CP -> BI	-0.046	-0.045	0.053	0.879	0.380
CP -> IB	-0.077	-0.076	0.038	2.000	0.046
FC -> ATT	0.202	0.203	0.046	4.403	0.000
FC -> AU	0.184	0.186	0.042	4.366	0.000
FC -> BI	0.138	0.140	0.036	3.844	0.000
FC -> IB	0.131	0.133	0.032	4.100	0.000
LE -> AU	0.063	0.063	0.026	2.455	0.014
LE -> IB	0.045	0.045	0.018	2.502	0.013
PEOU -> ATT	0.192	0.193	0.056	3.451	0.001
PEOU -> AU	0.077	0.077	0.024	3.159	0.002
PEOU -> BI	0.131	0.132	0.040	3.305	0.001
PEOU -> IB	0.055	0.055	0.018	3.062	0.002
PU -> ATT	0.260	0.261	0.056	4.628	0.000
PU -> AU	0.104	0.104	0.025	4.090	0.000
PU -> BI	0.178	0.178	0.038	4.708	0.000
PU -> IB	0.074	0.074	0.019	3.913	0.000

Path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
RP -> ATT	-0.281	-0.279	0.036	7.914	0.000
RP -> AU	-0.239	-0.237	0.047	5.041	0.000
RP -> BI	-0.282	-0.281	0.046	6.180	0.000
RP -> IB	-0.170	-0.170	0.035	4.854	0.000

The results presented in Table 5.8 provide a comprehensive view of how each construct in the model influences the others in totality. The study used the total effect to capture both direct and indirect relationships between variables. In this model, actual use has emerged as the strongest influencer of investment behaviour. The result shows that when investors start using fintech tools regularly, their behaviour in the stock market changes clearly. They begin to take more risks, shift strategies and increase activity. Behavioural intention also strongly impacts actual use, confirming that intention serves as the entry point to actual behavioural engagement. Attitude toward technology has a high total effect on intention and also extends influence to actual use and investment behaviour. This indicates that when investors develop a positive view of fintech, they are more likely to demonstrate commitment and engage deeply. Constructs such as perceived usefulness and perceived ease of use support this view, as they positively influence attitude. The ease of use and usefulness of the tools increase user acceptance. As investors find platforms helpful and straightforward, they develop a positive attitude, leading to more intention and behavioural change. Facilitating conditions also play a strong role in this model. Total effects show that support from the environment, stable internet and government policies positively influence behavioural intention and use. This implies that surrounding infrastructure plays a crucial role in adoption and eventual change.

The effects of negative constructs, such as risk perception and cost perception, are also strong in the model. Risk perception clearly shows a negative influence on attitude, intention, use and investment behaviour. This means that if investors believe technology tools may lead to loss or are unreliable, they avoid using them. This result underscores the importance of building confidence and trust in digital systems. Cost perception has weaker total effects compared to risk, but still affects attitude and actual use. Investors who believe tools are expensive or not cost-efficient may reduce their usage, but this effect is not strong on their behavioural intention. This finding suggests that financial cost is less critical than risk when it comes to technology adoption in investment. Learning experience has a positive total effect on use and behaviour, confirming that prior exposure to similar systems improves user involvement. The total effect of facilitating conditions on investment behaviour proves that a good support structure can shape investor response. Constructs that show the most decisive influence on investment behaviour in total effect are actual use, followed by behavioural intention, attitude and facilitating conditions. This flow confirms the design of the extended TAM model used in the study. The total effect analysis helps to validate the strength and nature of each construct across the whole model path. It also shows that specific constructs, such as behavioural intention and actual use, serve as bridges that connect perception to final behaviour. The study used this model to map out the complete interaction system behind investor behaviour in response to financial technology innovation.

5.13 Collinearity Statistics (VIF) for Inner Model

Table 5.9 below presents the collinearity statistics (VIF) for the inner model, indicating the degree of multicollinearity among the predictor constructs. VIF values indicate a high likelihood of high correlations among independent variables, which can lead to incorrect path estimates. Low values of all VIF correlations do not necessarily indicate the presence of serious multicollinearity problems, which ensures the model's strength.

Table 5.9

Collinearity Statistics (VIF) for Inner Model

	VIF
ATT -> BI	1.409502
AU -> IB	1
BI -> AU	1.703342
CP -> ATT	1.421735

	VIF
CP -> AU	1.402482
CP -> BI	1.483048
FC -> ATT	1.75224
FC -> AU	1.530837
LE -> AU	1.007922
PEOU -> ATT	2.736893
PU -> ATT	1.842756
RP -> ATT	1.356978
RP -> AU	1.485914
RP -> BI	1.48663

As per Table 5.9, the variance inflation factor values for the inner model paths remain well below the acceptable threshold. According to Hair et al. (2019), a VIF value below five indicates that collinearity is not a concern and the estimates are not biased due to multicollinearity. All the inner model paths in this study, including those from attitude, behavioural intention, cost perception, facilitating conditions, learning experience, perceived ease of use, perceived usefulness, and risk perception to their respective endogenous constructs, fall under this acceptable range. This confirms that the predictive relationships among the constructs are stable and can be interpreted without distortion due to multicollinearity. The absence of collinearity issues strengthens the model's structural integrity, allowing for a reliable interpretation of direct, indirect, and total effects.

5.14 Collinearity Statistics (VIF) for Outer Model

The table contains the collinearity statistics (VIF) of the outer model, which measure the collinearity of the measurement items for each construct. The values of the Variance Inflation Factor (VIF) help identify indicators that are too highly correlated, thus impacting construct validity. The acceptable values of the VIF suggest that there is no issue of collinearity, and hence, the reliability of the measurement model is ensured.

Table 5.10

Collinearity Statistics (VIF) for Outer Model

Items	VIF
ATT1	1.969046
ATT2	2.123543
ATT3	2.476447
ATT4	2.214786
ATT5	2.382623
AU1	3.09904
AU2	2.979081
AU3	2.746237
AU4	3.748132
AU5	3.732942
BI1	2.39196
BI2	2.308973
BI3	2.446363
BI4	2.581177
BI5	2.710722
CP1	1.645907
CP2	1.718892
CP3	1.745481
CP4	1.549601
CP5	1.50833
FC1	1.451214
FC2	1.547607
FC3	1.738349
FC4	1.321867
FC5	1.562954
IB1	1.94273
IB2	1.615934
IB3	1.585132
IB4	1.797394

Items	VIF
IB5	2.440925
Level of Education	1
PEOU1	1.563459
PEOU2	1.65416
PEOU3	1.939539
PEOU4	1.856908
PEOU5	1.872556
PU1	1.708731
PU2	1.533593
PU3	1.923581
PU4	1.958302
PU5	1.483872
RP1	2.81139
RP2	2.958875
RP3	2.930614
RP4	2.496647
RP5	2.656828

In Table 5.10, the outer model shows the VIF values for all individual items used to measure the latent constructs. All items across constructs such as attitude toward technology, actual use, behavioural intention, cost perception, facilitating conditions, investment behaviour, perceived ease of use, perceived usefulness, and risk perception show VIF scores below the cut-off value of 5 suggested by Hair et al. (2019). This supports that the reflective measurement items are not collinear and do not interfere with each other's explanatory power. The indicators are statistically independent within their constructs, indicating that the item-level measurement model maintains discriminant validity. Since acceptable collinearity statistics support all item loadings, the outer measurement model is reliable, and the construct scores reflect the variance from their indicators without redundancy or bias.

5.15 f-square

Table 5.11 presents the values of f-squared, which provide an effect size indicating the impact of each exogenous construct on the endogenous constructs in the model. This statistic helps to understand the relative contribution of individual predictor variables to the determined R-squared value of the dependent variable. Therefore, the f values, according to standard guidelines, reflect the small, medium or large size of the effect and, thus, can be viewed as an indicator of the practical significance of the relationships.

Table 5.11

f-square

Path	f-square
ATT -> BI	0.644584
AU -> IB	1.034848
BI -> AU	0.401825
CP -> ATT	0.046034
CP -> AU	0.009334
CP -> BI	0.006192
FC -> ATT	0.054014
FC -> AU	0.01392
LE -> AU	0.00794
PEOU -> ATT	0.031123
PU -> ATT	0.084728
RP -> ATT	0.134711
RP -> AU	0.007456
RP -> BI	0.010525

As shown in Table 5.11, the path from actual use to investment behaviour exhibits a large effect size, indicating that actual use has a strong influence on investment behaviour. Behavioural intention also shows a moderate effect on actual use. Attitude toward technology has a substantial impact on behavioural intention, meaning that people's positive perception of using fintech tools directly shapes their intent to adopt them. The results support the objective, which focuses on how behavioural and technological factors influence the actual use of fintech platforms and how this, in turn, affects trading behaviour. Among the antecedents of attitude, perceived usefulness shows a moderate effect, while risk perception and facilitating conditions also show small to moderate effect sizes. These findings explain how users form an attitude based on both enabling factors and concerns about risk. Cost perception and perceived ease of use also have low but meaningful contributions to shaping attitude. The remaining paths show small effect sizes, including those from cost perception, facilitating conditions, and learning experience toward actual use. Similarly, cost perception and risk perception have minor effects on behavioural intention. These values suggest that although these factors contribute to shaping technology acceptance and use, their relative impact is lower than constructs like attitude and behavioural intention. The effect sizes confirm that actual system use and investment activity depend more on internal beliefs about the system than external conditions. Therefore, in line with the objective, the model demonstrates how perceived benefits and confidence in using fintech tools matter more than concerns or support systems when it comes to forming firm behavioural intention and converting that into actual fintech usage and stock market activity.

5.16 R-Square and Adjusted R-Square

Table 5.12 presents the R-squared and Adjusted R-squared values for the endogenous variables of the model. R-Square indicates what proportions of variance in the dependent constructs are explained by the predictor constructs, and Adjusted R-Square gives a more proper reflection because it takes into consideration the number of predictors. These values show the explanatory capabilities and the goodness-of-fit of the structural model.

Table 5.12

R-Square and Adjusted R-Square for Endogenous Constructs

	R-square	R-square adjusted
ATT	0.56701	0.56178
AU	0.502754	0.496749
BI	0.486578	0.482875
IB	0.508563	0.507387

The values in Table 5.12 indicate that the model explains a moderate proportion of the variance in each of the four endogenous variables. The construct of attitude toward technology is described by its predictors, including perceived usefulness, perceived ease of use, cost perception, risk perception, and facilitating conditions. This suggests that users form their attitude based on their overall assessment of the usability and safety of fintech tools, as well as their perception of value and support. Behavioural intention is predicted by constructs such as attitude, risk perception and cost perception. The R-squared value indicates that these constructs collectively have a significant influence on the intention to adopt fintech platforms for investment purposes.

Actual use of fintech tools is another key outcome in this model. The construct is predicted by behavioural intention, facilitating conditions, cost perception, risk perception, and learning experience. The R Square value confirms that nearly half of the variation in actual use is explained by these predictors. Investment behaviour, which is the ultimate dependent variable in this model, is directly influenced by actual use and indirectly by the other predictors through mediating paths. The model explains a moderate portion of the variance in investment behaviour, validating the model as a tool for examining the adoption of technological innovations and their impact on investor activity. The R-squared values support the notion that fintech adoption is not random but depends powerfully on how users perceive the technology, the intention they form, and their eventual usage patterns.

5.17 Model Fit Indices

Model fit indices, such as the Standardised Root Mean Square Residual (SRMR) and the other global fit measures, are also presented in Table 5.13. The index can be used to determine the goodness of the fit between the proposed structural model and the existing data. Acceptable values of SRMR and associated values demonstrate an excellent model fit, confirming the reliability and validity of the research framework.

Table 5.13

Model Fit Indices – Standardised Root Mean Square Residual and Other Global Fit Measures

Statistics	Saturated model	Estimated model
SRMR	0.063345	0.071004
d_ULS	6.509124	7.089227
d_G	1.936037	2.143285
Chi-square	6103.59	6213.633
NFI	0.910291	0.89688

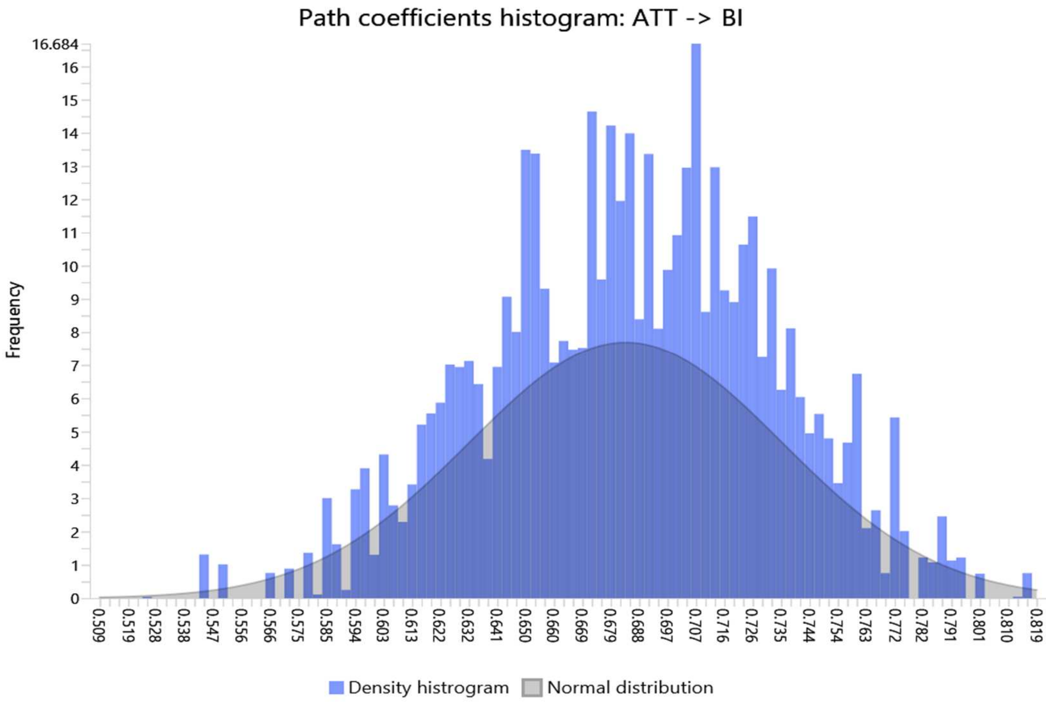
Table 5.13 presents the model fit indices for evaluating the overall fit of the PLS SEM model developed for examining the adoption of technological innovation and its impact on investment behaviour among stock market investors. The Standardised Root Mean Square Residual value is well within the acceptable threshold, indicating that the discrepancy between the observed and predicted correlations is minimal. The Normed Fit Index also falls in the acceptable range, suggesting the model fits the empirical data adequately. Additionally, the other fit indices, such as dG, dULS, and chi-square, support the conclusion that the structural model is acceptable and appropriate for further analysis. These values support that the proposed conceptual model has a sufficient degree of model-data correspondence, aligning with recommendations for model evaluation in PLS SEM-based studies.

5.18 Histogram of Path Coefficients

The three histograms shown in Figures 5.4, 5.5, and 5.6 present the bootstrapped sampling distribution of the path coefficients between ATT and BI, BI and AU, and AU and IB, respectively. These visuals serve as graphical representations to validate the stability of the estimated path coefficients.

Figure 5.4

Histogram of Path Coefficients for ATT -- BI



In Figure 5.4, the histogram for ATT to BI shows a near-normal distribution, suggesting consistency in the coefficient across multiple bootstrap resamples. This visual support affirms that attitude toward technology maintains a reliable and stable influence on behavioural intention. The smooth alignment with the standard curve also supports the observation that the data fit well with the model expectations, highlighting the robustness of the ATT to BI relationship in the model estimation.

Figure 5.5

Histogram of Path Coefficients for BI -- AU

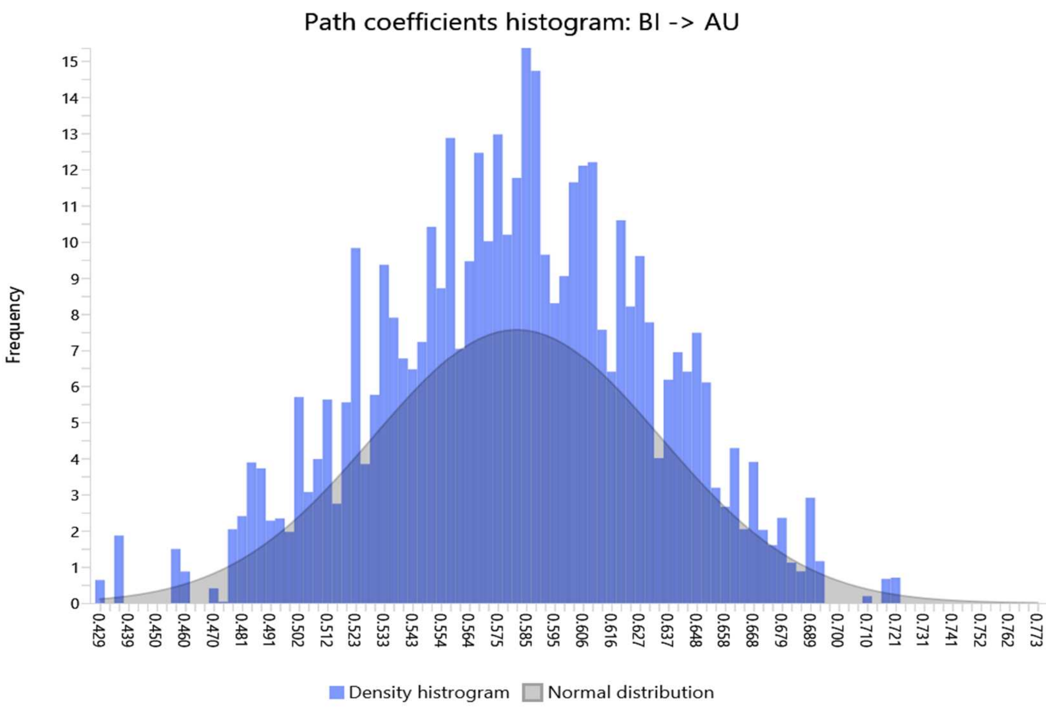
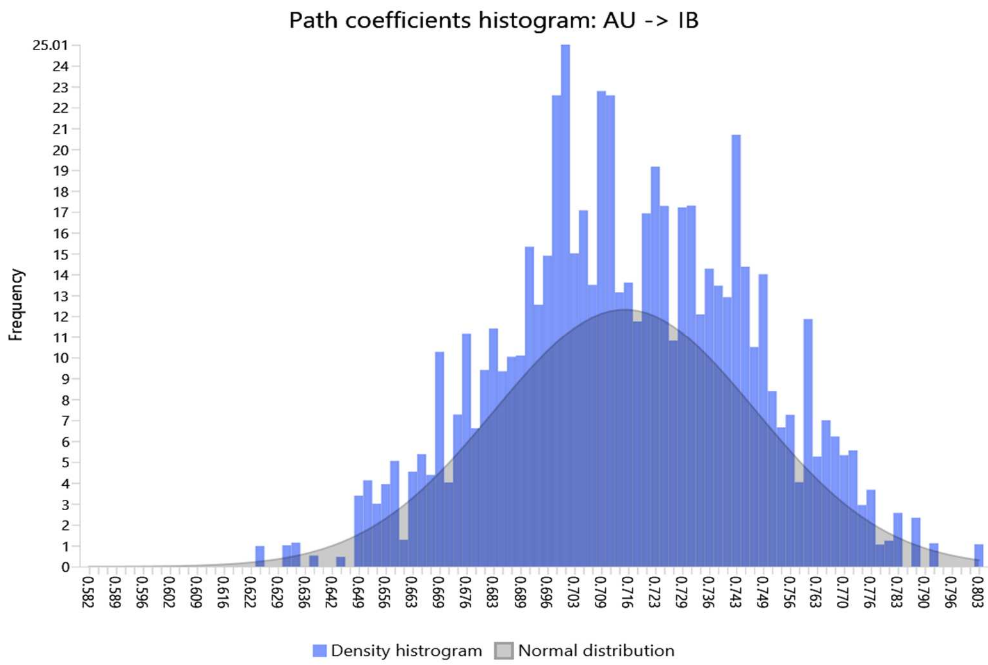


Figure 5.5, which illustrates the path from BI to AU, also reflects a symmetrical distribution centred closely around the mean coefficient. The bell-shaped curve again indicates that the bootstrapped estimates do not vary drastically, suggesting low sampling variability. This consistency enhances confidence in the conclusion that behavioural intention has a significant impact on actual use. The narrow spread seen in the histogram reflects a tighter confidence interval around the path estimate, which further suggests that the path coefficient is not sensitive to sampling variations and maintains its strength across the bootstrap iterations.

Figure 5.6

Histogram of Path Coefficients for AU--IB



The last histogram in Figure 5.6, depicting the path from AU to IB, is also normally shaped and sharply peaked, which implies a robust and stable relationship between actual use and investment behaviour. The tall and narrow distribution indicates a high degree of certainty and low standard error in the path coefficient. Such graphical stability across all three critical structural paths demonstrates that random sampling fluctuations do not drive the model results. Therefore, the path coefficients reported for ATT to BI, BI to AU, and AU to IB are robust and can be interpreted with high confidence in supporting the hypothesised framework of the study.

5.19 Importance Performance Map

The Importance-Performance Map Analysis (IPMA) is used to gain a greater insight into how various constructs play influential roles in key outcomes, not only due to their importance (related to their total effects), but also due to their performance (average scores). The following diagrams are used to display the relative contribution of antecedent constructs to actual use (AU), attitude toward technology (ATT), and investment behaviour (IB). These maps help determine constructs to prioritise in the development of plans that lead to increased adoption of fintech and investment. The combination of the three maps used collectively can be used to prioritise resources, strengthen investor intention and encourage good use of technology-driven investment platforms.

Figure 5.7

Importance Performance Map for Actual Use (AU)

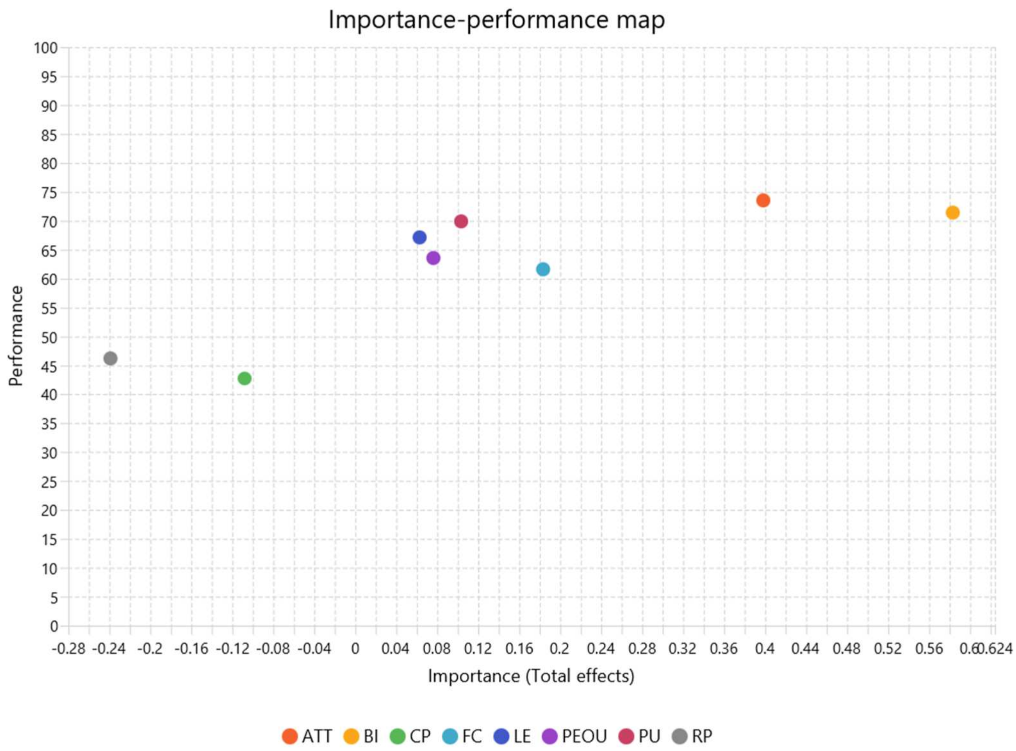


Figure 5.7 presents the importance-performance map for the endogenous construct actual use. The map displays both the total effects (importance) of each antecedent construct on actual use and the respective average latent variable scores (performance). The orange marker representing behavioural intention (BI) stands out with the highest importance and relatively strong performance, indicating that the behavioural intention construct plays a dominant role in explaining actual use. This placement supports that respondents with higher levels of intention to adopt technology are more likely to use fintech platforms for investment. The subsequent significant construct is attitude toward technology (ATT), shown in red-orange, which also lies in the high importance and performance region. This confirms that when investors have a favourable attitude toward technological applications in trading, they are more inclined to engage in actual use. The strength of these relationships supports

their prioritisation in strategies promoting the adoption of fintech investment tools. On the other side of the map, constructs such as risk perception (RP) and cost perception (CP) appear in the low importance and low performance quadrant. These constructs have a minimal impact on actual use and score lower in performance, meaning that even though investors may recognise risk and cost factors, these do not strongly influence their actual technology usage. The green dot for cost perception and the grey dot for risk perception fall far from the right end of the map, suggesting their role in determining usage behaviour is weak. Other constructs, such as perceived ease of use (PEOU), facilitating conditions (FC), and perceived usefulness (PU), fall within the mid-importance range, exhibiting moderate to good performance. Their location suggests that, although they make meaningful contributions to actual use, they are less influential than behavioural intention or attitude toward technology. The overall spread in the map helps visually prioritise which factors should receive attention in practical investment technology design and outreach.

Figure 5.8

Importance Performance Map for Attitude Toward Technology (ATT)

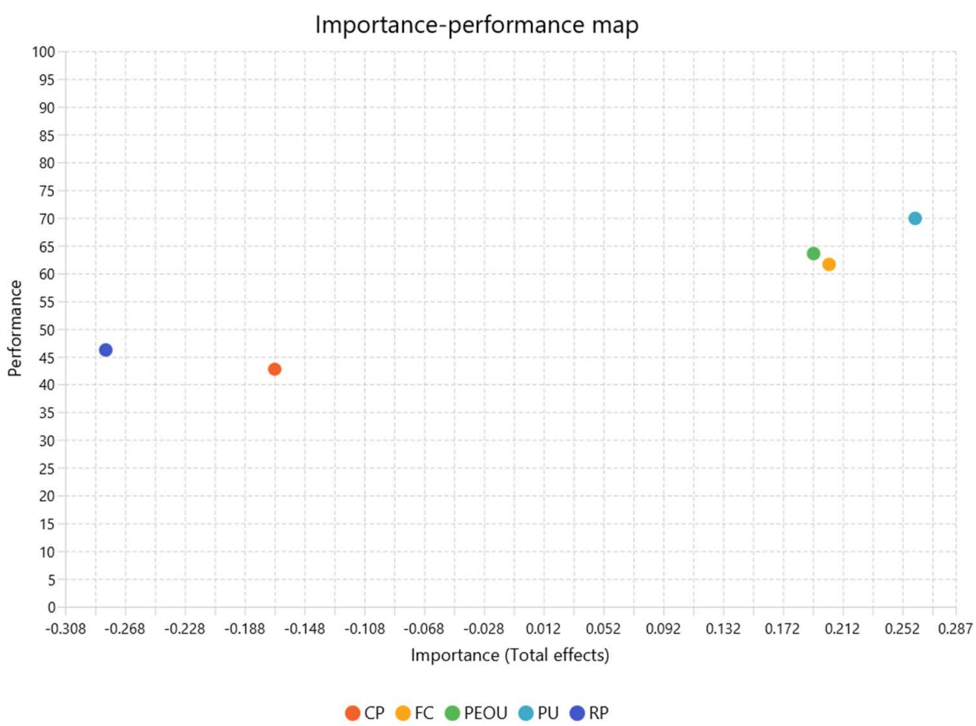


Figure 5.8 shows the importance-performance map for the construct attitude toward technology. The blue marker for risk perception (RP) is placed on the far left side of the map, indicating very low importance and low performance. This placement suggests that risk perception does not significantly influence investors' attitudes toward technology, and it also scores low in terms of its performance among respondents. Similarly, the orange marker for cost perception (CP) also lies in the low importance and low performance quadrant, suggesting that cost-related concerns are not highly influential on forming a positive or negative attitude toward adopting financial technology. These constructs, although theoretically expected to have an adverse effect, appear to lack practical significance when it comes to shaping the attitudes of stock market investors in this context. On the right side of the figure, facilitating conditions (FC), perceived ease of use (PEOU), and perceived usefulness (PU) are located in the high importance zone, with moderate to high performance. The turquoise marker for perceived usefulness stands slightly ahead in importance and performance, suggesting that investors' perceptions about the effectiveness of fintech tools strongly contribute to shaping their attitude. Facilitating conditions also demonstrate competitive performance, suggesting that external support factors, such as training or access to infrastructure, enhance investors' confidence in utilising technology. Perceived ease of use lies close to both, meaning that user-friendly interfaces and easy operation also contribute meaningfully to attitude formation.

Figure 5.9

Importance Performance Map for Investment Behaviour (IB)

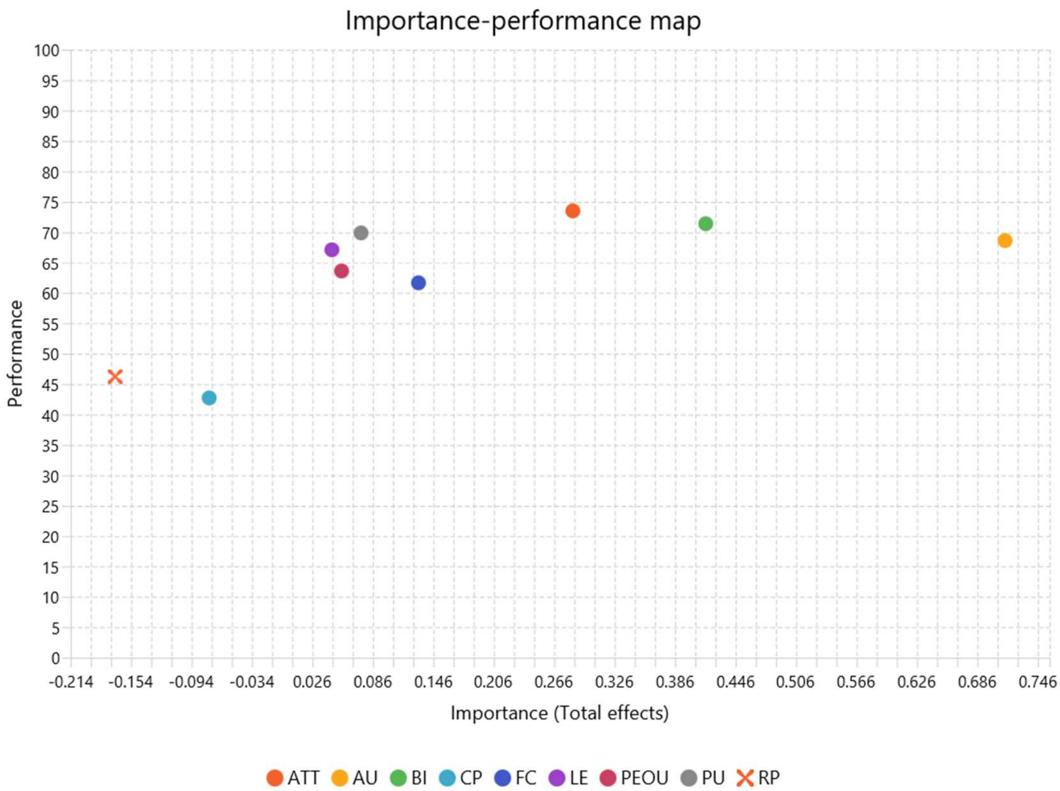


Figure 5.9 displays the importance-performance map for the construct investment behaviour. This map presents the contribution of various constructs in terms of their total effect (importance) and their average latent construct score (performance) on investment behaviour among stock market investors. Behavioural intention (BI), which is shown on the far-right side, has the highest importance. This placement suggests that the willingness or intention to use financial technologies plays a central role in shaping actual investment behaviour. Actual use (AU) and attitude toward technology (ATT) also lie in the high importance zone, with good performance levels, indicating that usage behaviour and a positive mindset toward digital tools are both critical in promoting enhanced investor activity through technology. In contrast, cost perception (CP) and risk perception (RP) appear in the left section of the map. Their negative importance values imply a reverse relationship, confirming their inhibitory effect on investment behaviour. Their placement also indicates low performance, which aligns with their theoretical position as barriers to the adoption of technology.

The middle cluster includes constructs such as facilitating conditions (FC), perceived usefulness (PU), perceived ease of use (PEOU), and level of education (LE). These constructs offer moderate importance and performance, indicating they play a supportive role in shaping investment behaviour but are not the primary drivers. Hence, the map shows that positive intention and actual engagement with technology act as direct enablers of improved investment practices. At the same time, cost and risk concerns can hinder participation if not addressed.

5.20 Conclusion

The results indicate that attitude towards technology and behavioural intention are the most significant factors influencing the actual usage of technology; therefore, a strong belief and a desire to use technology translate into real usage. On the other hand, constructs such as cost perception, risk perception, and facilitating conditions do not significantly influence investor behaviour based on the explanatory power demonstrated by these constructs. The results of the total effect analysis substantiate that actual use is the most influential determinant of investment behaviour, with the behavioural intention, attitude, and facilitating conditions as the significant supporting drivers. Negative beliefs, such as perceptions of risk and cost, reduce adoption; however, their effects are less intense than those of the positive facilitators, including usefulness, ease of use, and supportive infrastructure. Generally, the results confirm the expanded TAM model whereby the perceptions influence attitude, followed by intention, which in turn leads to behavioural actualisation, which leads to investor behaviour transformation.

Reference

Hair, J. F., Hauff, S., Hult, G. T. M., Richter, N. F., Ringle, C. M., & Sarstedt, M. (2017). *Partial Least Squares Strukturgleichungsmodellierung*. https://doi.org/10.15358/9783800653614

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2–24. https://doi.org/10.1108/ebr-11-2018-0203

Hair, J., Hollingsworth, C. L., Randolph, A. B., & Chong, A. Y. L. (2017). An updated and expanded assessment of PLS-SEM in information systems research. *Industrial Management & Data Systems*, *117*(3), 442–458. https://doi.org/10.1108/imds-04-2016-0130.

Chapter 6

SUMMARY, FINDINGS AND CONCLUSIONS

6.1 Introduction

This chapter provides an overview of the study, commencing with a summary of the research carried out. It presents the most important findings based on the analysis, which are organised in a logical flow according to the research objectives. The study particularly aims at investigating how technological innovations affect the investment behaviour of stock market investors in Kerala. The final section of the chapter comprises the significant revelations made by the findings.

6.2 Summary

The research report is divided into seven chapters. The first chapter presents the background of the research, including the research problem, significance, scope, objectives, operational definitions, hypotheses, conceptual model, research methodology, limitations, and the overall scheme of the thesis. The second chapter provides a review of the existing literature on the research topic and identifies the gaps in the current research. The third chapter summarises the theoretical basis of stock market trading, technological innovations, and their influences on investment behaviour. In the fourth chapter, technology adoption and investment behaviour of stock market investors are discussed. The fifth chapter employs Partial Least Squares Structural Equation Modelling (PLS-SEM) to analyse the factors affecting technology adoption and its role in investment behaviour. The sixth chapter delivers the important findings and conclusions of the study. The seventh chapter examines recommendations, practical implications, and future research directions.

The study examines how emerging technologies have influenced investor attitudes, decision-making, and stock market trading behaviour. The study is grounded in an integrated model that considers essential technological drivers, namely artificial intelligence applications, algorithmic trading, blockchain technology, mobile trading, and robo-advisor services that exert influence on investor behaviour. The research also emphasised variation in behavioural shifts across different genders, age groups, educational qualifications, and employment statuses, providing insights into how technology influences investment decisions.

6.3 Findings of the study

This section presents the major findings of the study, organised into five key areas in accordance with the research objectives and the respective findings, analysis, and interpretation.

6.3.1 The first objective of the study is **to analyse changes in investment behaviour due to technological advancements**. The study examined how technological advancements are influencing the behaviour of investors in the stock market. Based on the descriptive analysis, it was observed that several technologies are already playing a significant role in shaping investor decisions. The findings related to the objectives are presented below.

6.3.1.1 Algorithmic trading emerged as one of the strongest influences on behaviour. Investors believed that algorithmic systems help them make better decisions based on data, rules and market trends.

6.3.1.2 Advanced screeners also supported investor activity by making stock selection easier and more structured. The availability of these tools helped investors filter stocks quickly and act more confidently.

6.3.1.3 Payment systems like UPI were also found to have a strong influence. Faster and easier fund transfers helped increase investor participation.

6.3.1.4 Mobile trading applications contributed to the ease of access, which in turn encouraged frequent trading.

6.3.1.5 Robo-advisors, while automated and useful, were also found to be gaining trust among users. The findings suggest that technology is being used not just for market research but also for decision-making and trade execution.

6.3.1.6 The lower impact observed for auto rebalancing and smart order routing shows that some tools are not yet well known or understood by all investors. The general investor who trades occasionally may not frequently interact with these features.

6.3.1.7 Similarly, blockchain as a back-end technology had a moderate level of influence. While blockchain ensures trust and safety, the average investor might not directly feel or recognise its role.

6.3.1.8 Artificial intelligence tools for forecasting also received mixed opinions. Some investors showed trust, while others remained cautious. This could be due to a lack of understanding or experience, leading to inaccurate predictions.

6.3.1.9 The responses in general were consistent, as shown in the combined score. Most investors rated the impact of technological tools positively, which shows an overall acceptance of change.

6.3.1.10 When the study explored gender differences, it was seen that male and female investors do not always behave the same in response to technology. Male investors responded more positively to tools such as blockchain, algorithmic trading, and robo-advisors. This could be due to higher exposure, better confidence in technology, or more frequent usage of such platforms among male investors.

6.3.1.11 Tools like UPI and mobile apps did not show much difference between male and female users. This indicates that all types of investors equally accept certain features.

6.3.1.12 The combined result for all technological variables showed a substantial difference. Male investors had significantly higher scores. This confirms that gender influences the way technology is adopted and experienced in investment activities. The results support the notion that male investors are currently more attuned to technological advancements in investing. These findings also highlight the need for more awareness and confidence-building among female investors.

6.3.1.13 Education was another critical factor that showed significant influence in this study. The statistical results showed that investors with higher educational qualifications, like postgraduate and professional degrees, were more likely to agree that technological tools influenced their investment behaviour. These investors gave high ratings to tools like virtual trading, sentiment analysis, real-time alerts and intraday platforms. In contrast, those with SSLC education had lower scores. Better-educated investors are more comfortable exploring digital features, understanding their benefits, and incorporating them into their trading decisions. The tools that require learning and interpretation, such as sentiment tools or virtual platforms, were rated much higher by educated investors.

6.3.1.14 Investors with lower education levels gave higher scores to features such as UPI and technology that reduced costs. The differences in ratings across education levels indicate that some investors prioritise technology based on ease and simplicity, while others opt for more advanced tools.

6.3.1.15 The combined analysis of all items confirmed that education plays a strong role in shaping how technology is experienced in stock market investing.

6.3.1.16 These findings offer a real view of how gender and education shape behaviour in modern investment practices. The responses indicate that technology use is not uniform, influenced by the investor's gender and their education level. The hypotheses H1 and H2 were both validated through this analysis.

6.3.1.17 The analysis revealed apparent differences in investment behaviour due to technological advancements among investors from different employment backgrounds. The results showed that certain technological tools, such as those that reduce costs and improve accessibility, intraday trading platforms, UPI payment systems, real-time alerts, sentiment analysis tools, and virtual trading platforms, were perceived differently across employment categories.

6.3.1.18 Professionals consistently viewed these technologies as having a more substantial influence on their investment behaviour, while retired investors tended to perceive them as having less impact.

6.3.1.19 These findings indicate that employment status plays a key role in shaping how investors perceive and adapt to technological advancements in the investment field. They also highlight the importance of designing investor education and awareness programs that are tailored to different occupational groups, ensuring that the benefits of technology are effectively communicated and utilised by all segments of the investor community.

6.3.1.20 The analysis shows that age plays a vital role in shaping how investors respond to technological advancements in the investment field. Younger investors, particularly those in the 18–25 and 26–35 age groups, are more influenced by modern tools such as blockchain technology, robo-advisors, advanced screeners, real-time alerts, and sentiment analysis. They also place greater importance on features like lower costs, faster transactions through UPI systems, and the ability to engage in short-term trading via intraday platforms.

6.3.1.21 Investors in the 36–45 age group demonstrate a balanced approach, utilising both traditional methods and new technological solutions.

6.3.1.22 Investors in the 46–55 category show lower levels of adoption, indicating a more cautious approach towards incorporating technology in investment decisions.

6.3.1.23 The oldest group, above 55, tends to rely the least on these innovations, showing limited use of digital and automated tools.

6.3.1.24 Overall, the findings suggest that younger generations are quicker to adapt and integrate technology into their investment practices. In contrast, older investors tend to remain more conservative, relying more on established methods. This highlights the importance of tailoring financial education and technological awareness programs to suit the needs and comfort levels of different age groups.

6.3.2 The second objective of the study is to **evaluate the influence of social trading and real-time news platforms on trading habits.** The study explored how social trading and real-time news platforms shape investor behaviour in stock trading.

6.3.2.1 The descriptive analysis showed that most participants agreed that both types of platforms play a role in changing how they trade. The item with the highest level of agreement was about the influence of real-time news on trading. This means investors closely follow current updates and make decisions based on market developments shared instantly.

6.3.2.2 Many respondents agreed that social media platforms like Twitter, WhatsApp, and Telegram influenced their trade decisions. These platforms offer continuous updates, peer opinions, and sentiment, which investors seem to trust. People reported feeling more confident in their trading after checking social media groups or receiving alerts from influencers. This indicates that confidence is now derived not only from personal research but also from social validation and shared information.

6.3.2.3 Investors also believed that the speed and reliability of news reports affected their trading habits. Fast access to reliable information enabled them to make quicker decisions, which sometimes altered their approach to observing market trends.

6.3.2.4 Tools like real-time alerts were also mentioned to have helped traders act faster. Alerts helped reduce delay and created a feeling of control among investors.

6.3.2.5 Trading via social media is riskier than self-analysis, which received moderate scores. This means some people were not entirely comfortable relying on what others said online. The responses were varied, which shows that while many trust social input, others remain cautious.

6.3.2.6 Peer recommendations were accepted by many, but not all. Some participants believed suggestions from friends or online groups affected their trades, but others preferred their judgement. This could be because social influence varies based on personal networks and past experiences.

6.3.2.7 The ease of using real-time news platforms also showed moderate agreement. Some found it very helpful, while others may not have access to or regularly use these tools.

6.3.2.8 Overall, most investors agreed that both social platforms and news tools play a growing role in how they trade. These platforms provided information, alerts, and a sense of connection to the market, which altered their approach to trading.

6.3.2.9 The gender-based analysis showed that male and female investors did not always respond the same way to these technological changes. Male investors were found to be more influenced by real-time news, alerts, and social platforms. They agreed more strongly that these tools changed their trading frequency, strategies, and confidence.

6.3.2.10 The statistical analysis also showed that variables like timely news and alerts had substantial differences based on gender. Male investors appeared to follow live updates more actively and responded faster. On the other hand, female investors had slightly lower agreement levels. This could be due to differences in risk appetite, trust in digital tools, or habits formed over time.

6.3.2.11 Some variables did not show much difference between genders. The speed and reliability of news updates were rated similarly by male and female participants. This indicates that while some tools have universal appeal, others are used or valued differently.

6.3.2.12 The average rank scores across the groups showed that male investors gave higher ratings to most variables. This pattern highlights how trading habits are shaped by gender when it comes to using technology and online platforms.

6.3.2.13 The study also tested how education levels influence investor behaviour related to social and news platforms. Investors with professional degrees were found to be the most influenced by social and real-time platforms. They agreed more with statements about how platforms facilitate trading, enhance confidence, and provide timely updates. These investors may be more familiar with digital tools and may trust analytics and peer opinions shared online.

6.3.2.14 The investors with Plus Two or diploma qualifications also showed strong agreement in some items. The investors with SSLC-level education showed lower agreement in most items. They may have limited access to platforms or rely more heavily on traditional sources of information.

6.3.2.15 Some variables, social platforms influenced trade frequency and confidence in social media, exhibited interesting patterns. While the professional and two/diploma groups scored high, the SSLC group also achieved high ranks in a few items. This suggests that even less educated investors find comfort in group opinions.

6.3.2.16 The combined impact score confirmed that higher education leads to higher usage and belief in these tools. Educated investors are more likely to follow alerts, seek input from peers, and adjust trades quickly in response to updates.

6.3.2.17 The statistical evidence, along with consistent ranking scores, proves that gender and education both shape how investors change their habits due to social trading and real-time news. Therefore, the hypotheses H5 and H6 were both validated by the findings of this study.

6.3.2.18 The analysis revealed that employment status significantly influences the extent to which investors perceive social trading and real-time news platforms as impacting their trading habits. The Kruskal–Wallis H test results indicated statistically significant differences across employment categories for several variables, including the influence of social media on trading decisions, the role of peer recommendations, the effect of the speed and reliability of news, the importance of timely and accurate news in shaping strategies, the ease of trading through real-time news platforms, and the increase in trading confidence due to social media.

6.3.2.19 The combined measure of social/news platform impact also showed significant variation, confirming that overall perceptions are shaped by occupational background.

6.3.2.20 The mean rank analysis further demonstrated that professionals and private job holders consistently reported the highest influence scores for these significant variables, indicating greater integration of these tools into their trading practices.

6.3.2.21 Government employees showed high influence rankings in certain areas, particularly in trading confidence and responsiveness; however, their overall scores were lower compared to those of professionals.

6.3.2.22 Retired investors recorded the lowest mean ranks across most variables, suggesting minimal engagement with social trading and real-time news platforms.

6.3.2.23 Self-employed individuals and business owners reported moderate levels of influence, with rankings varying depending on the specific factor assessed.

6.3.2.24 These findings suggest that while technological tools like social trading and real-time news platforms are widely available, their adoption and perceived usefulness differ considerably by employment status. This highlights the need for targeted educational and training programs that address the unique needs and usage patterns of different occupational groups, ensuring broader and more effective utilisation of these platforms across the investor community.

6.3.2.25 The study found that age plays a vital role in how investors adopt and use social trading platforms and real-time news tools. Younger investors, particularly those aged 18–25 and 26–35, are more likely to let social media influence their trading decisions, follow peer recommendations, adjust their strategies based on timely and accurate news, and gain greater confidence in their trading through these platforms. They also reported the highest overall impact from using these technologies, suggesting that they actively integrate them into their investment routines.

6.3.2.26 The older investors, especially those above 55, reported much lower levels of influence from social media and real-time news tools. Their trading habits appear to be less affected by these technologies, indicating a preference for more traditional approaches to decision-making.

6.3.2.27 Middle-aged investors showed moderate engagement, falling between the younger and older groups in their reported influence levels.

6.3.2.28 Overall, the findings highlight a clear generational difference: younger investors are more enthusiastic about embracing technology-driven tools, while older investors remain comparatively cautious in their adoption.

6.3.3 The third objective of the study is to analyse **the impact of technological advancements in financial analytics on investment decision-making.** The study examined the effect of financial analytics tools on investor decisions in the stock market. The critical findings relating to this objective are listed below.

6.3.3.1 The descriptive analysis showed that most participants leaned toward agreement regarding the impact of financial analytics. Investors agreed that tools like stock screeners, platform usability, and data dashboards helped them in making decisions.

6.3.3.2 The highest agreement was noted in the variable about how the interface and usability influenced their decision-making. This suggests that user-friendly designs and smooth navigation in financial apps make a strong impression on investors. Features that offer clean layouts and easy access to key data points help investors make decisions faster and more confidently.

6.3.3.3 Another variable with high support was that platform data shaped investment choices. This suggests that when platforms offer structured insights, such as charts, alerts, or summaries, investors tend to rely on these instead of spending time collecting and interpreting raw data themselves. This pattern suggests that modern investors want tools that simplify decision-making by delivering direct and valuable information.

6.3.3.4 Some variables related to artificial intelligence showed slightly lower agreement. AI boosting investor confidence and AI shifting the preference toward automation had moderate scores. This indicates a cautious attitude among some investors. While AI tools are available and widely promoted, not every investor feels entirely comfortable trusting AI suggestions. Some respondents may not fully understand how AI works or may feel uncertain about relying on something they cannot control. The lower ratings in these areas suggest that many investors still prefer manual checks or personal judgement before making financial decisions.

6.3.3.5 Items like automation, reduced stock analysis time, also received average responses. This means not all investors feel that automation significantly saves time or reduces effort. Some may not know how to use these tools efficiently or may not have access to advanced versions.

6.3.3.6 The gender-based analysis revealed some apparent differences in perception. Male investors showed stronger agreement across several variables. In areas like AI-based stock selection, portfolio improvement, and goal matching, males reported higher agreement. This suggests that male investors are more inclined to trust analytics and utilise them in making structured investment decisions. They also showed more acceptance of AI influencing their preference for automation.

6.3.3.7 Female investors showed less agreement in most areas. This could be due to lower confidence in digital tools, less exposure, or a preference for traditional decision-making methods.

6.3.3.8 Some variables, like filtering tools and the use of platform data, showed no strong gender-based difference. This means that when tools are simple and directly helpful, both male and female investors find them useful.

6.3.3.9 The overall pattern shows that while both genders use financial analytics, male investors appear more trusting of AI and analytics tools for making critical decisions.

6.3.3.10 The education-wise comparison also showed meaningful results. Investors with professional qualifications or diplomas showed a higher level of agreement on most variables. For example, automation reduces stock analysis time, and AI boosts confidence, showing higher agreement among better-educated investors. This may be because more educated investors are familiar with such tools or have more access to platforms that offer these features. On the other hand, investors with SSLC education had lower agreement across most variables.

6.3.3.11 In some cases, SSLC holders scored higher in variables like data shaping decisions. This could be due to limited exposure to diverse tools, leading them to depend more heavily on a few features that are simple to use.

6.3.3.12 Variables such as the usability of the interface and AI confidence showed substantial differences across education levels. More educated investors gave higher scores, which shows they value smooth experiences and advanced features. This may mean that education helps investors adapt to newer tools, while less educated ones may rely more on familiar options.

6.3.3.13 The hypotheses tested under this objective are that there is a significant difference in investment decision-making due to financial analytics tools between male and female investors. The results of the Mann-Whitney U test confirmed that male and female investors differ in their perceptions and use of financial analytics tools.

6.3.3.14 The Kruskal-Wallis H test confirmed that investor responses also varied significantly based on education level. Participants with professional degrees and diplomas reported greater reliance on automation, usability, and AI support for their decision-making. This indicates that both gender and education play a role in determining the extent to which financial analytics influence investor decisions. Therefore, the study found strong support for both hypotheses H9 and H10.

6.3.3.15 The analysis revealed that perceptions of financial analytics tools in investment decision-making vary notably across different age groups. Younger investors, particularly those aged 18–25, tend to value automation, artificial intelligence, and user-friendly interfaces far more than older investors. They are more inclined to view automation as a means to save time in stock analysis, and they trust AI to enhance their confidence in making informed investment choices.

6.3.3.16 These younger groups also show a stronger preference for shifting from manual investment practices to automated approaches. Ease of use and intuitive platform designs are significant to them, influencing their willingness to adopt and rely on these tools.

6.3.3.17 In contrast, older investors, especially those above 55, are less enthusiastic about such technological features, showing lower reliance on automation and AI. Middle-aged investors fall somewhere in between, with moderate appreciation for these advancements but less enthusiasm than the youngest participants.

6.3.3.18 Overall, the findings suggest a generational divide, with younger investors embracing technological innovations in financial analytics as an essential part of their investment process. In comparison, older investors tend to be more cautious and less reliant on these tools.

6.3.4 The fourth objective of the study is to **assess the impact of mobile trading apps of discount brokers on the stock trading behaviour of investors**. The responses collected under this objective showed that mobile trading apps have a significant influence on various aspects of trading behaviour among investors. The results of the analysis are described below.

6.3.4.1 The results reflected that investors see mobile apps of discount brokers as tools that improve access, reduce cost, and make trading more convenient. Investors agreed that features such as low brokerage fees, an easy-to-use interface, and real-time access to data influence their decision-making.

6.3.4.2 The role of self-directed investing was also highlighted, where investors felt that mobile apps give them more control and confidence. This is because trading apps remove the dependency on brokers and reduce the need for technical skills.

6.3.4.3 The data also indicated that the user-friendly design of the app is one of the most valued features. This may be because investors prefer tools that are simple to navigate and do not require extensive learning.

6.3.4.4 Some items in the responses showed slightly mixed opinions. Real-time information from the apps did not receive the same level of agreement as other features. It is possible that not all apps provide live data or that investors are uncertain about the reliability of such data.

6.3.4.5 Another area where opinions varied was the influence of apps on participation in IPOs. While some investors use apps for IPO access, others may still rely on traditional services.

6.3.4.6 The responses also showed moderate agreement on whether apps influenced willingness to take a higher risk. This reflects a cautious approach, where some investors may trade more due to the ease of access, but are still not fully open to taking on risky trades through digital platforms.

6.3.4.7 The combined response score reflected a consistent and strong perception that mobile apps impact various dimensions of trading. The presence of a slight standard deviation also showed that most responses did not deviate much from the average, which supports the reliability of the finding.

6.3.4.8 Gender-based analysis showed that male and female investors responded differently to mobile trading apps. Male investors showed stronger agreement with statements related to trade frequency, cost saving, and convenience. This may reflect a higher comfort level among males with technology in general.

6.3.4.9 Male investors also showed higher scores in statements related to self-directed investing and platform choice. This suggests that men feel more confident in handling trades directly without relying on advisors. In contrast, female investors had lower mean ranks in these areas. Female investors may use apps for basic functions, but may not rely heavily on them for making investment decisions.

6.3.4.10 The gender gap was also seen in items related to confidence, trading volume, and perception of the future of trading. Male investors appeared to be more optimistic and active when using mobile apps.

6.3.4.11 In some areas, such as interface design and access to information, both genders received similar scores. This shows that when features are easy to use or directly helpful, all users value them equally.

6.3.4.12 The analysis based on education level revealed that respondents with higher qualifications were more likely to rate mobile apps as applicable in their trading activity. Participants with professional degrees and diploma holders showed stronger agreement on statements related to interface, platform choice, and risk-taking. Educated investors may better understand app features and be more open to trying them. They may also have better access to smartphones, the internet, and financial knowledge, which makes them more engaged.

6.3.4.13 The analysis revealed apparent differences in how mobile trading applications influence investors from different age groups in their stock trading behaviour. Younger investors, especially those in the 18–25 age group, were found to be the most influenced by mobile apps. They reported higher responsiveness to app features such as frequent trading, real-time decision-making, convenience in choosing trading platforms, improved accessibility, and user-friendly interfaces. These investors were also more willing to take risks, more likely to see apps as tools for learning and enhancing investment knowledge, and more inclined to believe that mobile trading apps shape the future of trading.

6.3.4.14 The 26–35 age group also showed strong influence from mobile app features, though slightly less than the youngest group.

6.3.4.15 Middle-aged investors (aged 36–45 and 46–55) demonstrated moderate levels of influence, utilising mobile app functionalities but not relying on them heavily.

6.3.4.16 In contrast, investors aged 55 years of age showed the least impact from mobile trading applications. Their trading habits were less influenced by features such as real-time alerts, convenience, and app-based tools, possibly due to lower technological adoption or a preference for traditional investment methods.

6.3.4.17 The study tested three hypotheses under this objective. Hypothesis H12 stated that there is a significant difference in stock trading behaviour influenced by mobile trading apps between male and female investors. Hypothesis H13 stated that there is a significant difference in stock trading behaviour due to mobile trading apps among investors with different levels of education. H14 stated that there is a significant difference in stock trading behaviour due to mobile trading apps among investors with various age groups. All these hypotheses were tested using the combined score of the mobile app impact. The results showed a statistically significant difference in all cases.

6.3.4.18 Overall, the findings suggest that mobile trading apps have a significantly greater impact on the trading habits of younger investors compared to older investors, with the youngest group exhibiting the highest engagement and adaptability to app-based trading.

6.3.5 The fifth objective of the study is to examine **the key factors influencing the adoption of technological innovations and assess their impact on investment behaviour among stock market investors.** The findings of the fifth objective explain how stock market investors adopt technology and how their use changes their behaviour. The model used for this objective was based on the extended Technology Acceptance Model. It included constructs such as perceived usefulness, perceived ease of use, risk perception, cost perception, attitude toward technology, facilitating conditions, behavioural intention, actual use, and investment behaviour.

6.3.5.1 The results showed that the strongest factor affecting investment behaviour was actual use. Investors who used mobile apps, robo-advisors, and AI-based analytics more frequently exhibited greater changes in their investment style. They traded more and employed more data-driven methods. This change occurred indirectly, following a process of intention and attitude. The first point in the process was the investor's perspective on technology. A positive attitude led to an intention, which in turn led to actual use. Then the actual use created the changes in behaviour.

6.3.5.2 Attitude toward technology was shaped mainly by perceived usefulness and perceived ease of use. When investors found fintech tools helpful in making decisions and also found them easy to handle, their attitude toward them improved. Investors believed that digital platforms facilitated trading, provided accurate insights, and offered greater control. This positive feeling made them more open to trying the technology.

6.3.5.3 Risk perception had the opposite effect. If investors thought the technology was risky or unreliable, their attitude dropped.

6.3.5.4 Cost perception also reduced attitude, but not as much as risk. When investors felt the tools were too expensive, they became less interested in using them.

6.3.5.5 Facilitating conditions such as internet access, support from financial providers, and government policy also played a role. These helped investors feel more comfortable and increased their attitude toward technology. So, attitude was a combination of how easy and helpful the technology felt and how safe and supported the investor felt in using it.

6.3.5.6 Once attitude was formed, it affected behavioural intention. A positive attitude made investors more likely to plan to use fintech tools. Among all the paths to intention, attitude had the most substantial impact. Risk and cost perception had minimal effect on intention. This indicates that once the investor made up their mind and adopted a positive attitude, fears of risk and cost became less critical.

6.3.5.7 Investors with a good attitude were more willing to try new tools. This intention then evolved into actual usage. If someone planned to use digital platforms, they usually did so. This use included checking AI suggestions, following robo-advice, and using apps to place trades. So, the actual use came from intention, and intention came from attitude.

6.3.5.8 Facilitating conditions also helped actual use to some extent. For example, having a stable internet connection or platform training made usage easier. Risk and cost perception had little impact at this level. So, concerns about safety and price mostly affected attitude, but did not continue beyond that. Once the user intended to try, they followed through, despite any earlier doubts.

6.3.5.9 The final part of the objective focused on how actual use changed investment behaviour. This was the strongest finding. Actual use led to changes, including more active trading, better risk-taking, and more informed decision-making. Users of fintech tools became more involved in the stock market. They paid more attention, used more data, and made more confident choices. This shows that the behaviour of investors changed once they started using the tools regularly. Cost and risk did not play a significant role at this point. Instead, earlier positive experiences, training, and helpful interfaces played a stronger role.

6.3.5.10 The results also showed several indirect paths. For example, perceived usefulness did not directly affect investment behaviour, but instead did so through attitude, intention, and actual use. The same pattern applied to perceived ease of use and facilitating conditions. All these worked by first improving attitude, which led to intention, which then became usage, and then ultimately changed investment behaviour. Cost and risk perception also had indirect negative paths—these reduced attitude and intention, which then led to lower usage and behaviour change. However, the adverse effect became smaller over the stages. In the early stage, risk and cost were barriers, but they lost their impact once the investor developed a good attitude and intention.

6.3.5.11 The hypothesis for this objective included the following: perceived usefulness has a significant positive impact on attitude toward technology (H15), perceived ease of use has a significant positive impact on attitude toward technology (H16), risk perception has a significant negative impact on attitude toward technology (H17), cost perception has a significant negative impact on attitude toward technology (H18), risk perception has a significant negative impact on behavioural intention (H19), cost perception has a significant negative impact on behavioural intention (H20), risk perception has a significant negative impact on actual use (H21), cost perception has a significant negative impact on actual use (H22), facilitating conditions have a significant positive impact on behavioural intention (H23), facilitating conditions have a significant positive impact on actual use (H24), attitude toward technology has a significant positive impact on behavioural intention (H25), behavioural intention has a significant positive impact on actual use (H26), and actual use has a significant positive impact on investment behaviour (H27).

6.3.5.12 The results supported the hypotheses H15, H16, H17, H18, H23, H24, H25, H26, and H27. These findings indicated that usefulness, ease of use, and attitude contributed to forming an intention, which in turn facilitated actual use. Actual use created changes in investment behaviour.

6.3.5.13 The hypotheses H19, H20, H21, and H22 were not supported. These were related to risk and cost perception in terms of behavioural intention and actual use. These did not show strong statistical results. This suggests that even if investors have concerns about risk and cost, these concerns do not deter them from adopting technology, provided they have a positive attitude. The findings confirm that investor behaviour is shaped more by what they believe and feel than by practical issues like cost or safety. The model used for this objective confirms that technology adoption in stock market investment follows a chain of psychological and behavioural processes that start from perception and end in real trading behaviour.

6.4 Conclusion

This study examined the impact of technological innovations on the investment behaviour of stock market investors in Kerala. It focused on multiple digital tools. These included algorithmic trading systems, advanced screeners, robo-advisors, social trading platforms, real-time news applications, financial analytics dashboards, and mobile trading apps. The research explored how these tools shape investor decisions and trading habits. The study addressed a gap in existing research. Past studies looked at single technologies in isolation. Few have analysed how a combination of tools influences investor behaviour. Little was known about differences by gender, education, employment and age. Social trading and news platforms received limited attention. The study aimed to fill these gaps and provide an applied perspective on fintech adoption in a real-world market context.

The study used a mixed-method approach. It combined descriptive statistics, non-parametric tests, and PLS-SEM. The primary data were collected through a structured survey of 420 active investors. Respondents represented a diverse range of genders, age groups, educational levels, and employment statuses. Descriptive analysis measured tool usage and perceived impact. Mann-Whitney U and Kruskal-Wallis tests were used to assess the effects of gender, age, employment status, and educational level. PLS-SEM was employed to test the extended Technology Acceptance Model.

Objective one examined changes in investment behaviour due to technological advancements. The study found that algorithmic trading emerged as the most decisive influence. Investors noted that algorithms enhanced decision-making through data-driven rules. Advanced screeners received high ratings for making stock selection a structured and efficient process. UPI and other instant payment systems lowered barriers to entry and led to higher trade participation. Mobile trading apps boosted trading frequency by offering anytime access. Robo-advisors gained trust gradually as users saw reliable recommendations. Auto rebalancing and smart order routing showed a lower impact. These tools remained less known to occasional traders. Blockchain influence proved moderate at best. Most investors did not see blockchain directly in their trades. Overall, the study found that core fintech tools reshaped how investors research, choose, and execute trades. The combined score for all tools confirmed positive acceptance of digital solutions. However, awareness gaps remain for complex features.

Objective two focused on social trading and real-time news platforms. The Study found that real-time news had a clear impact on trading habits. Investors reported that instant updates allowed timely decisions. Speed and accuracy of news alerts drove higher trading agility. Social platforms such as Twitter and Telegram influenced trades through peer opinions and sentiment signals. Real-time alerts further reduced lag and built a sense of control. Some investors perceived social trading as riskier than personal analysis. They rated reliance on peer tips with caution. Peer recommendations saw uneven acceptance. A subset of investors regularly used social tips. Others stuck to independent research. The study concluded that social and news platforms play a growing role in shaping trade timing and strategies. They serve as both information hubs and confidence boosters. However, they also introduce new risks when accuracy is uncertain.

Objective three analysed the impact of financial analytics tools on decision-making. The study found that interface usability ranked highest. Investors valued clean dashboards and intuitive navigation. Structured insights, such as charts and summary metrics, helped save time. Basic filtering and screening features were widely accepted across all groups. AI-driven tools for portfolio improvement and risk management saw moderate adoption. Some investors have adopted AI recommendations for portfolio allocation. Investors appreciated tools that support rather than replace personal judgement. Overall, the study found that financial analytics foster more data-driven decisions.

Objective four assessed the impact of mobile trading apps of discount brokers on trading behaviour. The study found that apps greatly improved access and convenience. Features such as low brokerage and user-friendly interfaces attracted high ratings. Self-directed investing gained traction as apps removed broker dependency. Real-time market data on apps enabled investors to react more quickly. Some investors still questioned the reliability of live data. IPO participation via apps varied by experience level. Frequent traders used app-based margin features more. The overall positive scores and low variation in responses showed wide acceptance of mobile apps. The study concluded that mobile apps transformed trading from a broker-led service to a self-service model. They empowered investors to act on insights, albeit with caution in unverified conditions.

Objective five examined key factors influencing the adoption of technological innovations and their effect on investment behaviour. The study tested an extended Technology Acceptance Model. It linked perceived usefulness and ease of use to attitude. It then connected attitude to behavioural intention. Actual use followed intention. Finally, actual use drove changes in investment behaviour. The study found that perceived usefulness and ease of use had a strong positive effect on attitude. Investors formed positive feelings when they saw clear benefits and simple operations. Risk perception and cost perception had a adverse impact on attitude, but weaker ones. Facilitating conditions such as internet quality and provider support also boosted attitude. Attitude proved the strongest predictor of intention. Once the intention was formed, investors followed through with actual usage. Actual usage then led to higher trading frequency, more data-driven choices, and greater willingness to take calculated risks. Cost and risk concerns lost influence once positive attitudes led to use. The study concluded that actual usage serves as the central driver of behaviour change. It also showed that initial perceptions matter most at the attitude stage. Facilitating conditions help at every step.

Chapter 7

RECOMMENDATIONS

7.1 Recommendations

Based on the findings of this study, some recommendations will be formulated to attract the attention of stock market players, regulators, policymakers, and financial services providers. The recommendations in this section are intended for retail investors, discount and full-service brokers, fintech platforms, and government authorities responsible for developing the regulatory framework in the stock market. These recommendations aim to increase investor awareness, promote responsible adoption of technological innovations, and foster a balanced and sustainable investment world.

7.1.1 Simplify stock screeners with step-by-step guides. The Study found that advanced screeners helped investors filter options quickly; easy-to-follow instructions can increase use among occasional traders. It is advisable to simplify the stock screeners so that all investors can use them.

7.1.2 Embed UPI and other instant payments directly in apps. The faster fund transfers led to higher participation, and seamless payment flows can reduce barriers to trade execution.

7.1.3 Optimise mobile apps for low-bandwidth environments. The Study found that mobile access encouraged frequent trading, ensuring reliable performance on slower networks can extend reach to rural users.

7.1.4 Publish regular performance summaries for robo-advisors. The growing user trust in automated advice and concise reports on past recommendations can reinforce confidence.

7.1.5 Offer workshops on auto rebalancing and smart order routing. The Study found that these tools had a lower impact; however, hands-on sessions can raise awareness and skill among experienced traders.

7.1.6 Improve transparency of algorithmic trading parameters. Algorithmic trading had the most decisive influence on behaviour; a clear display of rules and past performance can boost investor trust and usage.

7.1.7 Create short tutorials on AI forecasting and sentiment analysis. The Study reported mixed opinions on these tools; real examples of successful forecasts can reduce hesitation. So short tutorials on AI forecasting and sentiment analysis will help to increase the use of these tools by the investors.

7.1.8 Integrate verified real-time news and social trading feeds. Instant updates shape trading habits, and curated alerts and community insights can guide faster and safer decisions. It is advisable to integrate verified real-time news and social trading feeds into the platforms themselves.

7.1.9 Design tailored training for female and lower-educated investors. The Study revealed gender, age, employment, and education differences in adoption; customised sessions can build confidence and help these groups use advanced tools effectively.

7.2 Implications of the Study

The study has important theoretical and practical implications for the topic of stock market investment. Theoretically, it contributes to the existing body of literature on the changes in the behaviour and the nature of their decision-making patterns resulting from technological innovations. Practically, the results provide valuable insights for investors, brokers, and policymakers who need to coordinate their strategies with the evolving nature of the digital investment environment.

7.2.1 Theoretical Implication

The findings strengthen technology adoption theory in financial contexts. Perceived usefulness and ease of use shaped investor attitudes toward digital tools. Risk perception and cost perception emerged as negative drivers at the attitude stage. Facilitating conditions influenced both attitude formation and actual use, showing their broader role in adoption models. Actual use explained behavioural change more strongly than intention, refining the Technology Acceptance Model (TAM) by placing usage at the centre of the causal chain. Attitude and intention remained relevant but were not sufficient on their own. Demographic factors moderated key relationships. Gender influenced trust in algorithmic trading and robo-advisors, while education shaped the adoption of tools such as sentiment analysis and virtual trading. These findings suggest that adoption models should include demographic segmentation. The research also extended social learning theory by showing that social trading platforms and real-time news shaped investor confidence through peer-based learning. Social validation boosted confidence and led to action, which supports the integration of digital peer networks into social cognitive theory. The study offered empirical support for the diffusion of innovation theory in capital markets. It showed faster fintech adoption among high-exposure groups and slower diffusion among occasional traders, indicating that future theory should account for exposure and familiarity. It also contributed to behavioural finance by linking the use of fintech tools with shifts in decision-making patterns. Algorithmic systems and advanced screeners have changed the way investors select and time trades. Manual checks remained relevant for AI tools when trust was low. These findings suggest that theoretical models should distinguish between assistive tools and fully automated systems. The study establishes a connection between classic adoption theory and finance research, laying the groundwork for future theoretical work in fintech behaviour.

7.2.2 Policy Implication

The findings inform regulatory and policy responses to the adoption of technology in investing. Since ease of use shapes attitudes, regulators can mandate basic usability standards for trading platforms, including straightforward navigation and concise labels. Facilitating conditions such as digital access and investor support influenced actual use. This supports public investment in rural broadband and fintech literacy programmes. Social trading platforms affected behaviour, making it essential for regulators to require disclaimers and verified news feeds on such apps. Cost-related concerns reduced adoption. Policymakers can review brokerage fees and encourage pricing transparency. Zero-cost models for entry-level services may support broader participation. Demographic differences were evident. Targeted training for women and regional-language content could address inclusion gaps. Real-time news influenced trading frequency. Equal access to reliable news feeds and smoother licensing for aggregators could reduce information asymmetry. Features like auto-rebalancing and smart order routing remained underutilised. Regulators can support awareness campaigns and education partnerships with fintech providers. Together, these steps can create a safer and more inclusive environment, reduce hidden costs, and enhance the responsible use of advanced trading tools.

7.2.3 Practical Implication

The findings offer design and communication guidance for fintech firms. Usability was a top concern for investors. Developers should prioritise simple dashboards with key metrics prominently displayed and avoid using financial terminology. Perceived usefulness strongly influenced positive attitudes. Marketing teams can highlight tool-specific benefits, share case studies, and use interactive tutorials. Low awareness of advanced features, such as auto-rebalancing, suggests a need for tutorials, tooltips, and bundling options. Social feeds and news inputs influenced confidence. Firms should oversee trusted content, provide source filters, and moderate community forums. Demographic variations in adoption call for tailored onboarding flows. Firms can offer video guides, regional language support, and onboarding tracks for different user types. Active usage had the strongest link to behaviour change. Push notifications and gamification can improve engagement. Usage analytics can help identify inactive users and prompt re-engagement through custom tutorials. These actions can drive adoption and better engagement across user segments.

7.2.4 Research Implication

The study lays the groundwork for future research in technology adoption in financial markets. Its design, based on Indian retail investors, can be replicated in other countries or among institutional users to test for generalisability. Future studies can benefit from combining survey data with platform-generated usage logs to improve behavioural validity. In addition to gender and education, age and employment status, future models can explore moderators such as income, risk tolerance, and location using multi-group SEM. Social trading emerged as a significant influence, highlighting the value of social network analysis in mapping information flow and peer influence. Misinformation patterns on platforms also merit further study. The mixed adoption of advanced features necessitates the use of qualitative methods, including interviews and user testing, to gain a deeper understanding of adoption barriers. Findings can inform the design of pilot interventions and trials. Though focused on equity markets, this framework can be applied to cryptocurrency markets, where risk perceptions may differ. Overall, the study outlines future directions for theory, method, and domain-specific fintech research.

7.3 Scope for Future Research

The current research can serve as a valuable source of information about the influence of technological innovations on the investment patterns of stock market investors; however, it also introduces a variety of prospective research areas. Financial markets and technology are continually evolving, offering opportunities to expand this research through the exploration of new tools, investor segments, and geographical analysis. Future research can further develop the present study to enhance the information regarding how digital development keeps on changing the way investments are conducted and how the market is participated.

7.3.1 Adoption of Auto Rebalancing Routing among Retail Investors

This study will investigate why this tool has a low impact and how awareness and usage differ between occasional and regular traders.

7.3.2 Demographic Influences on Algorithmic Trading Adoption: This research will analyse how gender and education shape trust in algorithmic systems and drive differences in usage patterns.

7.3.3 Impact of Embedded Instant Payments on Investor Participation: This project will assess how integrating UPI into trading platforms affects trade frequency and market entry for retail investors.

7.3.4 Trust and Use of Robo Advisors across Investor Experience Levels: This research will explore how novice and experienced investors differ in acceptance of automated portfolio advice.

7.3.5 Investor Perceptions of AI Forecasting Tools and Adoption Barriers: This project will measure factors that drive or hinder the use of artificial intelligence predictions in decision-making.

7.3.6 Effects of Sentiment Analysis on Retail Investor Confidence: This research will evaluate how sentiment signals shape trade timing, risk-taking, and confidence in market moves.

7.3.7 Peer Influence in Social Trading Platforms by Gender and Education: This study will map how social validation from online groups affects trading choices among different demographic segments.

7.3.8 Role of Real-Time News Feeds in Shaping Long-Term Trading Strategies: This project will track how the use of instant news services influences portfolio performance and strategy evolution over time.

BIBLIOGRAPHY

Abdul-Azeez, N. O., Ihechere, N. a. O., & Idemudia, N. C. (2024). Transformational leadership in SMEs: Driving innovation, employee engagement, and business success. *World Journal of Advanced Research and Reviews*, *22*(3), 1894–1905. https://doi.org/10.30574/wjarr.2024.22.3.1888

Abdullah, E. M. E., Rahman, A. A., & Rahim, R. A. (2018). Adoption of financial technology (Fintech) in mutual fund/ unit trust investment among Malaysians: unified theory of acceptance and use of technology (UTAUT). *International Journal of Engineering & Technology*, *7*(2.29), 110. https://doi.org/10.14419/ijet.v7i2.29.13140

Abdullah, E. M. E., Rahman, A. A., & Yakob, R. (2024). The factor influencing the adoption of fintech in investment among Malaysians: A Unified Theory of Acceptance and Use of Technology (UTAUT) perspectives. *Journal of Advanced Research in Applied Sciences and Engineering Technology*, *49*(2), 231–247. https://doi.org/10.37934/araset.49.2.231247

Abdullah, S. S., Rahaman, M. S., & Rahman, M. S. (2013). Analysis of stock market using text mining and natural language processing. *2013 International Conference on Informatics, Electronics and Vision (ICIEV)*. https://doi.org/10.1109/iciev.2013.6572673

Abushaqra, Mouhamad, Quantum Portfolio Rebalancing Algorithm (QPRA): An Integrating Quantum Computing and AI for Dynamic Portfolio Optimization (October 30, 2024). Available at SSRN: https://ssrn.com/abstract=5004146 or http://dx.doi.org/10.2139/ssrn.5004146

Addy, N. W. A., Ajayi-Nifise, N. a. O., Bello, N. B. G., Tula, N. S. T., Odeyemi, N. O., & Falaiye, N. T. (2024). Machine learning in financial markets: A critical review of algorithmic trading and risk management. *International Journal of Science and Research Archive*, *11*(1), 1853–1862. https://doi.org/10.30574/ijsra.2024.11.1.0292

Addy, N. W. A., Ajayi-Nifise, N. a. O., Bello, N. B. G., Tula, N. S. T., Odeyemi, N. O., & Falaiye, N. T. (2024). Algorithmic Trading and AI: A Review of Strategies and Market impact. *World Journal of Advanced Engineering Technology and Sciences*, *11*(1), 258–267. https://doi.org/10.30574/wjaets.2024.11.1.0054

Aggarwal, M., Nayak, K. M., & Bhatt, V. (2023). Examining the factors influencing fintech adoption behaviour of gen Y in India. *Cogent Economics & Finance*, *11*(1). https://doi.org/10.1080/23322039.2023.2197699

Ahmad, M., & Wu, Q. (2022). Does herding behavior matter in investment management and perceived market efficiency? Evidence from an emerging market. *Management Decision*, *60*(8), 2148–2173. https://doi.org/10.1108/md-07-2020-0867

Ahmed, S., Alshater, M. M., Ammari, A. E., & Hammami, H. (2022). Artificial intelligence and machine learning in finance: A bibliometric review. *Research in International Business and Finance*, *61*, 101646. https://doi.org/10.1016/j.ribaf.2022.101646

Ahmed, Z., Rasool, S., Saleem, Q., Khan, M. A., & Kanwal, S. (2022). Mediating role of risk perception between behavioral biases and investor's investment decisions. *SAGE Open*, *12*(2). https://doi.org/10.1177/21582440221097394

Ajzen, I. (1985). From Intentions to Actions: A theory of planned behavior. In *Springer eBooks* (pp. 11–39). https://doi.org/10.1007/978-3-642-69746-3_2

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-t

Ajzen, I., & Fishbein, M. (1980). *Understanding attitudes and predicting social behavior*. https://ci.nii.ac.jp/ncid/BA21965086

Al-Gasawneh, J. A., Alzubi, K. N., Hasan, M., Joudeh, J. M., Ahmad, A. M. K., & Ngah, A. H. (2022). IMPACT OF PRIVACY ON THE MARKETING PERFORMANCE. *Zenodo (CERN European Organization for Nuclear Research)*. https://doi.org/10.5281/zenodo.7451025

Al-Jaroodi, J., & Mohamed, N. (2009). A Personalized Stock Investors Alert System. *J. Softw., 4*, 875-882. https://doi.org/10.4304/JSW.4.8.875-882

Almansour, B. Y., Elkrghli, S., & Almansour, A. Y. (2023). Behavioral finance factors and investment decisions: A mediating role of risk perception. *Cogent Economics & Finance*, *11*(2). https://doi.org/10.1080/23322039.2023.2239032

Alomari, M., Rababa'a, A. R. A., El-Nader, G., Alkhataybeh, A., & Rehman, M. U. (2021). Examining the effects of news and media sentiments on volatility and correlation: Evidence from the UK. *The Quarterly Review of Economics and Finance*, *82*, 280–297. https://doi.org/10.1016/j.qref.2021.09.013

Al-Shari, H. A., & Lokhande, M. A. (2023). The relationship between the risks of adopting FinTech in banks and their impact on the performance. *Cogent Business & Management*, *10*(1). https://doi.org/10.1080/23311975.2023.2174242

Aman, H., & Moriyasu, H. (2022). Effect of corporate disclosure and press media on market liquidity: Evidence from Japan. *International Review of Financial Analysis*, *82*, 102167. https://doi.org/10.1016/j.irfa.2022.102167

Amin, N. I. U., Bhat, N. I. H., Itoo, R. A., & Jan, A. (2025). Behavioural intention to adopt mobile trading apps: an integrated theoretical and digital framework, privacy concerns, and information richness model. *Sri Lanka Journal of Social Sciences*, *47*(02), 123–144. https://doi.org/10.4038/sljss.v47i02.8945

Ammann, M., & Schaub, N. (2020). Do individual investors trade on Investment-Related internet postings? *Management Science*, *67*(9), 5679–5702. https://doi.org/10.1287/mnsc.2020.3733

Ammar, I. B., Hellara, S., & Ghadhab, I. (2020). High-frequency trading and stock liquidity: An intraday analysis. *Research in International Business and Finance*, *53*, 101235. https://doi.org/10.1016/j.ribaf.2020.101235

Anifa, A. S., & Soegiharto, S. (2023). Does the psychology of investment decisions depend on risk perception and financial literacy? *MAKSIMUM*, *13*(2), 152. https://doi.org/10.26714/mki.13.2.2023.152-163

Anifa, M., Ramakrishnan, S., Joghee, S., Kabiraj, S., & Bishnoi, M. M. (2022). Fintech innovations in the financial service industry. *Journal of Risk and Financial Management*, *15*(7), 287. https://doi.org/10.3390/jrfm15070287

Ansari, Y., Yasmin, S., Naz, S., Zaffar, H., Ali, Z., Moon, J., & Rho, S. (2022). A Deep Reinforcement Learning-Based decision support system for automated stock market trading. *IEEE Access*, *10*, 127469–127501. https://doi.org/10.1109/access.2022.3226629

Aramonte, S., & Carl, M. (2021). *BIS Working Papers No 916 Firm-Level R&D after Periods of Intense Technological Innovation: The Role of Investor Sentiment, Bank for International Settlements*.

Araujo, T., Helberger, N., Kruikemeier, S., & De Vreese, C. H. (2020). In AI we trust? Perceptions about automated decision-making by artificial intelligence. *AI & Society*, *35*(3), 611–623. https://doi.org/10.1007/s00146-019-00931-w

Aravind Gangavarapu; P V S Pranay; Polisetti Likhit Sai. "Artificial Intelligence in Stock Market Trading." Volume. 9 Issue.9, September - 2024 International Journal of Innovative Science and Research Technology (IJISRT), www.ijisrt.com. ISSN - 2456-2165, PP:- 466-469, https://doi.org/10.38124/ijisrt/IJISRT24SEP330

Arbatskaya, M. (2005). An efficiency argument for balanced transaction costs. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.782340

Areiqat, A. Y., Abu-Rumman, A., Al-Alani, Y. S., & Alhorani, A. (2019). Impact of Behavioral finance on stock investment Decisions Applied Study on a sample of investors at Amman Stock Exchange. *Academy of Accounting and Financial Studies Journal*, *23*(2), 1. https://www.abacademies.org/articles/Impact-of-Behavioral-Finance-On-Stock-Investment-Decisions-1528-2635-23-2-375.pdf

Armansyah, R. F., Ardianto, H., & Rithmaya, C. L. (2023). UNDERSTANDING GEN Z INVESTMENT DECISIONS: CAPITAL MARKET LITERACY AND EMOTIONAL BIASES. *Jurnal Manajemen Dan Kewirausahaan*, *25*(2), 105–119. https://doi.org/10.9744/jmk.25.2.105-119

Arnoldi, J. (2015). Computer algorithms, market manipulation and the institutionalization of high frequency trading. *Theory Culture & Society*, *33*(1), 29–52. https://doi.org/10.1177/0263276414566642

Arthur, C., & Khindanova, I. (2023). Technological acquisitions: The impact of innovation on stock performance. *Journal of Applied Business and Economics*, *25*(4). https://doi.org/10.33423/jabe.v25i4.6351

Arumugam, D., Prasanna, P. K., & Marathe, R. R. (2022). Do algorithmic traders exploit volatility? *Journal of Behavioral and Experimental Finance*, *37*, 100778. https://doi.org/10.1016/j.jbef.2022.100778

Ashtiani, M. N., & Raahemi, B. (2023). News-based intelligent prediction of financial markets using text mining and machine learning: A systematic literature review. *Expert Systems With Applications*, *217*, 119509. https://doi.org/10.1016/j.eswa.2023.119509

Atwal, G., & Bryson, D. (2021). Antecedents of intention to adopt artificial intelligence services by consumers in personal financial investing. *Strategic Change*, *30*(3), 293–298. https://doi.org/10.1002/jsc.2412

Ayyappa, Y., & Kumar, A. P. S. (2024). Stock market prediction with political data Analysis (SP-PDA) model for handling big data. *Multimedia Tools and Applications*, *83*(34), 80583–80611. https://doi.org/10.1007/s11042-024-18610-4

Azzutti, A., Ringe, W. G., & Stiehl, H. S. (2021). Machine learning, market manipulation, and collusion on capital markets: Why the" black box" matters. *U. Pa. J. Int'l L.*, *43*, 79.

Babu, C. V. S., & Das, S. (2023). Impact of blockchain technology on the stock market. In *Advances in finance, accounting, and economics book series* (pp. 44–59). https://doi.org/10.4018/978-1-6684-8624-5.ch004

Balodi, K. C., Raizada, A., & Datta, S. (2024). Trading war: Evolving landscape of discount brokerage in India. *Journal of Information Technology Teaching Cases*. https://doi.org/10.1177/20438869241240492

Bank, S., Abdioglu, Z., & Kahraman, E. (2024). Asymmetric and nonlinear comovements of credit default swap and bond markets: evidence from an emerging market. *Spanish Journal of Finance and Accounting / Revista Española De Financiación Y Contabilidad*, *53*(2), 232–253. https://doi.org/10.1080/02102412.2023.2218182

Barbopoulos, L. G., Dai, R., Putniņš, T. J., & Saunders, A. (2021). Market efficiency in the age of machine learning.

Bartlett, R., Morse, A., Stanton, R., & Wallace, N. (2021). Consumer-lending discrimination in the FinTech Era. *Journal of Financial Economics*, *143*(1), 30–56. https://doi.org/10.1016/j.jfineco.2021.05.047

Batra, V. (2024). What is the impact of financial literacy on individual investment behaviour and wealth accumulation? *IOSR Journal of Business and Management*, *26*(12), 24–33. https://doi.org/10.9790/487x-2612142433

Bellia, M., Pelizzon, L., Subrahmanyam, M. G., Uno, J., & Yuferova, D. (2024). Low-Latency Trading and Price Discovery: Evidence from the Tokyo Stock Exchange in the Pre-Opening and Opening Periods. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2841242

Bershova, N., & Rakhlin, D. (2012). High Frequency Trading and Long-Term Investors: A View from the Buy-Side. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2066884

Betzer, A., & Harries, J. P. (2022). How online discussion board activity affects stock trading: the case of GameStop. *Financial Markets and Portfolio Management*, *36*(4), 443–472. https://doi.org/10.1007/s11408-022-00407-w

Bhatia, A., Chandani, A., Atiq, R., Mehta, M., & Divekar, R. (2021). Artificial intelligence in financial services: a qualitative research to discover robo-advisory services. *Qualitative Research in Financial Markets*, *13*(5), 632–654. https://doi.org/10.1108/qrfm-10-2020-0199

Bhatia, A., Chandani, A., Divekar, R., Mehta, M., & Vijay, N. (2021). Digital innovation in wealth management landscape: the moderating role of robo advisors in behavioural biases and investment decision-making. *International Journal of Innovation Science*, *14*(3/4), 693–712. https://doi.org/10.1108/ijis-10-2020-0245

Bilinski, P., Karamanou, I., Kopita, A., & Panayides, M. A. (2020). Does algorithmic trading affect analyst research production? *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3597356

Block, F. (2013). Democratizing finance. *Politics & Society*, *42*(1), 3–28. https://doi.org/10.1177/0032329213512976

Boehmer, E., Fong, K., & Wu, J. (2020). Algorithmic trading and market quality: international evidence. *Journal of Financial and Quantitative Analysis*, *56*(8), 2659–2688. https://doi.org/10.1017/s0022109020000782

Bonelli, M. I., & Liu, J. (2024). Revolutionizing robo-advisors: Unveiling global financial markets, AI-driven innovations, and technological landscapes for enhanced investment decisions. *Advances in Science, Technology and Engineering Systems Journal*, *9*(2), 33–44. https://www.astesj.com

Bradford, P. G., & Miranti, P. J. (2014). Technology and Learning: Automating Odd-Lot trading at the New York Stock Exchange, 1958–1976. *Technology and Culture*, *55*(4), 850–879. https://doi.org/10.1353/tech.2014.0128

Breitmayer, B., Massari, F., & Pelster, M. (2019). Swarm intelligence? Stock opinions of the crowd and stock returns. *International Review of Economics & Finance*, *64*, 443–464. https://doi.org/10.1016/j.iref.2019.08.006

Buckley, P. J., & Chapman, M. (1997). The use of native categories in management research. *British Journal of Management*, *8*(4), 283–299. https://doi.org/10.1111/1467-8551.00066

Bunkar, B., & Ramaiah, K. (2024). A serial mediation model for investigating the intention to use algorithmic trading platforms among retail investors in India. *Vilakshan – XIMB Journal of Management*. https://doi.org/10.1108/xjm-12-2023-0233

Busse, J., Jiang, L., & Tang, Y. (2017). Double-adjusted mutual fund performance. *Emory University, Tsinghua University, and University of Florida Working Paper*.

Butt, J. (2023, December 31). *Comparative analysis of regulatory approach and management practice for digital Crypto-Currency and the role of IFIs in developing global regulations*. https://www.dj.univ-danubius.ro/index.php/JAM/article/view/2586

Capponi, A., Olafsson, S., & Zariphopoulou, T. (2019). *Personalized robo-advising: Enhancing investment through client interaction* (arXiv:1911.01391). arXiv. https://doi.org/10.48550/arXiv.1911.01391

Capponi, A., Olafsson, S., & Zariphopoulou, T. (2021). Personalized Robo-Advising: Enhancing investment through client interaction. *Management Science*, *68*(4), 2485–2512. https://doi.org/10.1287/mnsc.2021.4014

Cen, X. (2018). Going mobile, investor behavior, and financial fragility. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3424405

Chakrabarty, B., & Pascual, R. (2022). Stock liquidity and algorithmic market making during the COVID-19 crisis. *Journal of Banking & Finance*, *147*, 106415. https://doi.org/10.1016/j.jbankfin.2022.106415

Chang, S. E., & Wang, M. (2023). Blockchain-Enabled Fintech Innovation: a case of reengineering stock trading services. *IEEE Access*, *11*, 137125–137137. https://doi.org/10.1109/access.2023.3339570

Chang, S., & Shih, C. (2018). The Influence and Application of Artificial Intelligence &Blockchain on Financial Service. *HOLISTICA – Journal of Business and Public Administration*, *9*(3), 45–54. https://doi.org/10.2478/hjbpa-2018-0022

Chartier, E., Bowden, I., Pinkerton, M., & Townley, A. (2021). Behavioral Finance: The impact of artificial intelligence and social media analytics. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3794039

Chen, C., Gong, Y., & Wu, J. M. (2022). Impact of technical indicators and leading indicators on stock trends on the internet of things. *Wireless Communications and Mobile Computing*, *2022*, 1–15. https://doi.org/10.1155/2022/9916310

Chen, T., & Nie, C. (2022). The impact of stock market development and credit market development on technological innovation: an empirical study based on Cross-Country panel data. *Asian Economic and Financial Review*, *12*(5), 329–340. https://doi.org/10.55493/5002.v12i5.4488

Cheng, Y., Mutuc, E. B., Tsai, F., Lu, K., & Lin, C. (2018). Social capital and stock market participation via Technologies: the role of households' risk attitude and cognitive ability. *Sustainability*, *10*(6), 1904. https://doi.org/10.3390/su10061904

Chheda, S. D. (2014). *Method and system for generating stock price alerts based on real-time market data*. https://patents.google.com/patent/US20140289165A1/en

Chin, W. W. (2009). How to write up and report PLS analyses. In *Springer eBooks* (pp. 655–690). https://doi.org/10.1007/978-3-540-32827-8_29

Chong, L., Ong, H., & Tan, S. (2021). Acceptability of mobile stock trading application: A study of young investors in Malaysia. *Technology in Society*, *64*, 101497. https://doi.org/10.1016/j.techsoc.2020.101497

Chourmouziadis, K., Chourmouziadou, D. K., & Chatzoglou, P. D. (2020). Embedding four Medium-Term Technical Indicators to an intelligent stock trading fuzzy system for predicting: a portfolio management approach. *Computational Economics*, *57*(4), 1183–1216. https://doi.org/10.1007/s10614-020-10016-2

Chung, G., & Kissell, R. (2016). An application of transaction cost in the portfolio optimization process. *The Journal of Trading*, *11*(2), 11–20. https://doi.org/10.3905/jot.2016.11.2.011

Claessens, S., Frost, J., Turner, G., & Zhu, F. (2018). Fintech credit markets around the world: size, drivers and policy issues. *SSRN Electronic Journal*. https://papers.ssrn.com/sol3/Delivery.cfm/SSRN_ID3288096_code468680.pdf?abstractid=3288096&mirid=1

Clapham, B., Siering, M., & Gomber, P. (2021). Popular news are relevant news! How investor attention affects algorithmic Decision-Making and decision support in financial markets. *Information Systems Frontiers*. https://doi.org/10.1007/s10796-019-09950-w

Cookson, J. A., & Niessner, M. (2019). Why Don't We Agree? Evidence from a Social Network of Investors. *The Journal of Finance*, *75*(1), 173–228. https://doi.org/10.1111/jofi.12852

Cordella, A., & Bonina, C. M. (2012). A public value perspective for ICT enabled public sector reforms: A theoretical reflection. *Government Information Quarterly*, *29*(4), 512–520. https://doi.org/10.1016/j.giq.2012.03.004

Cornelli, G., Frost, J., Gambacorta, L., Rau, P. R., Wardrop, R., & Ziegler, T. (2022). Fintech and big tech credit: Drivers of the growth of digital lending. *Journal of Banking & Finance*, *148*, 106742. https://doi.org/10.1016/j.jbankfin.2022.106742

Courdent, A., & McClelland, D. (2022). The impact of algorithmic trading on market quality: Evidence from the Johannesburg Stock Exchange. *Investment Analysts Journal*, *51*(3), 157–171. https://doi.org/10.1080/10293523.2022.2090056

Cucculelli, M., & Recanatini, M. (2022). Distributed Ledger technology systems in securities post-trading services. Evidence from European global systemic banks. *European Journal of Finance*, *28*(2), 195–218. https://doi.org/10.1080/1351847x.2021.1921002

Daga, S., & Yadav, K. (2023). Impact of Firm Specific Factors on the Indian Stock Returns: A Panel Data Approach. *IPE Journal of Management*, *13*(1), 17-28.

Dakalbab, F., Talib, M. A., Nasir, Q., & Saroufil, T. (2024). Artificial intelligence techniques in financial trading: A systematic literature review. *Journal of King Saud University - Computer and Information Sciences*, *36*(3), 102015. https://doi.org/10.1016/j.jksuci.2024.102015

Dalko, V., & Wang, M. H. (2020). High-frequency trading: Order-based innovation or manipulation? *Journal of Banking Regulation*, *21*(4), 289–298. https://doi.org/10.1057/s41261-019-00115-y

Dangkeng, N. A., & Munir, N. R. (2025). Fintech and Financial Inclusion: How Digital Payment Systems Empower Small Entrepreneurs. *Journal of Indonesian Scholars for Social Research*, *5*(1), 46–55. https://doi.org/10.59065/jissr.v5i1.172

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319. https://doi.org/10.2307/249008

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319. https://doi.org/10.2307/249008

Demir, A., Pesqué-Cela, V., Altunbas, Y., & Murinde, V. (2020). Fintech, financial inclusion and income inequality: a quantile regression approach. *European Journal of Finance*, *28*(1), 86–107. https://doi.org/10.1080/1351847x.2020.1772335

Deng, J., Yang, M., Pelster, M., & Tan, Y. (2023). Social trading, communication, and networks. *Information Systems Research*, *35*(4), 1546–1564. https://doi.org/10.1287/isre.2021.0143

Devan, M., Thirunavukkarasu, K., & Shanmugam, L. (2023). Algorithmic Trading Strategies: Real-Time Data Analytics with Machine Learning. *Journal of Knowledge Learning and Science Technology ISSN 2959-6386 (Online)*, *2*(3), 522–546. https://doi.org/10.60087/jklst.vol2.n3.p546

Dewi, A. S. (2024). Neurofinance: Decoding the Brain's Role in Investment Decision-Making. In *Elsevier eBooks*. https://doi.org/10.1016/b978-0-443-13701-3.00226-7

Di Maggio, M., & Yao, V. (2020). Fintech borrowers: Lax screening or Cream-Skimming? *Review of Financial Studies*, *34*(10), 4565–4618. https://doi.org/10.1093/rfs/hhaa142

Diaz-Rainey, I., Ibikunle, G., & Mention, A. (2015). The technological transformation of capital markets. *Technological Forecasting and Social Change*, *99*, 277–284. https://doi.org/10.1016/j.techfore.2015.08.006

Dietzmann, C., Jaeggi, T., & Alt, R. (2023). Implications of AI-based robo-advisory for private banking investment advisory. *Journal of Electronic Business & Digital Economics*, *2*(1), 3–23. https://doi.org/10.1108/jebde-09-2022-0037

Dorfleitner, G., & Scheckenbach, I. (2022). Trading activity on social trading platforms – a behavioral approach*. *The Journal of Risk Finance*, *23*(1), 32–54. https://doi.org/10.1108/jrf-11-2020-0230

Dorfleitner, G., Fischer, L., Lung, C., Willmertinger, P., Stang, N., & Dietrich, N. (2018). To follow or not to follow – An empirical analysis of the returns of actors on social trading platforms. *The Quarterly Review of Economics and Finance*, *70*, 160–171. https://doi.org/10.1016/j.qref.2018.04.009

Dubey, R. K. (2022). Algorithmic Trading: The intelligent trading systems and its impact on trade size. *Expert Systems With Applications*, *202*, 117279. https://doi.org/10.1016/j.eswa.2022.117279

Dubey, R. K., Babu, A. S., Jha, R. R., & Varma, U. (2021). Algorithmic Trading Efficiency and its Impact on Market-Quality. *Asia-Pacific Financial Markets*, *29*(3), 381–409. https://doi.org/10.1007/s10690-021-09353-5

Eden, L., Miller, S. R., Khan, S., Weiner, R. J., & Li, D. (2022). The event study in international business research: Opportunities, challenges, and practical solutions. *Journal of International Business Studies*, *53*(5), 803–817. https://doi.org/10.1057/s41267-022-00509-7

Elliott, T., Fatemi, D., Kim, J., & Su, Q. (2024). The Impact of Terrorism on Liquidity and Information Asymmetry: Evidence from Non-U.S. Stocks Listed on the NYSE. *Defence and Peace Economics*, 1–17. https://doi.org/10.1080/10242694.2024.2332168

Erdos, S., Papp, T., & Vörös, Z. (2022). The effects of community-based signals on investment decisions in copy trading. *Journal of Behavioral and Experimental Economics*, *97*, 101847. https://doi.org/10.1016/j.socec.2022.101847

Fan, L. (2022). Mobile investment technology adoption among investors. *International Journal of Bank Marketing*, *40*(1), 50–67. https://doi.org/10.1108/ijbm-11-2020-0551

Fan, R., Talavera, O., & Tran, V. (2020). Social media, political uncertainty, and stock markets. *Review of Quantitative Finance and Accounting*, *55*(3), 1137–1153. https://doi.org/10.1007/s11156-020-00870-4

Fassott, G., Henseler, J., & Coelho, P. S. (2016). Testing moderating effects in PLS path models with composite variables. *Industrial Management & Data Systems*, *116*(9), 1887–1900. https://doi.org/10.1108/imds-06-2016-0248

Feir-Walsh, B. J., & Toothaker, L. E. (1974). An empirical comparison of the Anova F-Test, Normal Scores Test and Kruskal-Wallis Test under violation of assumptions. *Educational and Psychological Measurement*, *34*(4), 789–799. https://doi.org/10.1177/001316447403400406

Feng, R., & Qu, X. (2021). Analyzing the Internet financial market risk management using data mining and deep learning methods. *Journal of Enterprise Information Management*, *35*(4/5), 1129–1147. https://doi.org/10.1108/jeim-03-2021-0155

Filimonov, V., & Sornette, D. (2012). Quantifying reflexivity in financial markets: Toward a prediction of flash crashes. *Physical Review E*, *85*(5). https://doi.org/10.1103/physreve.85.056108

Flavián, C., Pérez-Rueda, A., Belanche, D., & Casaló, L. V. (2021). Intention to use analytical artificial intelligence (AI) in services – the effect of technology readiness and awareness. *Journal of Service Management*, *33*(2), 293–320. https://doi.org/10.1108/josm-10-2020-0378

Fortagne, M. A., Reith, R., Nguyen, K., & Lis, B. (2023). Technology acceptance of Neo-Broker Applications: An Empirical investigation. *International Journal of Innovation and Technology Management*, *20*(05). https://doi.org/10.1142/s0219877023500293

Fouillet, C., Guérin, I., & Servet, J. (2021). Demonetization and digitalization: The Indian government's hidden agenda. *Telecommunications Policy*, *45*(2), 102079. https://doi.org/10.1016/j.telpol.2020.102079

Fox, Merritt B. and Glosten, Lawrence R. and Greene, Edward and Guan, Sue, Distributed Ledger Technology and the Securities Markets of the Future: A Stakeholder Survey (July 15, 2021). Columbia Business Law Review, Vol. 2021, No. 2, 2021, Columbia Law and Economics Working Paper Forthcoming, European Corporate Governance Institute - Law Working Paper Forthcoming, Available at SSRN: https://ssrn.com/abstract=4002689

Froot, K. A., O'Connell, P. G., & Seasholes, M. S. (2001). The portfolio flows of international investors. *Journal of Financial Economics*, *59*(2), 151–193. https://doi.org/10.1016/s0304-405x(00)00084-2

Fu, J., & Mishra, M. (2021). Fintech in the time of COVID‒19: Technological adoption during crises. *Journal of Financial Intermediation*, *50*, 100945. https://doi.org/10.1016/j.jfi.2021.100945

Gan, B., Alexeev, V., Bird, R., & Yeung, D. (2019). Sensitivity to sentiment: News vs social media. *International Review of Financial Analysis*, *67*, 101390. https://doi.org/10.1016/j.irfa.2019.101390

Genz, S., Janser, M., & Lehmer, F. (2019). The Impact of Investments in New Digital Technologies on Wages – Worker-Level Evidence from Germany. *Jahrbücher Für Nationalökonomie Und Statistik*, *239*(3), 483–521. https://doi.org/10.1515/jbnst-2017-0161

Gianstefani, I., Longo, L., & Riccaboni, M. (2022). The echo chamber effect resounds on financial markets: a social media alert system for meme stocks. *arXiv (Cornell University)*. https://doi.org/10.48550/arxiv.2203.13790

Giglio, S., Maggiori, M., Stroebel, J., & Utkus, S. (2021). Five Facts about Beliefs and Portfolios. *American Economic Review*, *111*(5), 1481–1522. https://doi.org/10.1257/aer.20200243

Glaser, F., & Risius, M. (2018). Effects of transparency: Analyzing social biases on trader performance in social trading. *Journal of Information Technology*, *33*(1), 19–30. https://doi.org/10.1057/s41265-016-0028-0

Golmohammadi, K., Zaiane, O. R., & Diaz, D. (2014). Detecting stock market manipulation using supervised learning algorithms. In *2014 International Conference on Data Science and Advanced Analytics (DSAA)*. https://doi.org/10.1109/dsaa.2014.7058109

Gomber, P., Kauffman, R. J., Parker, C., & Weber, B. W. (2018). On the Fintech Revolution: Interpreting the Forces of Innovation, Disruption, and Transformation in Financial Services. *Journal of Management Information Systems*, *35*(1), 220–265. https://doi.org/10.1080/07421222.2018.1440766

Gregoire, P., Dixon, M. R., Giroux, I., Jacques, C., Goulet, A., Eaves, J., & Sévigny, S. (2023). Gambling on the stock market: the behavior of at-risk online traders. *Review of Behavioral Finance*, *16*(2), 205–222. https://doi.org/10.1108/rbf-05-2022-0143

Grindsted, T. S. (2021). Algorithmic Finance: Algorithmic Trading across Speculative Time-Spaces. *Annals of the American Association of Geographers*, *112*(5), 1390–1402. https://doi.org/10.1080/24694452.2021.1963658

Guild, J. (2017, August 18). *Fintech and the future of finance*. Guild, James, Fintech and the Future of Finance (August 18, 2017). Asian Journal of Public Affairs, 2017 , Lee Kuan Yew School of Public Policy Research Paper. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3021684

Gulati, K., Kumar, S. S., Boddu, R. S. K., Sarvakar, K., Sharma, D. K., & Nomani, M. (2021). Comparative analysis of machine learning-based classification models using sentiment classification of tweets related to COVID-19 pandemic. *Materials Today Proceedings*, *51*, 38–41. https://doi.org/10.1016/j.matpr.2021.04.364

Gunjan, A., & Bhattacharyya, S. (2022). A brief review of portfolio optimization techniques. *Artificial Intelligence Review*, *56*(5), 3847–3886. https://doi.org/10.1007/s10462-022-10273-7

Gupta, S., & Dey, D. K. (2023). Risk perception and adoption of digital innovation in mobile stock trading. *Journal of Consumer Behaviour*, *23*(2), 639–654. https://doi.org/10.1002/cb.2225

Gupta, S., & Shrivastava, M. (2021). Herding and loss aversion in stock markets: mediating role of fear of missing out (FOMO) in retail investors. *International Journal of Emerging Markets*, *17*(7), 1720–1737. https://doi.org/10.1108/ijoem-08-2020-0933

Gursahani, W. R., & Lichtenstein, N. E. (2002). Technology Investing: A Buy-Side Perspective. *The Journal of Investing*, *11*(1), 84-93.

Hair, J. F., Hauff, S., Hult, G. T. M., Richter, N. F., Ringle, C. M., & Sarstedt, M. (2017). *Partial Least Squares Strukturgleichungsmodellierung*. https://doi.org/10.15358/9783800653614

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2–24. https://doi.org/10.1108/ebr-11-2018-0203

Hair, J., Hollingsworth, C. L., Randolph, A. B., & Chong, A. Y. L. (2017). An updated and expanded assessment of PLS-SEM in information systems research. *Industrial Management & Data Systems*, *117*(3), 442–458. https://doi.org/10.1108/imds-04-2016-0130.

Hair, Joseph F. and Ringle, Christian M. and Sarstedt, Marko, The Use of Partial Least Squares (PLS) to Address Marketing Management Topics (March 15, 2011). Journal of Marketing Theory and Practice, Volume 19, Issue 2, pp. 135-138, Spring 2011, Available at SSRN: https://ssrn.com/abstract=2228902

Hao, Y., Vand, B., Delgado, B. M., & Baldi, S. (2023). Market Manipulation in Stock and Power Markets: A Study of Indicator-Based Monitoring and Regulatory Challenges. *Energies*, *16*(4), 1894. https://doi.org/10.3390/en16041894

Hao, Z., & Chen-Burger, Y. J. (2022). An Investigation into Influences of Tweet Sentiments on Stock Market Movements. In *Smart innovation, systems and technologies* (pp. 87–97). https://doi.org/10.1007/978-981-19-3359-2_8

Hariyani, D. S., Ayuningdiah, M. R., & Saputra, A. (2023). The influence of financial technology, financial literacy and financial efficacy on student's interest in investing. *Business Management Analysis Journal (BMAJ)*, *6*(1), 22–37. https://doi.org/10.24176/bmaj.v6i1.8572

Hasan, M. K., Alkhalifah, A., Islam, S., Babiker, N. B. M., Habib, A. K. M. A., Aman, A. H. M., & Hossain, M. A. (2022). Blockchain technology on smart grid, energy trading, and big data: security issues, challenges, and recommendations. *Wireless Communications and Mobile Computing*, *2022*, 1–26. https://doi.org/10.1155/2022/9065768

Hasan, M. M., Popp, J., & Oláh, J. (2020). Current landscape and influence of big data on finance. *Journal of Big Data*, *7*(1). https://doi.org/10.1186/s40537-020-00291-z

Havakhor, T., Rahman, M. S., Zhang, T., & Zhu, C. (2021). Not Knowing What to Do With or Without Machine Intelligence: Evidence from a Natural Experiment Involving Retail Investors. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3434812

Havakhor, T., Rahman, M. S., Zhang, T., & Zhu, C. (2024). Tech-Enabled financial data access, retail investors, and Gambling-Like behavior in the stock market. *Management Science*. https://doi.org/10.1287/mnsc.2021.01379

Helmina, M. R. A., Rosari, N., Yusniar, M. W., & Utaminingsih, N. S. (2023). Mind Matters in Investments: Unveiling the Psychological Forces Shaping Decision Making Behavior. *JDM (Jurnal Dinamika Manajemen)*, *14*(2), 273-285.

Hendershott, T., & Riordan, R. (2013). Algorithmic trading and the market for liquidity. *Journal of Financial and Quantitative Analysis*, *48*(4), 1001–1024. https://doi.org/10.1017/s0022109013000471

Hendershott, T., Jones, C. M., & Menkveld, A. J. (2011). Does algorithmic trading improve liquidity? *The Journal of Finance*, *66*(1), 1–33. https://doi.org/10.1111/j.1540-6261.2010.01624.x

Hennart, J. F. (1998). Transaction-Cost Theory and the Free-Standing Firm. In *Oxford University Press eBooks* (pp. 65–98). https://doi.org/10.1093/oso/9780198290322.003.0009

Henseler, J., & Schuberth, F. (2020). Using confirmatory composite analysis to assess emergent variables in business research. *Journal of Business Research*, *120*, 147–156. https://doi.org/10.1016/j.jbusres.2020.07.026

Heredia, J., Castillo-Vergara, M., Geldes, C., Gamarra, F. M. C., Flores, A., & Heredia, W. (2022). How do digital capabilities affect firm performance? The mediating role of technological capabilities in the "new normal." *Journal of Innovation & Knowledge*, *7*(2), 100171. https://doi.org/10.1016/j.jik.2022.100171

Hilbert, M., & Darmon, D. (2020). How Complexity and Uncertainty Grew with Algorithmic Trading. *Entropy*, *22*(5), 499. https://doi.org/10.3390/e22050499

Hofmann, C. (2020). The changing concept of money: a threat to the monetary system or an opportunity for the financial sector? *European Business Organization Law Review*, *21*(1), 37–68. https://doi.org/10.1007/s40804-020-00182-z

Holzmeister, F., Huber, J., Kirchler, M., Lindner, F., Weitzel, U., & Zeisberger, S. (2020). What Drives Risk Perception? A Global Survey with Financial Professionals and Laypeople. *Management Science*, *66*(9), 3977–4002. https://doi.org/10.1287/mnsc.2019.3526

Hossnofsky, V., & Junge, S. (2019). Does the market reward digitalization efforts? Evidence from securities analysts' investment recommendations. *Journal of Business Economics*, *89*(8–9), 965–994. https://doi.org/10.1007/s11573-019-00949-y

Howell, S. T., Niessner, M., & Yermack, D. (2019). Initial Coin Offerings: Financing Growth with Cryptocurrency Token Sales. *Review of Financial Studies*, *33*(9), 3925–3974. https://doi.org/10.1093/rfs/hhz131

Huang, B., Huan, Y., Da Xu, L., Zheng, L., & Zou, Z. (2018). Automated trading systems, statistical and machine learning methods, and hardware implementation: a survey. *Enterprise Information Systems*, *13*(1), 132–144. https://doi.org/10.1080/17517575.2018.1493145

Huang, Y., Zhou, C., Cui, K., & Lu, X. (2024). Improving algorithmic trading consistency via human alignment and imitation learning. *Expert Systems With Applications*, *253*, 124350. https://doi.org/10.1016/j.eswa.2024.124350

Huber, J., Palan, S., & Zeisberger, S. (2019). Does investor risk perception drive asset prices in markets? Experimental evidence. *Journal of Banking & Finance*, *108*, 105635. https://doi.org/10.1016/j.jbankfin.2019.105635

Hull, J. C. (2017). *Options, Futures, and Other Derivatives* (9th ed.). Pearson Education.

Irimia-Die guez, A., Velicia-Martín, F., & Aguayo-Camacho, M. (2023). Predicting Fintech Innovation Adoption: the Mediator Role of Social Norms and Attitudes. *Financial Innovation*, *9*(1). https://doi.org/10.1186/s40854-022-00434-6

Itzkowitz, J., Itzkowitz, J., & Schwartz, A. (2023). Start small and Stay Small: Anchoring in App-Based investing. *Journal of Behavioral Finance*, *25*(4), 464–480. https://doi.org/10.1080/15427560.2023.2209233

Jacob, S.S., Patra, S., G, K., & V, T. (2022). Monitoring of Stocks using LSTM Model and Prediction of Stock Prices. *2022 International Conference on Edge Computing and Applications (ICECAA)*, 1689-1695. https://doi.org/10.1109/ICECAA55415.2022.9936204

Jain, V., Saini, D.S., & Ahluwalia, A. (2019). Real-time autonomous trading system. *Journal of Statistics and Management Systems, 22*, 403 - 413. https://doi.org/10.1080/ 09720510.2019.1582881

Janabi, M. a. A. (2021). Optimization algorithms and investment portfolio analytics with machine learning techniques under time-varying liquidity constraints. *Journal of Modelling in Management*, *17*(3), 864–895. https://doi.org/ 10.1108/jm2-10-2020-0259

Janssen, M., Weerakkody, V., Ismagilova, E., Sivarajah, U., & Irani, Z. (2019). A framework for analysing blockchain technology adoption: Integrating institutional, market and technical factors. *International Journal of Information Management*, *50*, 302–309. https://doi.org/10.1016/j.ijinfomgt. 2019.08.012

Jeanjean, F. (2020). Impact of technical progress on the relationship between competition and investment. *Journal of Industry Competition and Trade*, *21*(1), 81–101. https://doi.org/10.1007/s10842-020-00341-5

Jiang, Y., Ho, Y., Yan, X., & Tan, Y. (2018). Investor Platform choice: herding, platform attributes, and regulations. *Journal of Management Information Systems*, *35*(1), 86–116. https://doi.org/10.1080/07421222.2018.1440770

Jiao, P., Veiga, A., & Walther, A. (2020). Social media, news media and the stock market. *Journal of Economic Behavior & Organization*, *176*, 63–90. https://doi.org/10.1016/j.jebo.2020.03.002

Jin, X., & Yu, J. (2022). Does communication increase investors' trading frequency? Evidence from a Chinese social trading platform. *Financial Innovation*, *8*(1). https://doi.org/10.1186/s40854-022-00373-2

Jin, X., Li, R., & Zhu, Y. (2021). Could social interaction reduce the disposition effect? Evidence from retail investors in a directed social trading network. *PLoS ONE*, *16*(2), e0246759. https://doi.org/10.1371/journal.pone.0246759

Joao, A. R. B., Luzardo, F., & Vanderson, T. X. (2015). An interdisciplinary framework to study farmers decisions on adoption of innovation: Insights from Expected Utility Theory and Theory of Planned Behavior. *African Journal of Agricultural Research*, *10*(29), 2814–2825. https://doi.org/10.5897/ajar2015.9650

Josey, A., & N, N. A. (2024). Stock market prediction. *Indian Journal of Data Mining*, *4*(1), 34–37. https://doi.org/10.54105/ijdm.a1641.04010524

Jóźwicki, R., Trippner, P., & Kłos, K. (2021). Algorithmic Trading and Efficiency of the Stock Market in Poland.

Kaban, L. M., & Linata, E. (2024). The risk perception as a mediator between herding and overconfidence on investment decision by Gen Z in Indonesia. *MEC-J (Management and Economics Journal)*, *8*(1), 1–14. https://doi.org/10.18860/mec-j.v8i1.25462

Kalda, A., Loos, B., Previtero, A., & Hackethal, A. (2021). Smart(Phone) Investing? A within Investor-Time Analysis of New Technologies and Trading Behavior. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3765652

Kamil, H. H., & Tanno, A. (2022). Pengaruh Media Sosial Sebagai Sumber Informasi Dalam Pengambilan Keputusan Investor Berinvestasi, Latar Belakang Pendidikan dan Penghasilan Sebagai Variabel Kontrol. *Owner*, *6*(2), 1622–1637. https://doi.org/10.33395/owner.v6i2.568

Kang, Y., Cai, Z., Tan, C., Huang, Q., & Liu, H. (2020). Natural language processing (NLP) in management research: A literature review. *Journal of Management Analytics*, *7*(2), 139–172. https://doi.org/10.1080/23270012.2020.1756939

Karn, A. L., Qiang, Y. E., Karna, R. K., & Wang, X. (2018). News sentiment incorporation in real-time trading: Alpha testing the event trading strategy in HFT. *Journal of Global Information Management (JGIM)*, *26*(4), 18-35.

Kartika, H., Karmawan, I. G. M., & Rusmanto, T. (2023). The influence of financial literacy, financial experience, behavioral finance, and investor awareness on the use of fintech applications in making investment decisions. *2022 International Conference on Information Management and Technology (ICIMTech)*, 603–608. https://doi.org/10.1109/icimtech59029.2023.10277775

Kazan, E., & Damsgaard, J. (2016). Towards a new market entry framework for digital payment platforms. *Communications of the Association for Information Systems*, *38*, 761–783. https://doi.org/10.17705/1cais.03837

Keeley, N. G. (2023). Cash, Credibility, and Conversion: The influence of synthetic media on investment behavior. *arXiv (Cornell University)*. https://doi.org/10.48550/arxiv.2306.05033

Keswani, S., Dhingra, V., & Wadhwa, B. (2019). Impact of behavioral factors in making investment decisions and performance: Study on investors of National Stock Exchange. *International Journal of Economics and Finance*, *11*(8), 80. https://doi.org/10.5539/ijef.v11n8p80

Khan, D. (2020). Cognitive Driven biases, Investment Decision making: The moderating role of financial literacy. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3514086

Khan, S. U., Liu, X., Khan, I. U., Liu, C., & Rasheed, M. I. (2020). Assessing the investors' acceptance of electronic stock trading in a developing country.

Information Resources Management Journal, *33*(1), 59–82. https://doi.org/10.4018/irmj.2020010104

Khan, W., Malik, U., Ghazanfar, M. A., Azam, M. A., Alyoubi, K. H., & Alfakeeh, A. S. (2019). Predicting stock market trends using machine learning algorithms via public sentiment and political situation analysis. *Soft Computing*, *24*(15), 11019–11043. https://doi.org/10.1007/s00500-019-04347-y

Khare, T., & Kapoor, S. (2023). Behavioral biases and the rational decision-making process of financial professionals: significant factors that determine the future of the financial market. *Journal of Advances in Management Research*, *21*(1), 44–65. https://doi.org/10.1108/jamr-03-2023-0086

Khodabandehlou, S., & Golpayegani, S. a. H. (2022). Market manipulation detection: A systematic literature review. *Expert Systems With Applications*, *210*, 118330. https://doi.org/10.1016/j.eswa.2022.118330

Kim, D., Park, K., Lee, D., & Ahn, Y. (2020). Predicting mobile trading system discontinuance: The role of attention. *Electronic Commerce Research and Applications*, *44*, 101008. https://doi.org/10.1016/j.elerap.2020.101008

Kim, K., Lee, S. T., & Kauffman, R. J. (2023). Social informedness and investor sentiment in the GameStop short squeeze. *Electronic Markets*, *33*(1). https://doi.org/10.1007/s12525-023-00632-9

Kleist, V. F. (2004). A transaction cost model of electronic trust: transactional return, incentives for network security and optimal risk in the digital economy. *Electronic Commerce Research*, *4*(1/2), 41–57. https://doi.org/10.1023/b:elec.0000009281.05504.93

Kofman, P. (2024). Scoring The Ethics of AI Robo-Advice: Why we need gateways and ratings. *Journal of Business Ethics*. https://doi.org/10.1007/s10551-024-05753-5

Kogan, S., Moskowitz, T. J., & Niessner, M. (2021). Fake News: Evidence from Financial Markets. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3237763

Kollintza-Kyriakoulia, F., Maragoudakis, M., & Krithara, A. (2018). Measuring the impact of financial news and social media on stock market modeling using time series mining techniques. *Algorithms*, *11*(11), 181. https://doi.org/10.3390/a11110181

Kolte, A., Rossi, M., Mahajan, Y., & Chachad, S. (2024). Business newspaper stock recommendations for intraday trading: empirical analysis from India. *International Journal of Business and Globalisation*. https://doi.org/10.1504/ijbg.2024.138527

Konovalova, M. E., Kuzmina, O. Y., & Zhironkin, S. A. (2019). Digital technologies as a factor of expanding the investment opportunities of business entities. In *Lecture notes in networks and systems* (pp. 180–188). https://doi.org/10.1007/978-3-030-27015-5_23

Koo, J. (2024). AI is not careful: approach to the stock market and preference for AI advisor. *International Journal of Bank Marketing*, *42*(7), 2117–2142. https://doi.org/10.1108/ijbm-10-2023-0568

Kordzadeh, N., & Ghasemaghaei, M. (2021). Algorithmic bias: review, synthesis, and future research directions. *European Journal of Information Systems*, *31*(3), 388–409. https://doi.org/10.1080/0960085x.2021.1927212

Koul, S., & Eydgahi, A. (2017). A systematic review of technology adoption frameworks and their applications. *Journal of Technology Management & Innovation*, *12*(4), 106–113. https://doi.org/10.4067/s0718-27242017000400011

Ku-Mahamud, K. R., Omar, M., Bakar, N. a. A., & Muraina, I. D. (2019). Awareness, Trust, and Adoption of Blockchain Technology and Cryptocurrency among Blockchain Communities in Malaysia. *International Journal on Advanced*

Science Engineering and Information Technology, *9*(4), 1217–1222. https://doi.org/10.18517/ijaseit.9.4.6280

Kumar, J., & Rani, V. (2024). Investigating the dynamics of FinTech adoption: an empirical study from the perspective of mobile banking. *Journal of Economic and Administrative Sciences.* https://doi.org/10.1108/jeas-12-2023-0334

Kumar, P., Islam, M. A., Pillai, R., & Tabash, M. I. (2024). Risk Perception-Perceived Investor Performance Nexus: Evaluating the mediating effects of heuristics and prospects with gender as a moderator. *SAGE Open*, *14*(2). https://doi.org/10.1177/21582440241256444

Kumar, S., & Goyal, N. (2016). Evidence on rationality and behavioural biases in investment decision making. *Qualitative Research in Financial Markets*, *8*(4), 270–287. https://doi.org/10.1108/qrfm-05-2016-0016

Kuriakose, A., & Sajoy, P. (2022). Digital Transformation in the Stockbroking Industry and its Role in Strong Retail Investor Participation in the Indian Stock Market. *The Management Accountant Journal*, *57*(8), 50. https://doi.org/10.33516/maj.v57i8.50-54p

Kuriakose, A., Sajoy, P., & George, E. (2022). Modelling the Consumer Adoption Intention towards Unified Payment Interface (UPI): An Extended UTAUT2 Model with Relative Advantage, Add-on Services and Promotional Benefits. *Interdisciplinary Research in Technology and Management (IRTM)*, 1–7. https://doi.org/10.1109/irtm54583.2022.9791524

Kurnijanto, A. W., Joni, J., Sumbodo, K. V., Wijaya, L. I., & Sutejo, B. S. (2025). Influence of Behavioral Bias on Investment Decision with Risk Perception as a Mediating Variable: A Study on Generation Z at the Indonesia Stock Exchange. *Dinasti International Journal of Economics Finance & Accounting*, *5*(6), 5741–5752. https://doi.org/10.38035/dijefa.v5i6.3643

Kyari, A. K., & Akinwale, Y. O. (2020). An assessment of the level of adoption of financial technology by Nigerian Banks. *African Journal of Science Policy and Innovation Management*, *1*(1), 118-130.

Lachana, I., & Schröder, D. (2021). Investor sentiment, media and stock returns: The advancement of social media. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3842039

LeBlanc, D., & Biddle, R. (2012). Risk perception of internet-related activities. *2012 Tenth Annual International Conference on Privacy, Security and Trust*, *236*, 88–95. https://doi.org/10.1109/pst.2012.6297924

Lee, J., & Schu, L. (2022). Regulation of algorithmic trading: frameworks or human supervision and direct market interventions. *European Business Law Review*, *33*(Issue 2), 193–226. https://doi.org/10.54648/eulr2022006

Li, C., & Li, Y. (2023). Factors Influencing Public risk Perception of Emerging Technologies: A Meta-Analysis. *Sustainability*, *15*(5), 3939. https://doi.org/10.3390/su15053939

Li, L. (2022). Digital transformation and sustainable performance: The moderating role of market turbulence. *Industrial Marketing Management*, *104*, 28–37. https://doi.org/10.1016/j.indmarman.2022.04.007

Li, Y., & Wang, F. (2023). Impact of capital market openness on corporate green technology innovation: evidence from the Shanghai-Hong Kong Stock Connect program. *Economic Research-Ekonomska Istraživanja*, *36*(3). https://doi.org/10.1080/1331677x.2023.2190798

Li, Z., Diao, X., & Wu, C. (2022). The influence of mobile trading on return dispersion and herding behavior. *Pacific-Basin Finance Journal*, *73*, 101767. https://doi.org/10.1016/j.pacfin.2022.101767

Lin, S., & Huang, H. (2020). Improving deep learning for forecasting accuracy in financial data. *Discrete Dynamics in Nature and Society*, *2020*, 1–12. https://doi.org/10.1155/2020/5803407

Lin, W., Tsai, C., & Chen, H. (2022). Factors affecting text mining based stock prediction: Text feature representations, machine learning models, and news platforms. *Appl. Soft Comput., 130*, 109673. https://doi.org/10.1016/j.asoc.2022.109673

Litzenberger, R. H., Castura, J., & Gorelick, R. (2012). The impacts of automation and high frequency trading on market quality. *Annual Review of Financial Economics*, *4*(1), 59–98. https://doi.org/10.1146/annurev-financial-110311-101744

Liu, B. (2012). *Sentiment Analysis and Opinion Mining*. Morgan & Claypool Publishers. https://doi.org/10.2200/S00416ED1V01Y201204HLT016

Liu, C., Mithas, S., Pan, Y., & Hsieh, J. J. P. (2024). Mobile Apps, Trading Behaviours, and Portfolio Performance: Evidence from a Quasi-Experiment in China. *Information Systems Research*. https://doi.org/10.1287/isre.2020.0616

Liu, W., Wang, J., Jia, F., & Choi, T. (2022). Blockchain announcements and stock value: a technology management perspective. *International Journal of Operations & Production Management*, *42*(5), 713–742. https://doi.org/10.1108/ijopm-08-2021-0534

Liu, X., & Li, C. (2003). Competitive investment strategies in adoption of new technology with a further new technology anticipated. *Journal of Systems Science and Systems Engineering*, *12*(4), 493–502. https://doi.org/10.1007/s11518-006-0150-6

Liubkina, O., & Ihnatiuk, V. (2023). TRANSACTION COSTS OF TRADING IN ORGANIZED STOCK MARKETS: STRUCTURE AND IMPLICATIONS FOR MARKET EFFICIENCY. *Herald of Khmelnytskyi National University Economic Sciences*, *320*(4), 60–71. https://doi.org/10.31891/2307-5740-2023-320-4-9

Lopez, M.A., Nadal, S., Djedaini, M., Marcel, P., Peralta, V., & Furtado, P.N. (2015). An Approach for Alert Raising in Real-Time Data Warehouses. *Journées Francophones sur les Entrepôts de Données et l'Analyse en ligne*.

Lou, A. T. F., & Li, E. Y. (2017). *Integrating Innovation Diffusion Theory and the Technology Acceptance Model: The adoption of blockchain technology from business managers' perspective*. AIS Electronic Library (AISeL). https://aisel.aisnet.org/iceb2017/44

Lu, X., & Zhou, Z. (2022). Digital transformation, business risk and firm value. *Frontiers in Sustainable Development*, *2*(5), 25–32. https://doi.org/10.54691/fsd.v2i5.695

Lui, A. K. H., Lee, M. C. M., & Ngai, E. W. T. (2021). Impact of artificial intelligence investment on firm value. *Annals of Operations Research*, *308*(1–2), 373–388. https://doi.org/10.1007/s10479-020-03862-8

Luo, Z. (2024). Financial Innovation: Disruption and reinvention in the future financial sector. *Frontiers in Business Economics and Management*, *14*(3), 152–154. https://doi.org/10.54097/76782g38

Madhavan, A. (2000). Market microstructure: A survey. *Journal of Financial Markets*, 3(3), 205–258. https://doi.org/10.1016/S1386-4181(00)00007-0.

Mahardhika, A. S., & Zakiyah, T. (2020). Millennials' intention in stock Investment: Extended Theory of Planned Behavior. *Riset Akuntansi Dan Keuangan Indonesia*, *5*(1), 83–91. https://doi.org/10.23917/reaksi.v5i1.10268

Malhotra, S. (2020). Study of features of mobile trading apps: A silver lining of pandemic. *Journal of Global Information and Business Strategy*, *12*(1), 75–80. https://doi.org/10.5958/2582-6115.2020.00009.0

Malik, L., Ullah, K., & Soomro, M. (2024). The impact of cognitive and emotional biases on individual investor's investment decision: Mediating role of risk perception. *Pakistan Journal of Humanities and Social Sciences*, *12*(3), 2651–2660. https://doi.org/10.52131/pjhss.2024.v12i3.2471

Manahov, V., Hudson, R., & Urquhart, A. (2018). High-frequency trading from an evolutionary perspective: Financial markets as adaptive systems. *International Journal of Finance & Economics*, *24*(2), 943–962. https://doi.org/10.1002/ijfe.1700

Manrai, R., & Gupta, K. P. (2022). Investor's perceptions on artificial intelligence (AI) technology adoption in investment services in India. *Journal of Financial Services Marketing*, *28*(1), 1–14. https://doi.org/10.1057/s41264-021-00134-9

Marshall, B. R., Nguyen, N. H., & Visaltanachoti, N. (2016). Time series momentum and moving average trading rules. *Quantitative Finance*, *17*(3), 405–421. https://doi.org/10.1080/14697688.2016.1205209

Martínez-López, F. J., & Casillas, J. (2013). Artificial intelligence-based systems applied in industrial marketing: An historical overview, current and future insights. *Industrial Marketing Management*, *42*(4), 489–495. https://doi.org/10.1016/j.indmarman.2013.03.001

Menkveld, A. J. (2013). High frequency trading and the new market makers. *Journal of Financial Markets*, *16*(4), 712–740. https://doi.org/10.1016/j.finmar.2013.06.006

Miraz, M. H., Hasan, M. T., Rekabder, M. S., & Akhter, R. (2022). Trust, transaction transparency, volatility, facilitating condition, performance expectancy towards cryptocurrency adoption through intention to use. *Journal of Management Information and Decision Sciences*, *25*, 1-20.

Mishra, S., & Tiwari, V. (2021). A Study on Emerging Trends in Intraday Trading Tools and Strategies in India. *Indian Journal of Financial Research*, 9(2), 44–58.

Mitchell, R. B., Woolridge, R. W., & Johnson, V. (2020). The role of nontechnical skills in providing value in analytics-based decision culture. *Journal of Education for Business*, *96*(1), 1–9. https://doi.org/10.1080/08832323.2020.1719961

Mondal, S., & Kumar, S. (2024). A critical review of influence of technology on financial decision making and investor psychology. *Advances in Finance, Accounting, and Economics Book Series*, 103–134. https://doi.org/10.4018/979-8-3693-8583-8.ch004

Moorman, T. (2014). An empirical investigation of methods to reduce transaction costs. *Journal of Empirical Finance*, *29*, 230–246. https://doi.org/10.1016/j.jempfin.2014.09.004

Moro-Visconti, R., & Cesaretti, A. (2023). FinTech and Digital Payment Systems Valuation. In *Digital Token Valuation* (pp. 411–458). https://doi.org/10.1007/978-3-031-42971-2_13

Mu, H., & Lee, Y. (2021). How inclusive digital financial services impact user behavior: A case of proximity mobile payment in Korea. *Sustainability*, *13*(17), 9567. https://doi.org/10.3390/su13179567

Murinde, V., Rizopoulos, E., & Zachariadis, M. (2022). The impact of the FinTech revolution on the future of banking: Opportunities and risks. *International Review of Financial Analysis*, *81*, 102103. https://doi.org/10.1016/j.irfa.2022.102103

Nadeem, F., & Mazhar, S. S. (2019). Innovations in Investment Products and its Impact on Financial Services Sector. *International Journal of Management Studies*, *VI*(1(4)), 53. https://doi.org/10.18843/ijms/v6i1(4)/06

Nainggolan, C. I., & Handayani, P. W. (2023). Factors affecting individuals' behavioral intention to use online capital market investment platforms in Indonesia. *Interdisciplinary Journal of Information Knowledge and Management*, *18*, 001–029. https://doi.org/10.28945/5067

Nair, P. S., Shiva, A., Yadav, N., & Tandon, P. (2022). Determinants of mobile apps adoption by retail investors for online trading in emerging financial markets. *Benchmarking an International Journal*, *30*(5), 1623–1648. https://doi.org/10.1108/bij-01-2022-0019

Nasscom. (2022). *India Fintech Report 2022: Leveraging AI in Finance*. Retrieved from https://nasscom.in

National Stock Exchange of India. (2023). *NSE Investor Awareness Bulletin*. Retrieved from https://www.nseindia.com

Nawn, S., & Banerjee, A. (2018). Do Proprietary Algorithmic Traders Withdraw Liquidity during Market Stress? *Financial Management*, *48*(2), 641–676. https://doi.org/10.1111/fima.12238

Neale, F. R., Drake, P. P., Jin, L., & Lai, G. (2024). Technology investment and insurer efficiency. *The Geneva Papers on Risk and Insurance Issues and Practice*. https://doi.org/10.1057/s41288-024-00327-y

Ng, A. W., & Kwok, B. K. (2017). Emergence of Fintech and cybersecurity in a global financial centre. *Journal of Financial Regulation and Compliance*, *25*(4), 422–434. https://doi.org/10.1108/jfrc-01-2017-0013

Nguyen, H., Calantone, R., & Krishnan, R. (2019). Influence of social media emotional word of mouth on institutional investors' decisions and firm value. *Management Science*, *66*(2), 887–910. https://doi.org/10.1287/mnsc.2018.3226

Nourallah, M. (2022). One size does not fit all: Young retail investors' initial trust in financial robo-advisors. *Journal of Business Research*, *156*, 113470. https://doi.org/10.1016/j.jbusres.2022.113470

Ochuba, N. N. A., Amoo, N. O. O., Okafor, N. E. S., Usman, N. F. O., & Akinrinola, N. O. (2024). Conceptual development and financial analytics for strategic decision-making in telecommunications, focusing on assessing investment opportunities and managing risks in satellite projects. *International Journal of*

Management & Entrepreneurship Research, *6*(3), 594–607. https://doi.org/10.51594/ijmer.v6i3.847

Oehler, A., & Schneider, J. (2022). Social trading: do signal providers trigger gambling? *Review of Managerial Science*, *17*, 1269–1331.

Oksanen, A., Mantere, E., Vuorinen, I., & Savolainen, I. (2022). Gambling and online trading: emerging risks of real-time stock and cryptocurrency trading platforms. *Public Health*, *205*, 72–78. https://doi.org/10.1016/j.puhe.2022.01.027

Olanrewaju, N. O. I. K., Daramola, N. G. O., & Ekechukwu, N. D. E. (2024). Strategic financial decision-making in sustainable energy investments: Leveraging big data for maximum impact. *World Journal of Advanced Research and Reviews*, *22*(3), 564–573. https://doi.org/10.30574/wjarr.2024.22.3.1758

Orra, A., Bhambu, A., Choudhary, H., & Thakur, M. (2024). Dynamic Reinforced Ensemble using Bayesian Optimization for Stock Trading. *ICAIF '24: Proceedings of the 5th ACM International Conference on AI in Finance*, 361–369. https://doi.org/10.1145/3677052.3698595

Owolabi, O. S., Hinneh, E., Uche, P. C., Adeniken, N. T., Ohaegbulem, J. A., Attakorah, S., Emi-Johnson, O. G., Belolisa, C. S., & Nwariaku, H. (2024). Blockchain-Based system for secure and efficient Cross-Border Remittances: a potential alternative to SWIFT. *Journal of Software Engineering and Applications*, *17*(08), 664–712. https://doi.org/10.4236/jsea.2024.178036

Ozturk, S. S., & Bilgiç, M. E. (2021). Twitter & bitcoin: are the most influential accounts really influential? *Applied Economics Letters*, *29*(11), 1001–1004. https://doi.org/10.1080/13504851.2021.1904104

Padilla-Vega, R., Sénquiz-Díaz, C., & Ojeda, A. (2017). Toward a conceptual framework of technology adoption: Factors impacting the acceptance of the mobile technology in the international business growth. *International Journal of Scientific & Technology Research*, *6*(1), 81-86.

Pandey, I., & Guillemette, M. (2024). Social media, investment knowledge, and meme stock trading. *Journal of Behavioral Finance*, 1–17. https://doi.org/10.1080/15427560.2024.2361875

Paramita, N. M. P., & Wirakusuma, N. M. G. (2024). How investment behaviour of young investors? A case study on the Indonesia Stock Exchange. *World Journal of Advanced Research and Reviews*, *23*(1), 959–976. https://doi.org/10.30574/wjarr.2024.23.1.2072

Parasuraman, A. (2000). Technology Readiness Index (TRI). *Journal of Service Research*, *2*(4), 307–320. https://doi.org/10.1177/109467050024001

Paul, S., & Vishnoi, S. (2020). Real-Time stock trend prediction via sentiment analysis of news article. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3753015

Payzan-LeNestour, E., & Woodford, M. (2022). Outlier blindness: A neurobiological foundation for neglect of financial risk. *Journal of Financial Economics*, *143*(3), 1316–1343. https://doi.org/10.1016/j.jfineco.2021.06.019

Pelster, M., Breitmayer, B., Massari, F., & Massari, F. (2017). Swarm Intelligence? Stock Opinions of the Crowd and Stock Returns. *Social Science Research Network*. https://doi.org/10.2139/SSRN.2787744.

Peng, C., Yang, S., & Jiang, H. (2022). Does digitalization boost companies' outward foreign direct investment? *Frontiers in Psychology*, *13*. https://doi.org/10.3389/fpsyg.2022.1006890

Piehlmaier, D. M. (2022). Overconfidence and the adoption of robo-advice: why overconfident investors drive the expansion of automated financial advice. *Financial Innovation*, *8*(1). https://doi.org/10.1186/s40854-021-00324-3

Pothumsetty, R. (2020). Application of artificial intelligence in algorithmic trading. *Int. J. Eng. Appl. Sci. Technol*, *4*(12), 140-149.

Prabhakaran, D.P. (2024). Revolutionizing Stock Trading: The Impact of AI on Decision-Making and Efficiency. *International Journal for Research in Applied Science and Engineering Technology*. https://doi.org/10.22214/ijraset.2024.64018

Prakash, Diwakar and Garg, Saumya, Alarming Concerns Around Cyber Security in The Securities Market (July 27, 2024). Available at SSRN: https://ssrn.com/abstract=4907612 or http://dx.doi.org/10.2139/ssrn.4907612

Putrevu, J., & Mertzanis, C. (2023). The adoption of digital payments in emerging economies: challenges and policy responses. *Digital Policy Regulation and Governance*, *26*(5), 476–500. https://doi.org/10.1108/dprg-06-2023-0077

Quinn, W. (2019). Technological revolutions and speculative finance: evidence from the British Bicycle Mania. *Cambridge Journal of Economics*, *43*(2), 271–294. https://doi.org/10.1093/cje/bey029

Rahmantari, N. L. L., Mahyuni, L. P., & Maradona, A. F. (2024). Navigating the Digital Frontier: Motivations and Perceived Behaviors on Digital Investment Platforms. *10th International Conference on Smart Computing and Communication (ICSCC)*, 507–513. https://doi.org/10.1109/icscc62041.2024.10690446

Raji, N. M. A., Olodo, N. H. B., Oke, N. T. T., Addy, N. W. A., Ofodile, N. O. C., & Oyewole, N. a. T. (2024). Real-time data analytics in retail: A review of USA and global practices. *GSC Advanced Research and Reviews*, *18*(3), 059–065. https://doi.org/10.30574/gscarr.2024.18.3.0089

Rakovic, I., & Inal, Y. (2023). Dark Finance: Exploring deceptive design in investment apps. In *Lecture notes in computer science* (pp. 339–348). https://doi.org/10.1007/978-3-031-42280-5_20

Ram, S., & Sheth, J. N. (1989). Consumer Resistance to Innovations: The Marketing Problem and its solutions. *Journal of Consumer Marketing*, *6*(2), 5–14. https://doi.org/10.1108/eum0000000002542

Rane, N., Choudhary, S., & Rane, J. (2023). Blockchain and Artificial Intelligence (AI) integration for revolutionizing security and transparency in finance. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4644253

Raschner, P. (2021). Algorithms put to test: Control of algorithms in securities trading through mandatory market simulations? *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3807935

Rawal, D. (2009). Bringing Intelligent Decision-Making to Order Routing. *The Journal of Trading, 5*, 30 - 34. https://doi.org/10.3905/JOT.2010.5.1.030

Reith, R., Fischer, M., & Lis, B. (2019). Explaining the intention to use social trading platforms: an empirical investigation. *Journal of Business Economics*, *90*(3), 427–460. https://doi.org/10.1007/s11573-019-00961-2

Renn, O., & Benighaus, C. (2013). Perception of technological risk: insights from research and lessons for risk communication and management. *Journal of Risk Research*, *16*(3–4), 293–313. https://doi.org/10.1080/13669877.2012.729522

Rigopoulou, I. D., Chaniotakis, I. E., & Kehagias, J. D. (2017). An extended technology acceptance model for predicting smartphone adoption among young consumers in Greece. *International Journal of Mobile Communications*, *15*(4), 372. https://doi.org/10.1504/ijmc.2017.084860

Roca, J., Machado, J. G., & De La Vega, J. (2010). Personal innovativeness, security and privacy as determinants of e-trading adoption. *International Journal of Electronic Finance*, *4*(3), 269. https://doi.org/10.1504/ijef.2010.034033

Rochon, J., Gondan, M., & Kieser, M. (2012). To test or not to test: Preliminary assessment of normality when comparing two independent samples. *BMC Medical Research Methodology*, *12*(1). https://doi.org/10.1186/1471-2288-12-81

Rogers, E. M. (1962). *Diffusion of innovations*. https://blogs.unpad.ac.id/teddykw/files/2012/07/Everett-M.-Rogers-Diffusion-of-Innovations.pdf

Rogers, R. W. (1975). A Protection Motivation Theory of Fear Appeals and Attitude change1. *The Journal of Psychology*, *91*(1), 93–114. https://doi.org/10.1080/00223980.1975.9915803

Rothman, T. (2019). Trading the Dream: Does social media affect investors' activity - the story of Twitter, Telegram and Reddit. *International Journal of Financial Research*, *10*(2), 147. https://doi.org/10.5430/ijfr.v10n2p147

Rothman, T., & Yakar, C. (2019). Empirical analysis Towards the effect of social media on cryptocurrency price and volume. *European Scientific Journal ESJ*, *15*(31). https://doi.org/10.19044/esj.2019.v15n31p52

Rubin, E., Iriberri, A., & Ayaburi, E. (2025). Speculation in investment in technology firms: a trust-based perspective. *International Journal of Bank Marketing*. https://doi.org/10.1108/ijbm-02-2024-0084

Rumyantseva, A., & Tarutko, O. (2023). Sustainable development financing as a factor affecting on operational efficiency of the company. In *Springer proceedings in business and economics* (pp. 47–56). https://doi.org/10.1007/978-3-031-30498-9_6

Rumyantseva, A., & Tarutko, O. (2024). The Instruments of Sustainable Development Financing: Trend analysis and search for opportunities. In *Springer proceedings in business and economics* (pp. 53–69). https://doi.org/10.1007/978-3-031-56380-5_5

Sachin, M., Vignesh, G., & Praveenkumar, S. (2020). ALGORITHM TRADING USING DATA MINING AND DATA ANALYTICS. *International Journal of Advance Research and Innovative Ideas in Education, 6*, 1138-1141.

Sadaf, R., McCullagh, O., Sheehan, B., Grey, C., King, E., & Cunneen, M. (2021). Algorithmic trading, High-frequency trading: Implications for MIFID II and Market Abuse Regulation (MAR) in the EU. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3846814

Safitri, S. N., Fauziati, S., & Hidayah, I. (2024). *Analyzing Sentiment's Impact on Stock Price Prediction: A Comprehensive Survey*. 160–165. https://doi.org/10.1109/icitcom 62788.2024.10762263

Saivasan, R., & Lokhande, M. (2022). Influence of risk propensity, behavioural biases and demographic factors on equity investors' risk perception. *Asian Journal of Economics and Banking*, *6*(3), 373–403. https://doi.org/10.1108/ajeb-06-2021-0074

Salisu, A. A., Demirer, R., & Gupta, R. (2024). Technological shocks and stock market volatility over a century. *Journal of Empirical Finance*, 101561. https://doi.org/10.1016/j.jempfin.2024.101561

Schrettenbrunner, M. B. (2023). Artificial-Intelligence-Driven management: Autonomous Real-Time trading and testing of portfolio or inventory strategies. *IEEE Engineering Management Review*, *51*(3), 65–76. https://doi.org/10.1109/emr.2023.3288609

Selvakumar, P., Mishra, R. K., Budhiraja, A., Dahake, P. S., Chandel, P. S., & Vats, C. (2024). Social media influence on market sentiment. In *Advances in business strategy and competitive advantage book series* (pp. 225–250). https://doi.org/10.4018/979-8-3693-9380-2.ch009

Sembel, J. S. (2024, September 16). *Unlocking Generation Z's Minds on Stock Investment: Determinants of Mobile Stock Investment Application Adoption*. https://ojs.uph.edu/index.php/NCBMA/article/view/8824

Sembel, J. S., Widjaja, A. W., & Antonio, F. (2024). Determinants of mobile stock investment application adoption and its impact on intention to recommend the applications in emerging countries: a case study of Indonesia. *Management & Marketing*, *19*(3), 555–578. https://doi.org/10.2478/mmcks-2024-0025

Sembel, J. S., Widjaja, A. W., & Antonio, F. (2024). Determinants of mobile stock investment application adoption and its impact on intention to recommend the applications in emerging countries: a case study of Indonesia. *Management & Marketing*, *19*(3), 555–578. https://doi.org/10.2478/mmcks-2024-0025

Semenova, V. (2024). *Embracing technological advancements: blockchain as a driver for innovation and dynamic capability development*. https://doi.org/10.14267/phd.2024056

Sendstad, L. H., & Chronopoulos, M. (2020). Strategic technology switching under risk aversion and uncertainty. *Journal of Economic Dynamics and Control*, *126*, 103918. https://doi.org/10.1016/j.jedc.2020.103918

Sendstad, L. H., Chronopoulos, M., & Hagspiel, V. (2021). Optimal risk adoption and capacity investment in technological innovations. *IEEE Transactions on Engineering Management*, *70*(2), 576–589. https://doi.org/10.1109/tem.2021.3056142

Seo, J., & Chai, S. (2013). The role of algorithmic trading systems on stock market efficiency. *Information Systems Frontiers*, *15*(5), 873–888. https://doi.org/10.1007/s10796-013-9442-9

Shah, A., & Thomas, S. (2001). The evolution of the securities markets in India in the 1990s. *Indian Council for Research on International Economic Relations*. https://www.icrier.org/pdf/wp91.pdf

Shah, S. Z. A., Ahmad, M., & Mahmood, F. (2017). Heuristic biases in investment decision-making and perceived market efficiency. *Qualitative Research in Financial Markets*, *10*(1), 85–110. https://doi.org/10.1108/qrfm-04-2017-0033

Shaheen, F., Tariq, M. A., Zahoor, Q., & Mehmood, A. (2022). Role of Financial Literacy in Investment Decisions: Exploring the Individual Investors' Perspective through a Qualitative Approach. *Journal of Business and Social Review in Emerging Economies*, *8*(4). https://doi.org/10.26710/jbsee.v8i4.2521

Shamim, R. (2022). Machine learning's algorithm profoundly impacts predicting the share market stock's price. *International Journal for Multidisciplinary Research*, *4*(5). https://doi.org/10.36948/ijfmr.2022.v04i05.911

Shao, D., Marwa, N., & Matendo, D. (2023). Regulatory Strategies for Fostering Responsible AI Innovation in African Economies. In *2023 First International Conference on the Advancements of Artificial Intelligence in African Context (AAIAC)* (pp. 1–11). https://doi.org/10.1109/aaiac60008.2023.10465404

Sharma, P., Gupta, S., & Kapoor, D. (2024). Blockchain technology in the stock market. In *Advances in finance, accounting, and economics book series* (pp. 44–59). https://doi.org/10.4018/979-8-3693-1758-7.ch003

Shawaqfeh, G. N. (2025). The Impact of Ai on Enhancing Financial Predicting Accuracy and Improving Risk Management in Financial Market. *KeAi: Journal of Digital Economy*. https://doi.org/10.2139/ssrn.5097473

Shukla, A., & Nerlekar, S. (2019). Impact of digitization transformation on financial markets. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3342126

Sindakis, S., & Showkat, G. (2024). The digital revolution in India: bridging the gap in rural technology adoption. *Journal of Innovation and Entrepreneurship*, *13*(1). https://doi.org/10.1186/s13731-024-00380-w

Singh, B., & Kaunert, C. (2024). Revealing green finance mobilization. In *Advances in finance, accounting, and economics book series* (pp. 265–286). https://doi.org/10.4018/979-8-3693-1878-2.ch011

Singh, B., Abilasha, N., & Swarna, C. (2024). Real-Time Market Sentiment Analysis Using Natural Language Processing and ML. *2024 IEEE International Conference on Computing, Power and Communication Technologies (IC2PCT)*, 1585–1588. https://doi.org/10.1109/ic2pct60090.2024.10486228

Singh, D., Malik, G., Jain, P., & Abouraia, M. (2024). A systematic review and research agenda on the causes and consequences of financial overconfidence.

Cogent Economics & Finance, *12*(1). https://doi.org/10.1080/23322039.2024.2348543

Singh, R., & Kumar, A. (2021). Impact of Digital Tools on Retail Investment Decision-Making in India. *Journal of Finance and Technology*, 12(3), 45–58.

Singhal, A., Aggarwal, S., Jamwal, J., & Kumar, R. (2024). A study on novice investor behavior in Indian stock exchange. *International Journal for Multidisciplinary Research*, *6*(2). https://doi.org/10.36948/ijfmr.2024.v06i02.16848

Sironi, P. (2016). *FinTech innovation: From robo-advisors to goal based investing and gamification*. John Wiley & Sons. https://doi.org/10.1002/9781119227205.

Sismanoglu, G., Onde, M. A., Kocer, F., & Sahingoz, O. K. (2019). Deep Learning Based Forecasting in Stock Market with Big Data Analytics. *2019 Scientific Meeting on Electrical-Electronics & Biomedical Engineering and Computer Science (EBBT)*, 1–4. https://doi.org/10.1109/ebbt.2019.8741818

Sjoberg, L. (2003). The different dynamics of personal and general risk. *Risk Management*, *5*(3), 19–34. https://doi.org/10.1057/palgrave.rm.8240154

SKrishnaprabha, N. (2024). Exploring the impact of social media on investment behaviour of young investors. *Journal of Informatics Education and Research*, *4*(3). https://doi.org/10.52783/jier.v4i3.1860

Spatacean, I. O., & Todoran, D. (2025). The use of financial technologies in promoting and providing services in the financial intermediation industry. *Acta Marisiensis Seria Oeconomica*, *18*(1), 61–70. https://doi.org/10.62838/amso-2024-0005

Sperka, R., & Spsak, M. (2013). Transaction Costs Influence on the Stability of Financial Market: Agent-Based Simulation. *Journal of Business Economics and Management*, *14*(Supplement_1), S1–S12. https://doi.org/10.3846/16111699.2012.701227

Stein, R. (2020). The top 5 predictable effects of new entries in Robinhood's '100 most popular' list. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3694588

Strauss, N., & Smith, C. H. (2019). Buying on rumors: how financial news flows affect the share price of Tesla. *Corporate Communications an International Journal*, *24*(4), 593–607. https://doi.org/10.1108/ccij-09-2018-0091

Sugden, R. A., & Jones, T. M. F. S. a. R. P. (2000). Cochran's rule for simple random sampling. *Journal of the Royal Statistical Society. Series B*, *62*(4), 787–793. https://www.jstor.org/stable/2680621

Sukharev, A. (2023). Artificial intelligence in the stock market: present and future. *Obshchestvo I Ekonomika*, *2*, 80. https://doi.org/10.31857/s020736760024424-5

Sumant, C., Bhavsar, V., Sinha, B. K., & Bhatt, V. (2022). *Impact of stock trading apps on Indian millennial consumer behavior in the stock market*. In 2022 International Conference on Decision Aid Sciences and Applications (DASA) (pp. 382–386). IEEE. https://doi.org/10.1109/DASA54658.2022.9765220.

Sun, X., & Du, Z. (2024). Enhancing capital market efficiency: The role of data assets disclosure in reducing stock price synchronicity. *International Review of Economics & Finance*, *94*, 103351. https://doi.org/10.1016/j.iref.2024.05.030

Susanto, K. P., Mandagie, W. C., Endri, E., & Wiwaha, A. (2024). Financial literacy, technological progress, financial attitudes and investment decisions of Gen Z Indonesian investors. *Investment Management and Financial Innovations*, *22*(1), 25–34. https://doi.org/10.21511/imfi.22(1).2025.03

Syamala, S. R., & Wadhwa, K. (2020). Trading performance and market efficiency: Evidence from algorithmic trading. *Research in International Business and Finance*, *54*, 101283. https://doi.org/10.1016/j.ribaf.2020.101283

Taneja, B. (2024). Financial Innovations in FinTech. In *Advances in finance, accounting, and economics book series* (pp. 208–232). https://doi.org/10.4018/979-8-3693-0863-9.ch008

Tao, R., Su, C., Xiao, Y., Dai, K., & Khalid, F. (2020). Robo advisors, algorithmic trading and investment management: Wonders of fourth industrial revolution in financial markets. *Technological Forecasting and Social Change*, *163*, 120421. https://doi.org/10.1016/j.techfore.2020.120421

Taylor, V. F., & Martinovic, I. (2017). Short paper: A longitudinal study of financial apps in the Google Play Store. In *Lecture notes in computer science* (pp. 302–309). https://doi.org/10.1007/978-3-319-70972-7_16

Teplova, T., Sokolova, T., Tomtosov, A., Buchko, D., & Nikulin, D. (2022). The sentiment of private investors in explaining the differences in the trade characteristics of the Russian market stocks. *Journal of the New Economic Association*, *53*(1), 53–84. https://doi.org/10.31737/2221-2264-2022-53-1-3

Ter Braak, L., & Van Der Schans, M. (2023). Optimal Order Routing with Reinforcement Learning. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4611420

Tetlock, P. C. (2011). All the News That's Fit to Reprint: Do Investors React to Stale Information? *Review of Financial Studies*, *24*(5), 1481–1512. https://doi.org/10.1093/rfs/hhq141

Thapa, S., Panda, S., Ghimire, A., & Kim, D. J. (2024). From engagement to retention: Unveiling factors driving user engagement and continued usage of mobile trading apps. *Decision Support Systems*, *183*, 114265. https://doi.org/10.1016/j.dss.2024.114265

Theodorou, T., Zamichos, A., Skoumperdis, M., Kougioumtzidou, A., Tsolaki, K., Papadopoulos, D., Patsios, T., Papanikolaou, G., Konstantinidis, A., Drosou, A., & Tzovaras, D. (2021). An AI-Enabled Stock Prediction Platform

Combining News and Social Sensing with Financial Statements. *Future Internet*, *13*(6), 138. https://doi.org/10.3390/fi13060138

Torno, A., & Schildmann, S. (2020). What do Robo-Advisors recommend? - An analysis of portfolio structure, performance and risk. In *Lecture notes in business information processing* (pp. 92–108). https://doi.org/10.1007/978-3-030-64466-6_6

Tosun, O. K. (2021). Cyber-attacks and stock market activity. *International Review of Financial Analysis*, *76*, 101795. https://doi.org/10.1016/j.irfa.2021.101795

Upson, J., & Van Ness, R. A. (2016). Multiple markets, algorithmic trading, and market liquidity. *Journal of Financial Markets*, *32*, 49–68. https://doi.org/10.1016/j.finmar.2016.05.004

V, J., P, T., G, M., R, D., & R, S. (2024). Deep Learning for Sentiment Analysis with Adaptive Neural Networks for Emotion Classification. In *2024 International Conference on Sustainable Communication Networks and Application (ICSCNA)* (pp. 1019–1024). https://doi.org/10.1109/icscna63714.2024.10864172

Valle-Cruz, D., Fernandez-Cortez, V., López-Chau, A., & Sandoval-Almazán, R. (2021). Does Twitter affect stock market decisions? Financial Sentiment Analysis During Pandemics: A Comparative study of the H1N1 and the COVID-19 periods. *Cognitive Computation*, *14*(1), 372–387. https://doi.org/10.1007/s12559-021-09819-8

Vandanapu, M. K., Shaik, A., Nagamalla, S. K., & Balbhadruni, R. (2024). Quantum-Inspired AI for Optimized High-Frequency Trading. *International Journal of Finance*, *9*(7), 1–17. https://doi.org/10.47941/ijf.2301

Venkatesh, N., Morris, N., Davis, N., & Davis, N. (2003). User acceptance of information Technology: toward a unified view. *MIS Quarterly*, *27*(3), 425. https://doi.org/10.2307/30036540

Venkatesh, N., Thong, N., & Xu, N. (2012). Consumer Acceptance and use of Information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, *36*(1), 157. https://doi.org/10.2307/41410412

Vergari, C. (2005). Herd behaviour in adoption of network technologies. *Journal of Economics*, *86*(2), 161–182. https://doi.org/10.1007/s00712-005-0153-7

Vijay, N., Singh, S., & Malhotra, G. (2018). Sentiment analysis: Gauging the effect of news on stock prices in Indian stock market. *International Journal of Trade, Economics and Finance*, 9(4), 148–152. https://doi.org/10.18178/ijtef.2018.9.4.605

Wagner, S. M. (2006). A firm's responses to deficient suppliers and competitive advantage. *Journal of Business Research*, *59*(6), 686–695. https://doi.org/10.1016/j.jbusres.2006.01.006

Walia, N., & Kumar, R. (2007). Online stock trading in India: An empirical investigation. *Indian Journal of Marketing, 37*(1), 24–29.

Waliszewski, K. (2020). *Entrepreneurship and sustainability issues*. http://jssidoi.org/jesi/article/706

Wang, C., & Luo, Z. (2022). A review of the optimal design of neural networks based on FPGA. *Applied Sciences*, *12*(21), 10771. https://doi.org/10.3390/app122110771

Wang, H., et al. (2024). Robo-Advisors: Revolutionizing Wealth Management Through the Integration of Big Data and Artificial Intelligence in Algorithmic Trading Strategies. Journal of Knowledge Learning and Science Technology, 3(3), 33-45

Wang, W., & Li, L. (2024). Digital payment, money market fund and investment behavior. *Pacific-Basin Finance Journal*, *85*, 102348. https://doi.org/10.1016/j.pacfin.2024.102348

Wang, W., & Ma, W. (2023). Perceived Risk and Intelligent Investment Advisor Technology Adoption: A UTAUT Perspective. *2020 4th International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT)*, 1–6. https://doi.org/10.1109/ismsit58785.2023.10304953

Wang, Y., Duong, N. T., Ying, C., & Chang, Y. (2024). What drives people's cryptocurrency investment behavior. *Journal of Computer Information Systems*, 1–18. https://doi.org/10.1080/08874417.2024.2329127

Wasiuzzaman, S., Chong, L. L., & Ong, H. B. (2022). Influence of perceived risks on the decision to invest in equity crowdfunding: a study of Malaysian investors. *Journal of Entrepreneurship in Emerging Economies*, *14*(2), 208–230. https://doi.org/10.1108/jeee-11-2020-0431

Weller, B. M. (2017). Does algorithmic trading reduce information acquisition? *Review of Financial Studies*, *31*(6), 2184–2226. https://doi.org/10.1093/rfs/hhx137

Widyanto, H. A., Kusumawardani, K. A., & Yohanes, H. (2020). Safety first: extending UTAUT to better predict mobile payment adoption by incorporating perceived security, perceived risk and trust. *Journal of Science and Technology Policy Management*, *13*(4), 952–973. https://doi.org/10.1108/jstpm-03-2020-0058

Widyanto, H. A., Kusumawardani, K. A., & Yohanes, H. (2021). Safety first: extending UTAUT to better predict mobile payment adoption by incorporating perceived security, perceived risk and trust. *Journal of Science and Technology Policy Management*, *13*(4), 952–973. https://doi.org/10.1108/jstpm-03-2020-0058

Williams, D. J., & Noyes, J. M. (2007). How does our perception of risk influence decision-making? Implications for the design of risk information. *Theoretical Issues in Ergonomics Science*, *8*(1), 1–35. https://doi.org/10.1080/14639220500484419

Wohlgemuth, V., Berger, E. S., & Wenzel, M. (2016). More than just financial performance: Trusting investors in social trading. *Journal of Business Research*, *69*(11), 4970–4974. https://doi.org/10.1016/j.jbusres.2016.04.061

Woolson, R. F., Bean, J. A., & Rojas, P. B. (1986). Sample size for Case-Control studies using Cochran's statistic. *Biometrics*, *42*(4), 927. https://doi.org/10.2307/2530706

Wu, B. (2020). Investor behavior and risk contagion in an Information-Based Artificial stock market. *IEEE Access*, *8*, 126725–126732. https://doi.org/10.1109/access.2020.3008717

Wu, Y., Wang, J. B., & Li, Y. (2024). Quantum Computing for option portfolio analysis. *arXiv (Cornell University)*. https://doi.org/10.48550/arxiv.2406.00486

Xie, Q., Han, W., Chen, Z., Xiang, R., Zhang, X., He, Y., ... & Huang, J. (2024). Finben: A holistic financial benchmark for large language models. *Advances in Neural Information Processing Systems*, *37*, 95716-95743.

Xu, P., Lee, J., Barth, J. R., & Richey, R. G. (2021). Blockchain as supply chain technology: considering transparency and security. *International Journal of Physical Distribution & Logistics Management*, *51*(3), 305–324. https://doi.org/10.1108/ijpdlm-08-2019-0234

Xu, Q., Li, Q., Jiang, C., Wu, J., & Zhang, X. (2020). Social media, interaction information and stock market efficiency: evidence from the Shenzhen stock exchange easy interaction platform in China. *Asia-Pacific Journal of Accounting & Economics*, *29*(6), 1469–1496. https://doi.org/10.1080/16081625.2020.1829976

Xu, S. X., & Zhang, X. (2009). *How do social media shape the information environment in the financial market?* AIS Electronic Library (AISeL). https://aisel.aisnet.org/icis2009/56

Xu, X., Isaac, A., Hao, L., & Wang, D. (2019). Investor sentiment, innovation investment and cash dividend. *International Journal of Economics and Finance*, *11*(7), 97. https://doi.org/10.5539/ijef.v11n7p97

Yadav, M. P., Al-Qudah, A. A., Sandhu, K., & Gupta, N. (2022). Resolving an enigma of FinTech, digital assets and electronic commerce: insight to time-varying dynamic connectedness. *FIIB Business Review*. https://doi.org/10.1177/2319 7145241300899

Yadav, M., & Banerji, P. (2024a). Digital financial literacy, saving and investment behaviour in India. *Journal of Social and Economic Development*. https://doi.org/10.1007/s40847-024-00367-z

Yadav, M., & Banerji, P. (2024b). Systematic literature review on Digital Financial Literacy. *SN Business & Economics*, *4*(11). https://doi.org/10.1007/s43546-024-00738-y

Yadav, S., Jawa, R., Kabra, R., & Aggarwal, R. (2022). Investment Tech: The Rise of Discount Brokers in India. *International Journal of Research -Granthaalayah*, *10*(3), 176–193. https://doi.org/10.29121/granthaalayah.v10.i3.2022.4544

Yang, J., & Klassen, K. J. (2008). How financial markets reflect the benefits of self-service technologies. *Journal of Enterprise Information Management*, *21*(5), 448–467. https://doi.org/10.1108/17410390810904238

Yang, N. (2022). Social media and money: How our tweets affect the financial markets. *Rangahau Aranga AUT Graduate Review*, *1*(1). https://doi.org/10.24135/rangahau-aranga.v1i1.34

Yang, N., Fernandez-Perez, A., & Indriawan, I. (2023). Social media sentiment, investor herding and informational efficiency. *Investor Herding and Informational Efficiency (August 25, 2023).*

Yang, Xiurui and HU, Wei, "GME Frenzy on Social Media: The Impact of Short Squeezes on Market Volatility and Predictability" (2024). *PACIS 2024*

Proceedings. 18. https://aisel.aisnet.org/pacis2024/track17_socmedia/track17_socmedia/18

Yuferova, D. (2024). Algorithmic trading and market efficiency around the introduction of the NYSE Hybrid Market. *Journal of Financial Markets*, *69*, 100909. https://doi.org/10.1016/j.finmar.2024.100909

Zachariadis, M., Hileman, G., & Scott, S. V. (2019). Governance and control in distributed ledgers: Understanding the challenges facing blockchain technology in financial services. *Information and Organization*, *29*(2), 105–117. https://doi.org/10.1016/j.infoandorg.2019.03.001

Zafar, S., Ashraf, S., & Raza, T. (2024). The Investment Decision-making: Understanding Overconfidence, Herding and Risk Aversion among Individual Investors. *Journal of Social Sciences Development*, *3*(1), 32–44. https://doi.org/10.53664/jssd/03-01-2024-03-32-44

Zahera, S. A., & Bansal, R. (2018). Do investors exhibit behavioral biases in investment decision making? A systematic review. *Qualitative Research in Financial Markets*, *10*(2), 210–251. https://doi.org/10.1108/qrfm-04-2017-0028

Ze, Y., & Loang, O. K. (2024). The role of technological innovation in shaping investment strategies in emerging markets. In *Advances in business strategy and competitive advantage book series* (pp. 273–296). https://doi.org/10.4018/979-8-3693-9380-2.ch011

Zhang, C., Sjarif, N. N. A., & Ibrahim, R. (2023). Deep learning models for price forecasting of financial time series: A review of recent advancements: 2020–2022. *Wiley Interdisciplinary Reviews Data Mining and Knowledge Discovery*, *14*(1). https://doi.org/10.1002/widm.1519

Zhang, H., & Aumeboonsuke, V. (2022). Technological Innovation, Risk-Taking and Firm Performance—Empirical Evidence from Chinese Listed Companies. *Sustainability*, *14*(22), 14688. https://doi.org/10.3390/su142214688

Zhang, L., Pentina, I., & Fan, Y. (2021). Who do you choose? Comparing perceptions of human vs robo-advisor in the context of financial services. *Journal of Services Marketing*, *35*(5), 634–646. https://doi.org/10.1108/jsm-05-2020-0162

Zhang, W., Zhang, N., Yan, J., Li, G., & Yang, X. (2022). Auto uning of price prediction models for high-frequency trading via reinforcement learning. *Pattern Recognition*, *125*, 108543. https://doi.org/10.1016/j.patcog.2022.108543

Zhang, Y., & Qi, J. (2024). Digital trading platforms: bridging risk tolerance and increased trade frequency during the pandemic. *Applied Economics Letters*, 1–5. https://doi.org/10.1080/13504851.2024.2390980

Zhang, Y., Li, R., & Xie, Q. (2023). Does digital transformation promote the volatility of firms' innovation investment? *Managerial and Decision Economics*, *44*(8), 4350–4362. https://doi.org/10.1002/mde.3951

Zhang, Z., & Chen, Y. (2021). Tail risk early warning system for capital markets based on machine learning algorithms. *Computational Economics*, *60*(3), 901–923. https://doi.org/10.1007/s10614-021-10171-0

Zhavoronok, A., Popelo, O., Shchur, R., Ostrovska, N., & Kordzaia, N. (2022). The role of digital technologies in the transformation of regional models of households' financial behavior in the conditions of the National Innovative Economy development. *Ingénierie Des Systèmes D Information*, *27*(4), 613–620. https://doi.org/10.18280/isi.270411

Zhou, B., & Ge, J. (2023). Does corporate digitization affect investment efficiency? Evidence from China. *Applied Economics Letters*, *31*(20), 2144–2149. https://doi.org/10.1080/13504851.2023.2211329

Zhuang, X., Chen, Z., Wu, Y., & Guo, G. (2022). Quantum computational quantitative trading: high-frequency statistical arbitrage algorithm. *New Journal of Physics*, *24*(7), 073036. https://doi.org/10.1088/1367-2630/ac7f26

Zong, Z., & Guan, Y. (2024). AI-Driven intelligent data Analytics and predictive Analysis in Industry 4.0: Transforming knowledge, innovation, and efficiency. *Journal of the Knowledge Economy*. https://doi.org/10.1007/s13132-024-02001-z

Zou, J., Zhao, Q., Jiao, Y., Cao, H., Liu, Y., Yan, Q., Abbasnejad, E., Liu, L., & Shi, J. Q. (2022). Stock market prediction via Deep learning Techniques: a survey. *arXiv (Cornell University)*. https://doi.org/10.48550/arxiv.2212.12717.

APPENDIX

Appendix I

Serial No:

QUESTIONNAIRE

IMPACT OF TECHNOLOGICAL INNOVATIONS ON THE INVESTMENT BEHAVIOUR OF STOCK MARKET INVESTORS

Respected Sir/ Madam

I am Aghilesh M, a research scholar undertaking a Ph.D in the Post Graduate and Research Department of Commerce, Government College, Madappally, Vatakara. My Ph.D. thesis is based on the topic, "Impact of Technological Innovations on the Investment Behaviour of Stock Market Investors". The aim is to provide a credible and original opinion on the impact of technological innovations on the investment behaviour of stock market investors in Kerala. The supplied information will be confidential and used solely in the research. I would appreciate it if you could take the time to fill out the questionnaire.

Thanking you for your kind cooperation

Demographical Profile

Sl. No	Category	Options
1	Gender	a. Male b. Female c. Other
2	Age	a. 18-25 b. 26-35 c. 36-45 d. 46-55 e. Above 55
3	Level of Education	a. SSLC b. Plus Two/Diploma or equivalent c. Degree d. PG e. Professional Degree f. Others
4	Employment Status	a. Government Job b. Private Job c. Self-Employed d. Business e. Retired f. Professional g. Others
5	Level of Risk Tolerance	a. Low b. Medium c. High

6	Monthly Income	a. Less than 25,000 c. 50,000 - 1,00,000	b. 25,000 to 50,000 d. 1,00,000 and above
7	Type of Stockbroker Used	a. Full-Service Broker c. Both	b. Discount Broker

Objective 1: To Evaluate Changes in Investment Behaviour Due to Technological Advancements

Scale: 1 Strongly Disagree, 2 Disagree, 3 Neutral, 4 Agree, 5 Strongly Agree.

No	Statement	1	2	3	4	5
1	Blockchain technology in stock trading has increased trust and security.					
2	High-frequency trading (HFT) has led to increased trading frequency.					
3	Algorithmic trading has encouraged data-driven investment decisions.					
4	Artificial intelligence (AI) in stock market predictions has improved accuracy in forecasting stock trends.					
5	Robo-advisors have increased reliance on automated financial advice.					
6	Advanced stock screeners have helped in better selection of stocks.					
7	Discount brokers have lowered trading costs and increased accessibility.					
8	Intraday trading platforms have increased participation in short-term trading.					
9	Mobile trading apps have made investing more convenient and frequent.					
10	UPI and digital payment systems have enhanced ease of transactions in stock trading.					
11	Smart order routing systems have improved efficiency in executing trades.					

No	Statement	1	2	3	4	5
12	Real-time market alerts and AI-driven notifications have enabled timely decision-making.					
13	Automated portfolio rebalancing has helped in better risk management and diversification.					
14	Sentiment analysis tools for trading have influenced investment decisions based on news sentiment.					
15	Virtual trading platforms (simulated trading) have improved learning and stock market experimentation.					

Objective 2: To Evaluate the Influence of Social Trading and Real-Time News Platforms on Trading Habits

Response Scale: 1 No Influence, 2 Slight Influence, 3 Moderate Influence, 4 Strong Influence, 5 Very Strong Influence

Sl. No	Statement	1	2	3	4	5
1	Social media information has influenced my stock trading decisions.					
2	Stock trading based on social media information is riskier than self-analysis and traditional methods.					
3	Advice and recommendations from fellow investors on social media platforms have influenced my trading decisions.					
4	Real-time news platforms have influenced my stock trading decisions.					
5	The speed and reliability of real-time news feeds have influenced my trading habits.					
6	The accuracy and timeliness of news from real-time news platforms have impacted my investment strategies.					

Sl. No	Statement	1	2	3	4	5
7	The ease of use and accessibility of real-time news platforms have influenced my stock trading.					
8	Social trading platforms have influenced my frequency of stock trading.					
9	Discussions on social media have influenced my confidence in making stock trading decisions.					
10	Real-time news alerts and updates have influenced my ability to react quickly to stock market movements.					

Objective 3: To Analyze the Impact of Technological Advancements in Financial Analytics on Investment Decision-Making

Response Scale: 1 No Impact, 2 Slight Impact, 3 Moderate Impact, 4 Strong Impact, 5 Very Strong Impact

Sl. No	Statement	1	2	3	4	5
1	Advanced stock analytics tools have impacted the way I filter and select stocks.					
2	AI-driven financial analytics tools have improved the accuracy of my stock selection.					
3	Automated stock analysis tools have reduced the time I spend on stock selection.					
4	Financial analytic tools have improved the performance of my investment portfolio.					
5	AI-powered financial analytics have increased my confidence in making investment decisions.					
6	Financial analytics tools have influenced how I identify stocks that match my investment goals.					

Sl. No	Statement	1	2	3	4	5
7	Data provided by financial analytics platforms have influenced my investment choices.					
8	Financial analytics tools have helped me manage risk by evaluating stocks based on risk tolerance.					
9	The usability and interface of financial analytics tools have influenced my investment decision-making.					
10	AI-driven financial analytics tools have changed my preference from manual stock research to automated insights.					

Objective 4: To Assess the Impact of Mobile Trading Apps on Stock Trading Behaviour in Kerala

Response Scale: 1 No Impact, 2 Slight Impact, 3 Moderate Impact, 4 Strong Impact, 5 Very Strong Impact

Sl. No	Statement	1	2	3	4	5
1	Mobile trading apps have impacted my stock trading frequency.					
2	Lower brokerage fees offered by mobile trading apps have impacted my trading activity.					
3	Real-time market information from mobile trading apps has impacted my trading decisions.					
4	The convenience of mobile trading apps has impacted my choice of trading platforms.					
5	Mobile trading apps have impacted the accessibility of stock trading for retail investors.					
6	Mobile trading apps have impacted my preference for self-directed investing.					

Sl. No	Statement	1	2	3	4	5
7	The user-friendly interface of mobile trading apps has impacted my trading experience.					
8	Security concerns regarding mobile trading apps have impacted my confidence in online trading.					
9	Mobile trading apps have impacted my willingness to take higher risks in investments.					
10	The ability to track and manage investments through mobile apps has impacted my trading behaviour.					
11	Research and educational resources on mobile trading apps have impacted my investment knowledge.					
12	The service quality of mobile trading apps has impacted my decision to trade with them over full-service brokers.					
13	Mobile trading apps have impacted my participation in IPO investments.					
14	Margin trading options on mobile trading apps have impacted my trading volume.					
15	The rise of mobile trading apps has impacted my perception of the future of stock trading in Kerala.					

Objective 5: To analyze the impact of technological innovation adoption on investment behaviour among stock market investors.

Response Scale: 1 Strongly Disagree, 2 Disagree, 3 Neutral, 4 Agree, 5 Strongly Agree.

Construct	Measurement Item	1	2	3	4	5
Perceived Usefulness (PU)	Digital investment platforms enhance my investment decision-making process.					
	AI-driven analytics provide valuable insights for my investment strategies.					

Construct	Measurement Item	1	2	3	4	5
	Mobile trading applications facilitate efficient trading activities.					
	Robo-advisors assist in optimizing my investment portfolio.					
	Blockchain technology improves the security of my financial transactions.					
Perceived Ease of Use (PEOU)	Learning to operate digital investment platforms is straightforward.					
	Executing trades via mobile applications is user-friendly.					
	AI-based investment tools offer comprehensible recommendations.					
	Managing my portfolio with robo-advisors requires minimal effort.					
	Navigating fintech platforms is intuitive and simple.					
Risk Perception (RP)	Investing through digital platforms carries significant risks.					
	I worry about potential security threats when using fintech solutions.					
	Automated trading increases the possibility of financial losses.					
	I find AI-driven stock recommendations unreliable.					
	I am concerned about the accuracy of robo-advisors in volatile markets.					
Cost Perception (CP)	Mobile trading apps reduce my overall trading costs.					
	AI-powered investment tools offer cost-effective market insights.					
	The subscription fees for advanced fintech tools are reasonable.					
	The cost of using mobile trading apps is lower than traditional brokers.					

Construct	Measurement Item	1	2	3	4	5
	Robo-advisors offer better value than human financial advisors.					
Attitude Towards Technology (ATT)	I feel comfortable using AI-powered investment solutions.					
	I am optimistic about the role of fintech in financial markets.					
	Using digital investment platforms is an enjoyable experience.					
	I believe fintech will dominate stock market investing in the future.					
	The convenience of technology makes me more willing to invest.					
Facilitating Conditions (FC)	I have access to necessary resources to use fintech-based investment platforms.					
	I receive adequate support and training to use investment technology tools.					
	My financial service provider encourages the use of digital investment tools.					
	I have a stable internet connection to access trading platforms.					
	Government policies support the adoption of fintech in stock trading.					
Behavioral Intention (BI)	I intend to continue using digital investment platforms.					
	I plan to increase my use of AI-powered investment tools.					
	I will rely more on fintech solutions for investment decisions.					
	I am likely to recommend mobile trading apps to others.					
	I prefer automated investment strategies over traditional ones.					
Actual Use (AU)	I frequently use mobile trading apps to buy and sell stocks.					

Construct	Measurement Item	1	2	3	4	5
	I rely on robo-advisors for portfolio recommendations.					
	I use AI-powered analytics before making investment decisions.					
	I have transitioned from traditional brokers to discount brokers due to technological advancements.					
	I execute most of my trades using digital investment platforms.					
Investment Behavior (IB)	Technology-based investment platforms have increased my trading frequency.					
	Fintech tools have influenced my shift from short-term to long-term investing.					
	I take more calculated risks due to access to AI-powered analytics.					
	Social trading platforms have influenced my investment decisions.					
	Mobile trading apps have made me more engaged in stock trading.					