

BEARISH FEARS AND BULLISH CONFIDENCE:
FINANCIAL AWARENESS AND TECHNOLOGY
GROWTH RESHAPE INVESTMENT STRATEGIES
IN MALAYSIA

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BY

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A final year project submitted in partial fulfillment of the
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- (3) Equal contribution has been made by each group member in completing the FYP.
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DEDICATION

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TABLE OF CONTENTS

	Page
Copyright Statement	ii
DECLARATION.....	iii
ACKNOWLEDGEMENT	iv
DEDICATION	vi
LIST OF TABLES	xii
LIST OF FIGURES	xiv
LIST OF ABBREVIATIONS	xv
LIST OF APENDICES	xvii
Abstract.....	1
CHAPTER 1: RESEARCH OVERVIEW	2
1.0 Introduction	2
1.1 Research Background.....	2
1.2 Research Problem.....	5
1.3 Research Objective & Research Question	10
1.3.1 Research Objective	10
1.3.2 Research Question	11
1.4 Research Significance	11
1.5 Conclusion.....	13
CHAPTER 2: LITERATURE REVIEW	14
2.0 Introduction	14
2.1 Underlying Theories.....	14
2.1.1 Behavioural Finance Theory	14
2.1.2 Technology Acceptance Model.....	16
2.1.3 Unified Theory of Acceptance and Use of Technology (UTAUT 3).....	17
2.2 Review of Variables	18
2.2.1 Reshape Investment Strategies (Dependent Variable).....	19
2.2.2 Herding Effect (Independent Variable).....	23
2.2.3 Habit (Independent Variable).....	27
2.2.4 Performance Expectancy (Independent Variable)	30

2.2.5 Personal Innovativeness in Information Technology (Independent Variable).....	34
2.2.6 Market Sentiment	38
2.2.7 Market Sentiment (Moderating Effect)	40
2.2.8 Market Sentiment (No Moderating Effect)	41
2.3 Conceptual Framework	42
2.4 Hypotheses Development.....	44
2.4.1 Herding Effect and Reshape Investment Strategies	44
2.4.2 Habit and Reshape Investment Strategies	45
2.4.3 Performance Expectancy and Reshape Investment Strategies	45
2.4.4 Personal Innovativeness in IT and Reshape Investment Strategies.....	46
2.4.5 Moderating Effect of Market Sentiment on the relationship between Independent Variables and Reshape Investment Strategies.....	47
2.5 Conclusion.....	48
CHAPTER 3: METHODOLOGY	48
3.0 Introduction	49
3.1 Research Design.....	49
3.2 Sampling Design	49
3.2.1 Target respondents of the Study	50
3.2.2 Sampling Location.....	50
3.2.3 Sampling method.....	50
3.2.4 Sampling Techniques.....	51
3.2.5 Sample Size of the Study	51
3.3 Data Collections Methods	52
3.3.1 Data Collection.....	53
3.3.2 Questionnaire.....	53
3.3.3 Pre-Test.....	54
3.3.4 Pilot Test	54
3.3.4.2 Measurement Model Assessment.....	56
3.3.4.3 Validity and reliability.....	56
3.3.4.4 Multicollinearity Test.....	57
3.3.4.5 Discriminant Validity	57
3.3.4.6 Structural Model Assessment.....	58
3.3.4.7 Coefficient of Determination (R^2)	58
3.3.5 Nominal Scale.....	59

3.3.6 Ordinal Scale	59
3.3.7 Origin of Construct.....	59
3.3.8 Questionnaire Design	61
3.3.8.1 Section A.....	61
3.3.8.2 Section B.....	62
3.3.8.2.1 Herding Effect.....	62
3.3.8.2.2 Habit.....	63
3.3.8.2.3 Performance Expectancy	63
3.3.8.2.4 Personal Innovativeness in Information Technology.....	64
3.3.8.2.5 Market Sentiment as a Moderator Between Independent and Dependent Variables	65
3.3.8.3 Section C.....	66
3.3.8.3.1 Reshape Investment Strategies	66
3.3.9 Data Checking, Filtering and Coding.....	67
3.4 Proposed Data Analysis Tool	69
3.4.1 Reliability test.....	69
3.4.1.1 Internal consistency test.....	69
3.4.1.2 Validity test	70
3.4.2 Preliminary Data Screening.....	70
3.4.2.1 Multicollinearity	70
3.4.3 Inferential analysis.....	71
3.4.3.1 Partial Least Square (PLS) Structural Equation Modelling.....	71
3.5 Conclusion.....	72
CHAPTER 4: DATA ANALYSIS	72
4.0 Introduction	72
4.1 Descriptive Analysis.....	73
4.1.1 Respondents' Demographic Profile	73
4.1.1.1 Gender.....	73
4.1.1.2 Age	74
4.1.1.3 Ethnicity.....	76
4.1.1.4 State.....	77
4.1.1.5 Occupation	78
4.1.1.6 Investment Status	80
4.1.2 Central Tendencies and Dispersion Measurement of Constructs	80

4.1.2.1 Reshape Investment Strategies	81
4.1.2.2 Herding Effect.....	83
4.1.2.3 Habit.....	85
4.1.2.4 Performance Expectancy	86
4.1.2.5 Personal Innovativeness in IT	88
4.1.2.6 Market Sentiment.....	90
4.2 Scale Measurement	93
4.2.1 Reliability Test.....	93
4.3 Preliminary Data Screening	94
4.3.1 Measurement Model Assessment	94
4.3.2 Validity and reliability	96
4.3.3 Multicollinearity Test.....	97
4.3.4 Discriminant Validity.....	98
4.4 Inferential Analysis	100
4.4.1 Structural Model Assessment	100
4.4.2 Assess Path Coefficients	101
4.4.3 Analysis of Moderating effect	102
4.4.4 Coefficient of Determination (R^2)	103
4.4.5 Assess Effect Size f^2	104
4.5 Conclusion.....	105
CHAPTER 5: DISCUSSION, CONCLUSION AND IMPLICATIONS.....	105
5.0 Introduction	105
5.1 Statistical Analysis Summary.....	106
5.2 Discussions of Major Findings.....	107
5.2.1 Herding Effect	107
5.2.2 Habit	109
5.2.3 Performance Expectancy	110
5.2.4 Personal Innovativeness in IT.....	111
5.2.5 Moderating effect of market sentiment towards herding effect and reshaping investment strategies	112
5.2.6 Moderating effect of market sentiment towards habit and reshaping investment strategies.....	113
5.2.7 Moderating effect of market sentiment towards performance expectancy and reshaping investment strategies	114

5.2.8 Moderating effect of market sentiment towards personal innovativeness in IT and reshaping investment strategies	116
5.3 Implications of the Study	118
5.4 Limitations of the Study	120
5.5 Recommendations for Future Research	122
5.6 Conclusion.....	125
References	127
Appendix	163

LIST OF TABLES

	Page
Table 2.1: Market sentiment with significant moderating effect	40
Table 2.2: Market sentiment with insignificant moderating effect	41
Table 3.1: Determining Sample Size Based on Population	52
Table 3.2: Cronbach's Alpha Reliability Analysis	55
Table 3.3: Origin of Construct	59
Table 3.4: Section A Code	68
Table 3.5: Cronbach's Alpha Rule of Thumbs	70
Table 4.1: Gender	73
Table 4.2: Age	74
Table 4.3: Ethnicity	76
Table 4.4: State	77
Table 4.5: Occupation	78
Table 4.6: Investment Status	80
Table 4.7: Central Tendencies Measurement – Reshape Investment Strategies	81
Table 4.8: Central Tendencies Measurement – Herding Effect	83
Table 4.9: Central Tendencies Measurement – Habit	85
Table 4.10: Central Tendencies Measurement – Performance Expectancy	87
Table 4.11: Central Tendencies Measurement – Personal Innovativeness in IT	88
Table 4.12: Central Tendencies Measurement – Market Sentiment	90
Table 4.13: Cronbach's Alpha Reliability Analysis	93

Table 4.14: Factor Loadings	94
Table 4.15: Construct Validity and Reliability	96
Table 4.16: Collinearity (VIF)	98
Table 4.17: Heterotrait-Monotrait Ratio (HTMT) Output	99
Table 4.18: Path Coefficient, Standard Error, T-Value, P-Value and Hypotheses Testing	101
Table 4.19: Path Coefficient, Standard Error, T-Value, P-Value and Hypotheses Testing (Moderating)	102
Table 4.20: Determination of co-efficient (R^2)	103
Table 4.21: Determination of effect size (f^2)	104
Table 5.1: Statistical Analysis Summary	106

LIST OF FIGURES

	Page
Figure 1.1: New Central Depository System (CDS) Account Opened	6
Figure 1.2: Number of Investment Scam	7
Figure 1.3: MYFLIC Scores	8
Figure 2.1: Behavioural Finance Theory	15
Figure 2.2: Technology Acceptance Model (TAM)	16
Figure 2.3: Unified Theory of Acceptance and Use of Technology (UTAUT 3)	17
Figure 2.4: Conceptual Framework.	43
Figure 4.1: Descriptive Analysis – Gender	74
Figure 4.2: Descriptive Analysis - Age	75
Figure 4.3: Descriptive Analysis – Ethnicity	76
Figure 4.4: Descriptive Analysis – State	78
Figure 4.5: Descriptive Analysis – Occupation	79
Figure 4.6: Structural Model Assessment	100

LIST OF ABBREVIATIONS

AI	Artificial Intelligence
AVE	Average Variance Extracted
CDS	Central Depository System
DPR	Dividend Payout Ratio
EE	Effort Expectancy
EPS	Earnings Per Share
FC	Facilitating Expectancy
HB	Habit
HM	Hedonic Motivation
HTMT	Heterotrait-Monotrait Ratio
IDT	Innovation Diffusion Theory
IT	Information Technology
MS	Market Sentiment
MYFLIC	Malaysia Financial Literacy and Capability
P/B	Price to Book Value Ratio
P/E	Price to Earnings Ratio
PBV	Price to Book Value
PE	Performance Expectancy
PEOU	Perceive Ease of Use

PR	Perceived Risk
PU	Perceived Usefulness
PV	Price Value
RI	Reshape Investment Strategies
SI	Social Influence
TAM	Technology Acceptance Model
TRA	Theory of Reasoned Action
UTAUT	Unified Theory of Acceptance and Use of Technology
VIF	Variance Inflation Factor

LIST OF APENDICES

	Page
Appendix 1: Factor Loadings	163
Appendix 2: Construct Validity and Reliability	164
Appendix 3: Collinearity (VIF)	164
Appendix 4: Heterotrait-Monotrait Ratio (HTMT) Output	165
Appendix 5: Structural Model	166
Appendix 6: Determination of co-efficient (R^2)	166

Abstract

With online trading emerging as a prevailing norm, investors have gained unprecedented accessibility to investment opportunities and wealth management avenues. Malaysia's accelerated technological development combined with the financial awareness of its population has significantly broadened the investor base, underscoring the necessity to evaluate whether these drivers have resulted in heterogeneous strategic adaptations among investors. Given that existing investors already possess established investment strategies, this study investigates how Malaysia's technology growth and financial awareness on reshaping Malaysia's investors' strategies and further analyses the moderating role of market sentiment within this dynamic. This study employed purposive sampling to survey 395 existing investors which were randomly selected from three states including Selangor, Johor, and Penang. Guided by the Unified Theory of Acceptance and Use of Technology 3 (UTAUT3) and Behavioural Finance Theory, this research aims to investigate investor behaviour by examining factors such as herding effect, habit, performance expectancy, and personal innovativeness in Information Technology. Additionally, the study explores the moderating effect of market sentiment on these factors among existing investors in Malaysia. The results indicate that all four independent variables have significant direct relationships with the reshaping of investment strategies and market sentiment only significantly moderate interaction with personal innovativeness in IT. Consequently, this findings expected to provide valuable insights into behavioural patterns which may contribute and affect to more effective strategies for engaging investors within the Malaysian financial market.

Keywords: Reshape investment strategies; technology growth; financial awareness; market sentiment; UTAUT3; Behavioural Finance Theory; Malaysia

Subject Area: HG4001-4285 Finance management. Business finance. Corporation finance

Subject Area: HM1176-1281 Social influence. Social pressure

Subject Area: T58.5-58.64 Information technology

CHAPTER 1: RESEARCH OVERVIEW

1.0 Introduction

This study aims to explore the influence of financial awareness and technological growth on investors to reshape their existing investment strategies. With the rapid evolution of financial technology (FinTech), investors are increasingly exposed to new tools, platforms, and features that can transform traditional investment approaches and may alter the way they approach investment decisions. In this context, the study seeks to understand how well-informed investor about ongoing market trends are, their readiness to embrace new financial technologies and how this awareness influences their strategic choices. The scope of the study is limited to individuals who have prior investment experience, as it focuses on how experienced investors perceive changes in the financial landscape and whether they are inclined to adjust their strategies accordingly. In this study, reshape investment strategies will be the dependent variable, with herding effect, habit, performance expectancy and personal innovativeness in Information Technology (IT) as independent variables, and market sentiment serving as a moderating variable.

1.1 Research Background

In modern days, society as a whole are experiencing a technological revolution, accelerated from the early days of analogy computing to the emergence of the

internet, smartphones, cloud computing, Artificial Intelligence (AI) and blockchain technologies, and these innovations have profoundly changed the way individuals communicate, make decisions and interact with services across all industries, including financial services (Hosseinalizadeh et al., 2022; Alsmadi et al., 2023). Malaysia as an emerging country, has also structured specific plans and phases towards its transformation towards digital economy (Lee, 2023). Notably, the rapid advancement of financial technology has profoundly influenced how people conduct transactions, select investments, and access financial information (Dubey et al., 2023). Alongside financial technology growth, a person's level of financial awareness is also a strong factor impacting how an investor manages their finances (Tang, 2024). Individuals with strong financial awareness possess a greater ability to identify and better perceive information of an investment fraud (Padil, 2022). Despite advancements in Financial Technology (FinTech) and Information Technology (IT) that have made investing more accessible through user-friendly platforms, a significant number of investors still lack adequate financial awareness which makes them more likely to fall into financial difficulties (Alam & Chen, 2021).

Financial awareness is defined as the acknowledgement of an individual's own finances and their own capabilities in managing it, recognizing risks and preventing financial issues (Ardhiani & Panjaitan, 2023). Financial awareness, a component within a broader term of financial literacy along with others such as skills, knowledge, and financial decisions (Dewi, 2022; Onofrei & Paşa, 2022; Yin et al., 2024). Insufficient financial awareness can prevent individuals from utilizing available financial services, as they lack confidence and knowledge about investment options (Aziz & Naima, 2021). Notably, even when individuals possess the necessary financial knowledge, their lack of awareness regarding the importance of responsible financial behaviour, or the presence of overconfidence, may still lead to poor strategic to reshape their investment (Tang, 2024). Looking at Financial Capability and Inclusion Demand Side Survey 2024 by Bank Negara Malaysia, despite an overall increase in financial knowledge over the past nine years from 2015 to 2024 (refer to Figure 1.3) (Bank Negara Malaysia, 2024), but the number of cases of investment scams related to non-existence investment has been

increasing over the past years (refer to Figure 1.2) (Department of Statistics Malaysia, 2024). These statistics along with Tang (2024) prove that financial awareness is the key in identifying financial scams instead of financial literacy. Understanding the extent to which financial awareness influences investment decisions is therefore essential, especially in the context of today's rapidly advancing technological landscape (Panos & Wilson, 2020). Against this backdrop, this study aims to explore how investors reshape their strategies amid technological growth and evolving levels of financial awareness.

The advancement of technology has drastically impacted towards the financial investing environment (Vangala, 2024). Financial technology facilitates broader access to financial services, enhances the efficiency of traditional banking, lowers operational costs, and streamlines regulatory compliance (Jović & Nikolić, 2022). However, in emerging markets such as Vietnam, Myanmar, Indonesia, Malaysia and other ASEAN nations, digital financial inclusion also raises critical concerns regarding risk management. As digital transactions expand, so does the exposure to cyber threats including hacking and malware, which pose risks not only to banks but also to end users (Thach et al., 2021). Cyber risk, which involves the threat of financial losses, operational disruption, or reputational damage due to IT system failures, has emerged as one of the most significant challenges accompanying financial technological advancement (Vučinić & Luburić, 2022). Furthermore, the increasing reliance on AI in financial analysis presents new risks, including concerns over fairness, algorithmic transparency, robustness, and data privacy (Koshiyama et al., 2024). These issues highlight the double-edged nature of technological advancement in finance. In Malaysia, the adoption of FinTech is constrained by financial, regulatory, and cybersecurity concerns, particularly among individuals with limited IT knowledge (Ahmad et al., 2025). As FinTech continues to evolve, the development of an adaptive regulatory framework is essential to safeguard investor protection, ensure market stability, and support sustainable growth (Hamid et al., 2024). Therefore, there is an undermining need for a study to better understand the relationship between financial technology advancement, and its influence upon Malaysian investors.

As an open economy, Malaysia has experienced both global financial booms and through over these past years as a developing country with emerging market (Chan et al., 2024). Within the financial market, an upwards, bullish trend refers to positive effect upon the rising asset prices due to optimistic information and market expectations, while a downward, bearish trend refers to negative effect upon the declining asset prices due to pessimistic information and market expectations (Abbas et al., 2024; Chan et al., 2024). Investors' emotions and psychological states play a crucial role in shaping their judgment as they affect risk perception, distort logical reasoning, and ultimately affect the quality of investment decisions, exposing investors to the risk of losses. (Griffith et al., 2020). In stable markets, positive sentiment boosts liquidity through active trading (Briere et al., 2019), but in times of turmoil, sentiment shifts sharply, causing significant liquidity swings and heightened unpredictability (Naidoo et al., 2025). Therefore, the understanding of market sentiment's impact towards Malaysian investors, particularly in relation to financial awareness and technology advancement is in need for a study.

Malaysia is a developing country with huge development potential and an emerging financial market. However, prior research has tended to overlook how investment strategies respond to changing market sentiments especially in the context of emerging markets and adjust dynamically. In addition, there has been limited exploration of how investor sentiment interacts with technological innovation and financial awareness to influence strategic shifts in investment behaviour. With the sentiment of the nation's market influencing, how will the fast-paced global fintech advancement as well as the degree of investors' financial awareness effect Malaysian investors reshaping of their investment strategies would therefore be the background on this study.

1.2 Research Problem

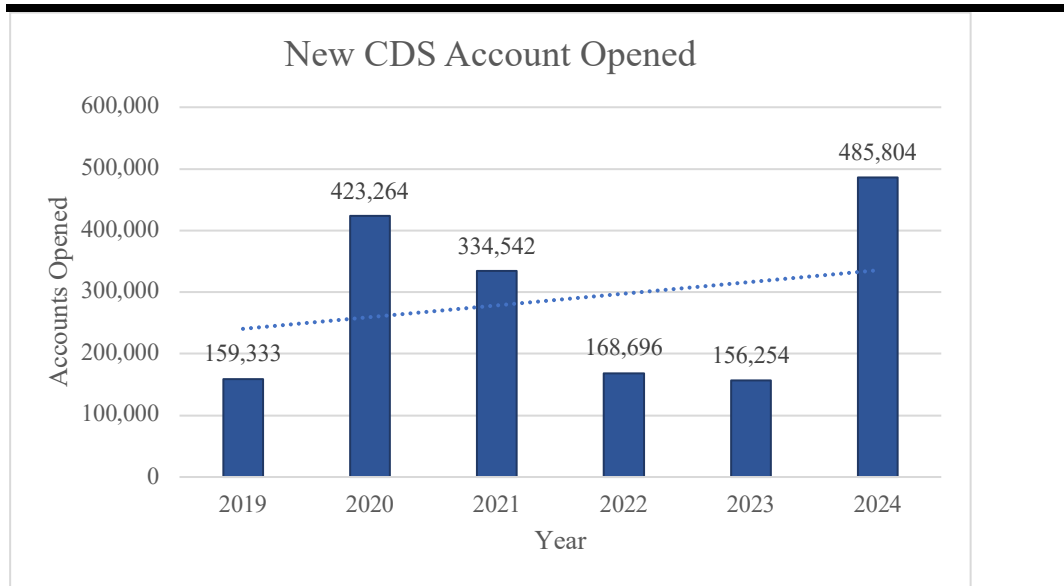


Figure 1.1 New Central Depository System (CDS) Account Opened. Source: Bursa Malaysia (2025).

In today's technology-driven era, anyone can participate in the equity market with just a smartphone and an internet connection (Sembel et al., 2024). Online trading has become widespread, allowing participants to invest anytime and anywhere which provide more accessibility and convenience (Chong et al., 2021; Johri et al., 2023; Shen et al., 2025; Liu et al., 2025). In Malaysia, technological innovation and development, particularly in the investment sector, have significantly increased investor participation in the equity market. Yulius et al. (2023) and Shivani et al. (2022) further declared that young investor is more attracted to involved in equity market with the rise of technology innovation especially in mobile stock investing apps. This trend is evident from the growing number of Central Depository System (CDS) accounts, which are mandatory for investors who wish to trade securities on Bursa Malaysia (Bursa Malaysia, n.d.). As shown in Figure 1.1, although the number of new CDS accounts opened fluctuates annually, at least 100,000 new accounts are registered each year (Bursa Malaysia, 2025). Notably, in 2020, the number of new CDS accounts surged sharply compared to 2019, reached 423,264. This indicates that during the outbreak of COVID-19 period and the technology advancement had increase people's interest and popularity towards stock investment which more people turned to the equity investment sector tend to

advance their financial capability (Ahmed et al., 2022; Wilson et al., 2024). While the number of new accounts declined in the following year, it rose again in 2024, reaching 485,804 highest level in recent years (Bursa Malaysia, 2025). This suggests that more Malaysian are becoming aware of investment opportunities and actively participating in the financial market in recent year. Such growth in market participation has contributed to increased liquidity and volatility in the equity market and has played a role in driving the economy forward (Ozik et al., 2021).

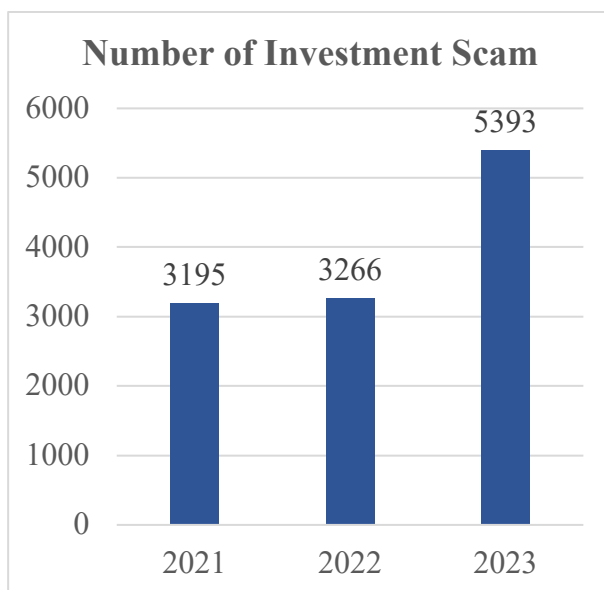


Figure 1.2 Number of Investment Scam. Source: Department of Statistics Malaysia (2024).

However, the technology innovation and surge in market participation has also brought certain risks, particularly for inexperienced investors or investors that lack of financial awareness (Wilson et al., 2024; Ahmad, 2025). Yulius et al. (2023) declared that many newly registered account holders may lack adequate financial awareness and risk management skills, making them more vulnerable to poor investment decisions and fraudulent schemes. This said as they mostly tend to follow the advice of experts or just anyone who claims to have experience in financial matters and stock investing (Rose, 2023; Sembel et al., 2024). Rand et al. (2025) support the statements by further noting that young investors in Malaysia

are more exposed to investment fraud due to their high trading frequency. According to the Department of Statistics Malaysia (DOSM) crime statistics report (2024), investment scams have shown an increasing trend, with 3,159 cases reported in 2021, 3,266 cases in 2022, and 5,393 cases in 2023. Over these years, many unauthorized entities and individuals have emerged under the guise of assisting investors to gain substantial or steady return with low risk (Ullah et al., 2022; DeLiema et al., 2023; Wilson et al., 2024). These schemes are designed to deceive individuals into investing in non-existent or illegitimate ventures, often exploiting the fear of missing out by presenting supposedly rare investment opportunities (Norton, 2022; Ahmad, 2025). This worrying trend highlights the vulnerability of many Malaysian investors, particularly those with low financial awareness, who may place unwarranted trust in such misleading offers without conducting proper due diligence (Badua, 2020).

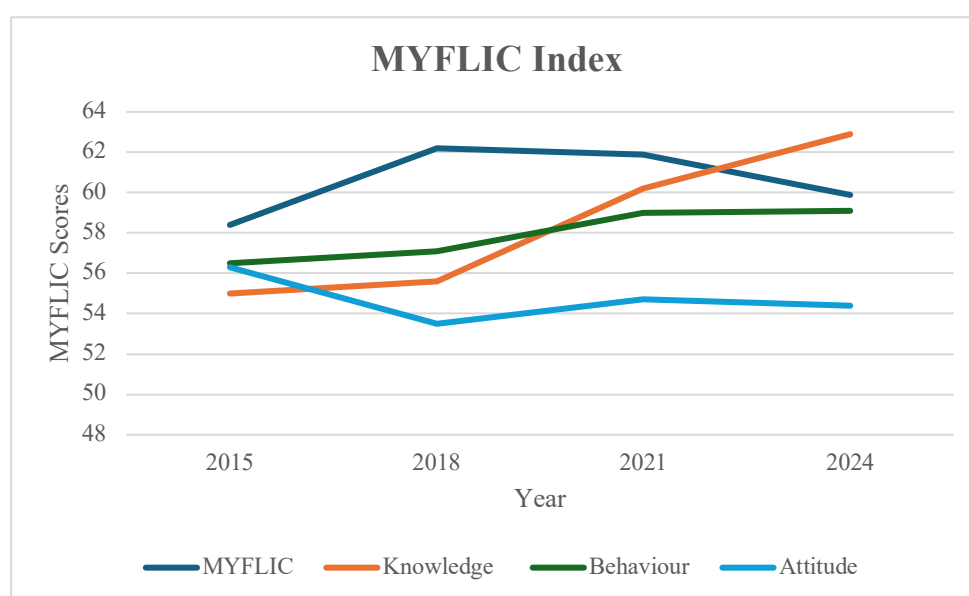


Figure 1.3 MYFLIC Scores. Source: Bank Negara Malaysia (2025).

The financial awareness of Malaysian investors can be reflected in the Malaysia Financial Literacy and Capability (MYFLIC) Index, which is an index that measures financial capability based on knowledge, behavior, and attitude. Research by Alam and Yong (2021) suggested that an overview regarding the degree of

financial literacy among youths in Malaysia has proven a lower level of financial awareness. According to Figure 1.3, the financial knowledge among Malaysians appears to be on an upward trend, but the MYFLIC shows a slight downward movement. This suggests that while individuals may possess more financial knowledge, their overall financial awareness remains low, as they often fail to translate that knowledge into sound decisions or healthy financial habits (Alam & Yong, 2021). Yu et al. (2023) further observed that investors with higher financial literacy are more vulnerable to investment scams. Supporting this, Toong et al. (2024) emphasized that the ability to apply knowledge effectively to recognize and avoid fraudulent schemes is crucial. In addition, Akims et al. (2023) declared that higher level of financial awareness will influence financial decisions, as to protect investor from investment losses. Moreover, the attitude component of the MYFLIC has also declined slightly, indicating that despite greater knowledge, many Malaysians may still adopt short-term, complacent, or overconfident attitudes toward money management. Consistent with Xiao et al. (2022), educated males with overconfidence are more likely to be involved in investment scams, as they believe high returns are guaranteed. As a result, even with sufficient financial knowledge, individuals who lack awareness of the importance of responsible financial behavior, or who display overconfidence, may still adopt ineffective strategies when attempting to reshape their investments (Tang, 2024).

In light of the current challenges faced by the Malaysian market, this study aims to examine how financial awareness and technological growth contribute to reshaping investment strategies, with market sentiment serving as a moderating variable. While numerous previous studies have explored investor decision-making, research on the impact of technological growth on reshaping investment strategies has only begun to increase, as reflected in the works of Vangala (2024), Ablazov et al. (2024) and Ze and Loang (2025) but such studies remain relatively limited. This study is particularly motivated by Almansour et al. (2023) and Vangala (2024), who emphasized the need for an in-depth investigation into reshaping investment strategies within the Malaysian context. Besides that, Nair et al. (2022), Vangala (2024) and Jagirdar and Gupta (2024) also recommended to investigate dive deeper into how technological advancements such as FinTech tools and robo-advisory

reshaping investment behaviors by giving a clearer picture of the changing trends and preferences that influence market. Besides, building on the findings of Hirdinis (2021) and Almansour et al. (2023), this study also examine investors' financial awareness in relation to reshaping investment strategies, with the broader aim of understanding investor behavior. Furthermore, inspired by the recommendations of Rawat (2023), Jagirdar and Gupta (2024), Sarkar and Rajput (2024) and Zainul et al. (2025), this study incorporates market sentiment as a moderator to assess its influence on the relationship between the variables. Shainy et al. (2025) stressed that integrating sentiment indicators into evaluations of market conditions can enhance research accuracy. Similarly, Gong et al. (2022) and Guo et al. (2023) underscored the significant effect of investor sentiment on decision-making in large capital markets. However, its application to emerging markets such as Malaysia remains underexplored, particularly in predicting stock volatility during critical periods, including financial crises.

1.3 Research Objective & Research Question

1.3.1 Research Objective

- i. To investigate the relationship between herding effect, habit, performance expectancy, and personal innovativeness in Information Technology (IT) on the reshaping of investment strategies.
 - ii. To investigate the relationship between herding effect, habit, performance expectancy, and personal innovativeness in Information Technology (IT) on the reshaping of investment strategies with market sentiment as a moderating variable.
 - iii. To investigate whether financial awareness and technology growth will influence investor to reshape investment strategies.
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1.3.2 Research Question

- i. Do any relationship between herding effect, habit, performance expectancy, personal innovativeness in Information Technology (IT) and the reshaping of investment strategies?
- ii. Does market sentiment moderate the relationships between factors such as herding effect, habit, performance expectancy, and personal innovativeness in Information Technology (IT) on reshaping investment strategies?
- iii. Do financial awareness and technology growth influence investor to reshape investment strategies?

1.4 Research Significance

This study aims to examine the impact of financial awareness and technological development on the reshaping of investment strategies under varying market sentiments in Malaysia. By analyzing investors' levels of financial awareness and their use of financial technology, the research explores how these factors drive investors to adjust and reshape their investment strategies. This study adopts Behavioural Finance Theory and the Unified Theory of Acceptance and Use of Technology 3 (UTAUT3) as analytical frameworks, focusing on the roles of herding effect, habit, performance expectancy, personal innovativeness in IT, and market sentiment in influencing investment strategies reshaping. The findings are expected to deepen the understanding of investor behaviour, including emotional and psychological tendencies in the context of technological advancement, and provide valuable insights for reshaping investment strategies in dynamic market environments.

For individual investors, the findings offer critical insights into whether technological advancements meaningfully enhance the efficiency of investment strategies. As financial platforms and tools become increasingly adopted due to habitual use and expectations of improved performance, this research enables investors to assess how such factors influence the effectiveness of their investment decisions. By examining the relationship between behavioural tendencies in technology usage and strategic investment outcomes, the study offers a clearer perspective on how technology-driven developments may reshape investment approaches in line with investor goals, personal preferences, and evolving market conditions.

From a corporate perspective, this research offers valuable insights for firms seeking to attract investors and sustain competitiveness in the market. By gaining deeper understanding of key determinants of investor behaviour such as financial awareness, performance expectations, and market sentiment, companies can refine their communication and disclosure strategies to align more effectively with investor priorities. Furthermore, firms may leverage these insights to enhance their business practices, thereby achieving stronger market positioning and improving ability to secure investment in an increasingly competitive financial environment.

At policy level, this study also provides essential insights for government agencies and regulators seeking to foster responsible investment and financial inclusion. By revealing public attitudes toward technology adoption and investors' financial awareness, the findings support the development of targeted educational initiatives and national strategies. In addition, policymakers are enabled to design more precise and effective intervention to enhance the security, privacy and satisfaction of investor. These efforts help bridge the gap between financial innovation and investor readiness, cultivating a more informed investment environment and strengthening Malaysia's financial ecosystem.

This research contributes to academic literature by deepening the understanding of how financial awareness and technological growth influence investment strategies in Malaysia's evolving financial market. By integrating the Behavioural Finance Theory and Unified Theory of Acceptance and Use of Technology 3 (UTAUT3), it offers a comprehensive framework for examining psychological and behavioural factors that affect investor decision-making. Extending beyond prior studies that focused mainly on decision-making, this research explores how these factors actively reshape investment approaches. The findings also lay a foundation for future studies on the relationship between technological innovation and investment outcomes, refining existing theories and encouraging the development of new frameworks that reflect the changing dynamics of investor behaviour in response to technological advancement and increasing financial awareness.

In conclusion, this research explains how financial awareness and technological growth reshape investment strategies in Malaysia. It contributes to both academic theory and practical insights, offering a foundation for future studies on the integration of technology in investment practices.

1.5 Conclusion

This chapter provides a detailed explanation of the ongoing technological developments worldwide and presents various statistics to support financial awareness, technological growth, and the reshaping of investment strategies in Malaysia. The chapter also addresses the limitations associated with each statistical source and highlights the significance of the study for individual investors, corporations, government bodies, and future research.

CHAPTER 2: LITERATURE REVIEW

2.0 Introduction

This chapter explores various theoretical frameworks and presents a comprehensive literature review covering the dependent variable, independent variables, and the moderating variable. The dependent variable in this study is reshaping investment strategies. Four independent variables are examined which are herding effect, habit, performance expectancy, and personal innovativeness in Information Technology (IT). In addition to investigating the relationships between the independent and dependent variables, this study also explores the interrelationships among the variables, with market sentiment acting as the moderating variable. Following this, the chapter presents the conceptual framework, accompanied by detailed explanations. Finally, the research hypotheses are outlined.

2.1 Underlying Theories

2.1.1 Behavioural Finance Theory

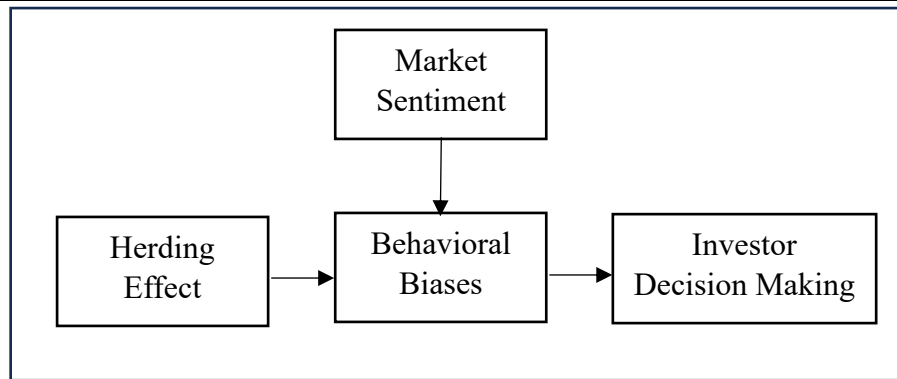


Figure 2.1 Behavioural Finance Theory. Adapted from Kengatharan, L. & Kengatharan, N. (2014).

Behavioural Finance Theory originated from psychological insights into financial decision-making, with Daniel Kahneman and Amos Tversky (1979) introducing Prospect Theory, this challenged traditional financial theories that assume rational decision making. In 1992, Banerjee published a paper titled "A simple Model of Herd Behavior", which formally proposed that the herd effect has a significant impact on behavioural finance and has become an important branch of Behavioural Finance Theory (Banerjee, 1992). Subsequently, Bikhchandani et al. (1992) expended on this concept, explaining how individuals make investments decisions based on the behaviour of other rather than their own information, further enriching and developing the concept. Furthermore, Shiller (2015) published papers to explores speculative bubbles and irrational market exuberance, further explores the bond between psychological factors in financial decision-making. Investor sentiment is an important area in the theoretical filed of behavioural finance such as, high investor sentiment could also lead to behavioural biases due to overconfidence (Odean, 1998). Market sentiment is crucial as it represents investors' collective emotions and frequently thus it could seem as influence behavioural in decision making (Liutvinavicius et al., 2020). These studies collectively enriched and developed Behavioural Finance Theory.

2.1.2 Technology Acceptance Model

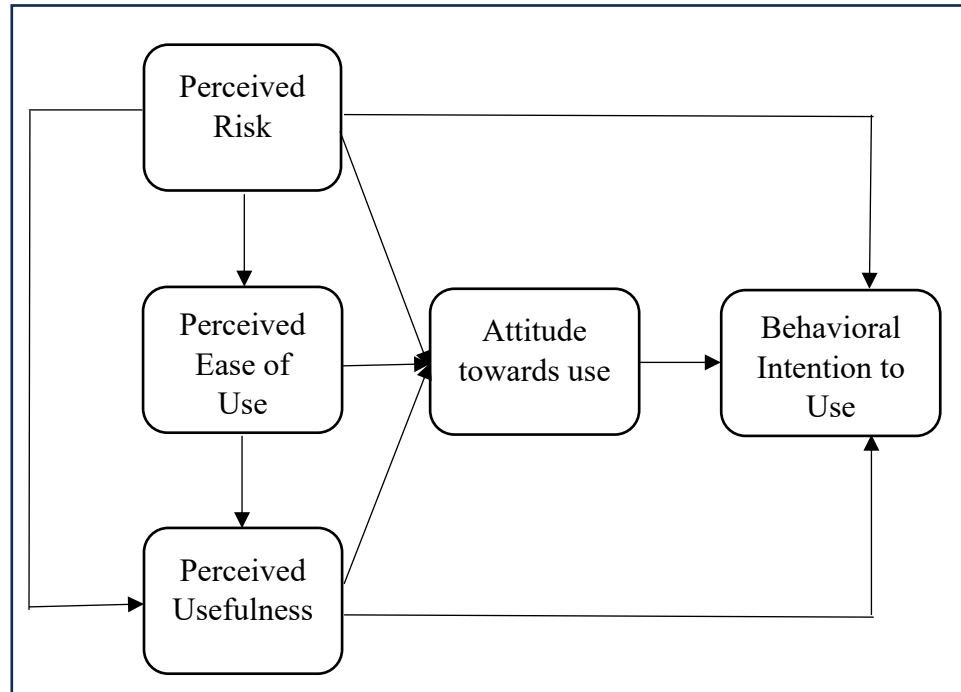


Figure 2.2 Technology Acceptance Model (TAM). Adapted from Lu, H., Hsu, C., & Hsu, H. (2005).

Rooted in the Theory of Reasoned Action (TRA), the Technology Acceptance Model (TAM) is a concise and specific framework developed by Davis (1989) to predict and explain the adoption of information technology in work settings. The primary objective of TAM is to identify the key determinants of computer acceptance among users. To achieve this, TAM replaces TRA's attitude beliefs construct with Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) (Benbasat & Barki, 2007). Research by Hu et al. (2015) indicates that Perceived Ease of Use (PEOU) influences both attitude and Perceived Usefulness (PU). Further extending TAM, Featherman and Fuller (2003) found that Perceived Risk (PR) significantly affects both PU and PEOU, ultimately impacting the intention to use technology. Additionally, attitude is shaped by PEOU, PU, and PR,

which together determine users' adoption intentions (Xie et al., 2017). Building upon TAM, the Unified Theory of Acceptance and Use of Technology (UTAUT) was introduced by Venkatesh et al. (2003). UTAUT refines and expands TAM by incorporating additional constructs derived from a comparative analysis of multiple technology acceptance models (Ammenwerth, 2019).

2.1.3 Unified Theory of Acceptance and Use of Technology (UTAUT 3)

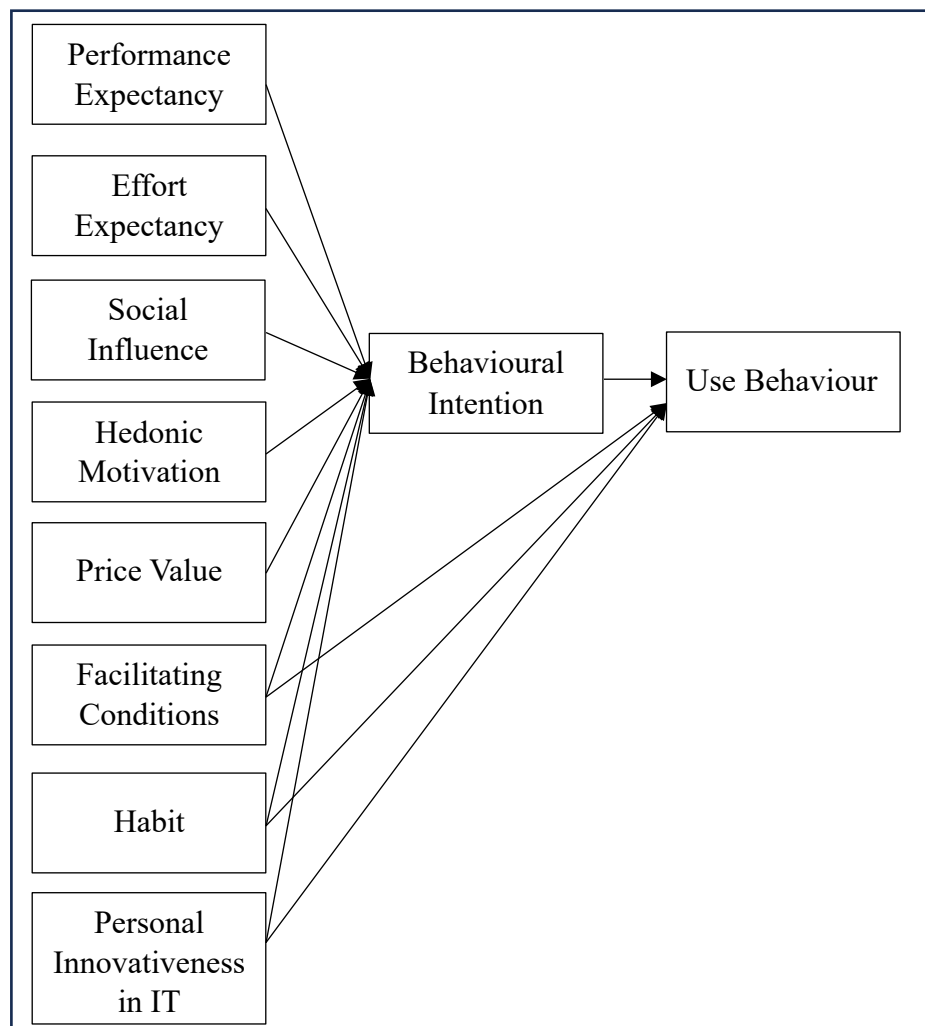


Figure 2.3 Unified Theory of Acceptance and Use of Technology (UTAUT 3). Adapted from Farooq, M. S., Salam, M., Jaafar, N., Fayolle, A., Ayupp, K., Radovic-Markovic, M., & Sajid, A. (2017).

Drawing on several established technology acceptance models including the Technology Acceptance Model (TAM), Innovation Diffusion Theory (IDT), and the Unified Theory of Acceptance and Use of Technology (UTAUT), recent research has shown that academic staff demonstrate relatively low explanatory power, ranging from 17% to 53% in the adoption of new technologies (Dwivedi et al., 2017). The UTAUT and UTAUT 2 models have since been expanded into the UTAUT 3 model, which incorporates additional variables to enhance the analysis of technology adoption (Salman, 2024). Farooq et al. (2017) developed the UTAUT 3 framework by integrating eight key factors influencing technology acceptance including Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Habit (HB), Hedonic Motivation (HM), Price Value (PV), and Personal Innovativeness in Information Technology (PI). Figure 2.2 illustrates the UTAUT 3 model structure as proposed by Farooq et al. (2017). Numerous studies have selected UTAUT 3 as a suitable and comprehensive model, as it encompasses all original UTAUT predictors along with the newly introduced factor of personal innovativeness in IT (Gunasinghe, 2020; Gupta et al., 2023). As a result, UTAUT 3 is considered the most complete model to date, with an explanatory power of up to 66% in predicting technology adoption (Akbar, 2021).

2.2 Review of Variables

2.2.1 Reshape Investment Strategies (Dependent Variable)

Reshaping investment strategies can be defined as the process by which investors modify or adjust their existing approaches. This process involves adapting and rearranging how retail investors allocate resources, diversify assets, and manage portfolios to align with emerging risks, opportunities, and realities (Ali, 2024). An individual investor is one who allocates money or resources into financial instruments, assets, or businesses with the expectation of generating profit or future returns (Cunha, 2021). Individual investors often develop their own strategies based on personal objectives, risk tolerance, preferences and needs, which play an essential role in guiding their decisions (Phan, 2023). Yet, Demirel et al. (2022) demonstrated that no single strategy can guarantee consistent returns, particularly in today's volatile environment where conditions may change at any moment. To cope with uncertainties such as financial crises, shifts in national policies, or fluctuations in the broader economic environment, investors are compelled to continually reshape their strategies in order to minimize risks (Flammer & Ioannou, 2021; Chandrakala et al., 2024; Challoumic, 2024). Singh (2025) further highlighted that historically, the reshaping of investment strategies has been shaped predominantly by the interplay of human intuition, rigorous fundamental analysis, and the application of relatively rudimentary quantitative methodologies, which collectively guided reshaping processes.

Market uncertainty can be driven by multiple factors, including changes in market conditions, economic trends, laws and regulations, as well as unexpected emergencies (Tao & Gupta, 2022). Demirel et al. (2022) noted that fluctuations in the equity market expose investors to various forms of risk that may result in financial losses and diminish their overall rate of return. Therefore, some investors driven by the universal preference for high returns with minimal risk and the aspiration for wealth, continuously adjust and reshape their strategies in response to prevailing market conditions in order to maximize returns and mitigate risks under different economic

environments (Zhang & He, 2023). However, investors vary in terms of their risk profiles, investment objectives, individual trading behaviors, and overall motives and preferences, influence how they react and behave when making investment decisions (Petukhina et al., 2021; Phan, 2023). This is further supported by Pakarinen (2021) and Swaraj and Shubhada (2024) who revealed that even under the same market conditions, investors reshape their strategies differently due to variations in backgrounds, capital, goals, as well as uneven access to market information. Consequently, market factors act as essential drivers that may influence investors to reshape their strategies (Flammer & Ioannou, 2021). Investor may either alter asset allocations or employ assistive tools like robo-advisory in order to better align with prevailing economic conditions (Challoumis, 2024).

Gupta and Rao (2025) highlighted insights from behavioral finance, which indicate that investment strategies are not solely influenced by prevailing economic conditions but also shaped by psychological and behavioral factors. This view is supported by Padmavathy (2024) who emphasized that investors' behaviors are often unpredictable and dynamic which significantly affect in reshaping of investment strategies. Traditional financial theory assumes that investors are always rational in their investment decision, believing that they evaluate all possible outcomes and choose the option that maximizes their utility under given constraints (Kamoune & Ibenrissoul, 2022; Arran, 2023). However, as markets evolve and research advances, many scholars found that investors are not always rational; rather they are influenced by cognitive biases, emotional responses and often have a limited understanding of their own strategies (Pakarinen, 2021; Tahir & Danarsari, 2023). Furthermore, investors frequently rely on cognitive shortcuts rather than purely rational processes to manage the overwhelming volume of information, particularly when reshaping their strategies in complex and rapidly changing contexts such as unstable markets (Xing, 2025). As a result, financial awareness plays a significant role in strengthening the process of reshaping investment strategies, thereby reducing the likelihood of investment losses (Almansour et al., 2023).

Over time, behavioral finance has evolved into a prominent paradigm in modern financial research, transforming traditional finance by incorporating psychological factors to examine the ways in which investor behavior shapes investment strategies (Cevik et al., 2022). Moreover, as scholars delve deeper into Behavioural Finance Theory, many branches of psychology have proven there have significant including mental accounting, time preference and self-control, regret aversion and disposition effect, disappointment theory, cognitive dissonance, money illusion, availability heuristic, representative heuristic, overconfidence, anchoring and adjustment, ambiguity aversion, ostrich effect and herding effect (Hon et al., 2021; Ogunlusi & Obademi, 2021). Behavioral finance posits that investor behavior is often shaped by emotions and cognitive psychology rather than purely rational economic reasoning (Zik-Rullahi et al., 2023; Sengupta & Mitra, 2023). Consequently, investors may rely on imperfect heuristics, preconceived notions, and bias-driven beliefs, which can distort their interpretation of information and result in the adoption of strategies misaligned with the prevailing economic environment, even when the underlying information is accurate (Phan et al., 2023).

Today's advancements in technology have greatly facilitated access to market information which enabling investors to adjust their strategy more frequently and prudently (Stanley et al., 2024). Ze and Loang (2025) and Li et al. (2024) illustrated that technological innovation and Artificial Intelligence (AI) have become crucial elements influencing investment strategies, particularly in emerging markets where rapid transformations present both opportunities and risks. Financial Technology (FinTech), as a core area of technological innovation, integrates financial services with technology, thereby significantly enhancing consumer engagement and trading activities through FinTech platforms (Giglio, 2021). Moreover, AI is capable of processing vast volumes of data at unprecedented speeds and identifying patterns or trends that might be overlooked by human analysts

which provides more accurate forecasts and deeper market insights, motivating investors to reshape their investment strategies (Onabowale, 2024; Upadhyay & Gadam, 2024). Koesoemasari et al. (2022) further depicts that some investors even reshape their investment strategies on a weekly basis by reviewing their portfolios to ensure better alignment with market conditions.

Given the growing influence of FinTech and AI on investment behaviour, understanding how investors adopt and integrate these technologies to reshape their investment strategies becomes essential (Abdeldayem & Aldulaimi, 2025; Nair, 2024; Upadhyay & Gadam, 2024). The Unified Theory of Acceptance and Use of Technology 3 (UTAUT3) which is widely researched and helpful in predicting how investor adopt new technologies like FinTech or robo-advisory to reshape their investment strategies (Aliu, 2024). The TAM model serves as the foundation for UTAUT, which is enhanced by incorporating social influence and positive factors, emphasizing four key concepts includes performance expectancy, effort expectancy, social characteristics, and enabling behavior (Dash et al., 2023). In order to enhance the explanation of UTAUT in technology usage behavior of user, Venkatesh et al. (2012) introduced the UTAUT 2 by including three more constructs, namely, hedonic motivation, price value and habit which supported by Rudhumbu (2022). The UTAUT 3 model is an extension of UTAUT 2 by introduces personal innovativeness in IT as a new feature, identifying it as a key predictor that provides a more comprehensive explanation of technology adoption behavior (Bhatnagr & Rajesh, 2024). Thus, the UTAUT 3 model is deemed suitable for adoption in examining how investors reshape their investment strategies using FinTech or AI (Augusto & Pinto, 2025).

As a result, investors' strategies are shaped by the combined effects behavioral finance influences, and technological developments. While traditional finance assumes rationality, behavioral finance highlights the

impact of cognitive biases, heuristics and herding effect, which often drive strategy reshaping in response to uncertainty. The rapid growth of FinTech and AI has further transformed investment practices by enabling faster information processing, improved market insights, and reshape the investment strategies. Models such as UTAUT 3 provide a useful framework for understanding how investors adopt these technologies, emphasizing factors like habit, performance expectancy and personal innovativeness in IT in shaping strategies adjustments.

2.2.2 Herding Effect (Independent Variable)

Herding effect within Behavioral Finance Theory refers to the specified scenario whereby investors give up on their convictions and instead choose to “move with the market” or to “follow the general market trend”, believing that this action will obtain access profits (Almansour et al., 2023). It is a phenomenon that happens when one loses the capability to conduct informed and conscious choice and believes that others “knows better” in comparison than they are and that their actions are better. As a result, they blindly follow the dominant, mimicking herd behavior (Ali & Amir, 2024). Many experts believe that the herding effect is pervasive and not at all rare among institutional and individual investors in the capital market and is often identified as the primary cause of market volatility and instability (Komalasari et al., 2022; Mand et al., 2023). Hon et al. (2021) suggested that this specified effect is manifested due to the human nature of investors’ low-risk inclination or risk-avoidance, motivated by their desire to reduce the chances of financial loss. In fact, trading techniques like the momentum investing strategy are developed as a direct result of herd behaviour in financial markets. Similar suggestions have also been made by Pham et al. (2023) that businesses and enterprises may utilize this behaviour to pique customers’ attention and manipulate the market into buying their goods.

Herding effect can clearly signifies investors' level of financial awareness in their investments decisions process. Financial awareness is a crucial dimension regarding one's financial wellbeing (Alshebami & Marri, 2022). Investors' awareness and their interpretations of investment information ensures the ability of theirs to conduct prudence, interpreted, effective decisions and eliminate irrational actions to obtain the desired profit (Suresh, 2024). Satsangi and Jain (2023) demonstrated that fintech applications and tools have brought along beneficial influence towards the increases of financial awareness among the studies' participants. This simultaneously indicates technological growth has played a significant role in increasing individual's financial awareness, alongside the achieves of better investment outcomes. Similarly, Akims et al. (2023) as well as Almansour et al. (2023) studies suggest that investors' decisions are influenced by their financial awareness, therefore showing the importance of increasing financial awareness in order to reduce investment losses and underlying social costs due to biased decisions such as herding effect. Consequently it could be concluded that the higher level of awareness and literacy, the lower the probability of irrational investment decisions such as herding effect, suggesting that aware investors are likely to make decisions based on objective reality facts rather than perceptions like herding effect (Wijaya et al., 2023; Matveeva et al., 2024).

According to Loang and Ahamad (2021), the herding effect seen among investors in the market is due to the volatility of the market. As the global financial landscape evolve with the advancement of technologies in the market, it is often required for investors to make quick investment decision to avoid missing out on investment opportunities within shorter period of time (Zhang et al., 2021). On the other hand, investors may not have the capacity to process all of the information, leading to the ignorance of some information when making investment decisions with only limited information to be taken into consideration (Alharbi & Hamid, 2024).

Furthermore, the reduction in timespan dedicated towards the decision-making of individual investment (Linn et al., 2024) is also another contributing factor, along with the mentioned ignorance of information, towards the occurrence of herding effect among investors. An example to help illustrate would be during times of political instability, Gavriilidis et al. (2024) proved that institutional investors are affected and tends to herd during times of political uncertainty. A recent close-to-date example of turbulent time would be the US-China trade war. Various tariffs and policies were taken effects and this causes the constant releases of all sorts of news into the capital market, causing volatility and extreme momentums in the market and leading to an active reaction effect towards market situation and causes herding behaviour on a regular basis by the investors (Nguyen et al., 2025). Notably, market sentiment typically exhibits persistence over time (Chan et al., 2024), whereas the herding effect lacks this characteristic, as it may arise during both prolonged events and short-term periods (Ng et al., 2022). This suggests that market sentiment does not necessarily impact towards herding effect (Loang, 2025). Loang and Ahmad (2021) supported this view and further illustrated that the occurrence of the herding effect is largely attributable to market volatility and is not confined to a specific timespan.

A study in 2021 focusing in the Jakarta area during the COVID-19 pandemic, herding effect significantly and favourably influences the financial choices made by investors, implying that investors in the Jakarta region may make more judgements about their investments as a result of the rise in investor herding behaviour and further suggests the positive relationship between the herding effect and investors' decision-making (Hirdinis, 2021). Another study in Vietnam stock market has suggested that herding effect not only effect the decision-making, but also brings positive impact onto the investors' relative investment performances in the stock market (Cao et al., 2021). Similar phenomenon can be observed in the investors from Indonesia. Results from the study, using Behavioural Finance Theory approach, suggests that when investors are forced upon to conduct an investment

decision, investors often overlook their own capability and rely greatly on other investors who are considered as skilful in investment analysis (Rahayu et al., 2021). In other words, people feel protected and think it might be safer when they join a throng. Therefore, people are more likely to be swayed by the opinions of those around them (Pham et al., 2023). Herding behaviour is therefore suggested to have positive significance towards investment decision-making by these studies (Nareswari et al., 2021).

Although, the opposite is not at all in non-existence. According to Prasetyo and Ratnawati (2023), a study focusing on Kediri City's Generation Z investors suggest that they do not follow the crowd when it comes to making their investment decisions. The study also suggests that the investors rely more towards the business financial data and fundamental analysis instead of basing their choices on the opinions and beliefs of brokers, nor other investors. According to Firdaus et al. (2022), a study at Jakarta concluded that the students in Mercu Buana University's Faculty of Economics and Business are not influenced by herding bias while making investing decisions. According to Nurbarani and Soepriyanto (2022), it also suggests that herd behaviour has no significant effect on investment decisions in cryptocurrency in the Greater Jakarta area. According to Ranaweera and Kawshala (2022), the study based on Colombo Stock Exchange even suggests that despite the influence was favourable, the data did not show that herding effect had a major impact and is insignificant on investment decision-making.

In conclusion, herding effect is a common psychological phenomenon that is commonly observed within active investors around the globe. This study considers the effect on governmental statements and macroeconomic conditions. Despite the fact that multiple studies suggesting that the impact is significant, there are also equally multiple studies that oppose the results. The differences between results among the studies that are being looked into, and this may be due to the differences between the geographical locations

and even age. These studies might have less accuracy for the targeted respondents of this study, which is Malaysian investors over the age of 18. Since the previous studies only focuses on decision making in investment, this study acts as an attempt to further explain the leading of this into the reshaping in investment strategies.

2.2.3 Habit (Independent Variable)

The word “habit” itself has been defined in a variety of ways. Under the UTAUT3 Model, habit is the degree to which one acts in an unconscious and automated manner due to accumulations of past experiences (Gunasinghe et al., 2020). Studies has shown that once a habit is formed, which takes an estimated span of 60 days, it continues to act as the main driver for behaviour regardless of the initial motives (Ambalov, 2021; Wood et al., 2022). Experience is a part among which creates a habit, but experience alone is not enough, as habit establish a mental commitment to a specified act together with the prevention of the alteration of the act (Gunasinghe et al., 2020). In general, as time and experience increase, habit eliminates intention as a predictor (Venkatesh et al., 2023). Study demonstrates that in investment market, investment experience possesses greater impact as compared to financial literacy (Zhao & Zhang, 2021). Initially, the act of directly experiencing a new behaviour tends to strengthen an individual’s overall attitude towards that behaviour, thereby making attitude the primary driving force behind its execution and repetition. However, over the long term, the impact of attitude gradually diminishes, and instead, habit begins to emerge as the dominant factor in shaping and determining one’s actions (Verplanken & Orbell, 2022).

In the most up-to-date phase of financial technology, financial solutions such as decentralised finance and Artificial Intelligence (AI) are deemed as

the driving force of financial development, and the global financial system has benefited and expanded with more digitisation and automation (Jafri et al., 2025). According to Ramadugu and Doddipatla (2022), with the advancement of financial technology, around 62% of the FinTech stakeholders of the study in North America suggests that they have developed reliance towards AI to improve their operational efficiency. As FinTech develops, investors also develop habit and are used to rely on the usage towards these technologies. In this regard, the concept of path dependency becomes particularly relevant. Path dependency, which was initially developed and widely applied within the field of institutions, has also found important applications in the domain of microeconomics (Barnes et al., 2022). Rooted in the idea that historical processes matter, path dependency emphasizes that the current state of a behaviour, process, or system is not independent, but rather significantly shaped and constrained by its past developments, previous experiences, and earlier decisions made along the way (Simoens et al., 2022).

In today's world, the common possession of smartphones and popularization of social media accelerates the spreading of information and investors are reviewing more information than ever (Zhang et al., 2022; Kumari et al., 2025). The continuous need for investors to process such volume of information is overwhelming (Bernales et al., 2024) and fatiguing towards investors, reducing their capabilities to properly interpret information (Eissa et al., 2024). However, results from Back et al. (2021) suggests that the using of robo-advisory helps reduce the discomfort caused by financial losses. As investors build habit for the usage of AI tools, the usage on them for investment strategy becomes a second nature for them. This leads to the dependence on investors for their formation of investment strategy, and this form of over-reliance may even lead to potential risks such as data security and lacking transparency (Kumar, 2020). Nevertheless, the habit of utilizing fintech leads to the reliance on it for more investment strategy, causing continuous re-adopt of financial technology (Saraswati et al., 2023) and having constant impact on investors' strategy. In fact, according to Back et

al. (2021), since such decisions have been found to be taken with reference on past experiences of one (Thakkar, 2021), due to accumulations of past experiences, a phenomenon might surface referred to as “confirmation bias”, which has been used to describe a number of different ways that expectations and beliefs might affect how evidence is chosen, retained, and assessed (Peters, 2022). In simpler words, when people only see what they want to see, it makes conversation harder and can lead to extremism and polarisation (Vedejová & Čavojová, 2022). As a result, the easing of cognitive strain in making investment decision (Friedman, 2023) given by investors’ habit also limits their flexibility to adjust with the market, leading to potential missing of investment opportunities (Singhal, 2023).

Several researches has demonstrated a strong and significant correlation between habit and investment decision-making. According to the results from Sonkar et al. (2023) and Arsyianti et al. (2023), both studies reveal that habit is a significant variable in influencing the investment behaviour of investors. Sonkar et al. (2023) suggests that habit is a significant variable in determining the intention of investors in adopting and utilizing newer financial technologies in India. Furthermore, Arsyianti et al. (2023) also proved that habit shows a result of positive as well as significant impact towards investment behaviour. These long-term investments demonstrate a significant phenomenon of path-dependency, suggesting the lack of flexibility due to the psychological commitment to a specific development path and reduced future options available for the adjustments towards unexpected changes (Haasnoot et al., 2020). Similarly, Sourirajan and Perumandla (2022) study suggests that even after adjusting for investors’ intentions and behavioural control, the result demonstrates that investing behaviours remain driven mostly by habit while the intentions to invest are also influenced by good emotions, expected regret and aspirations. Although limited, studies that suggest insignificant do exist. According to Amudha and Chander (2024), a study in Chennai in 2024 had a different discovery that there is no significance relationship between investment decisions and confirmation bias. According to Goswami et al. (2025), habit is shown to

have insignificant impact towards the adoption and integration of financial technology into financial services, opposing result against Sonkar et al. (2023).

In conclusion, there is both sides of studies suggesting that there are significance and insignificance relationship between habit and investment decision-making. A clear indication of trend suggests that habit will significantly affect decision-making, despite fewer numerous opposite examples, showing signs of insignificance. It is important to acknowledge that despite the previous studies relevance to measures significances of habit against investment decision-making, the studies failed to determine and further expand into discussion of whether habit will affect the decision-making to reshape investment strategies, which is what this study will attempt to answer and develop upon this blank field. The focus is not to see if habit will affect whether the decision to invest, but whether or not if the made investment strategies and decisions will be reshaped. The study considers the relationships between habit development and examples of phenomena including path dependency. Therefore, this study aims to determine does habit of Malaysia investor whose above 18 will influence their investment strategies reshaping process to gain or prudence in the financial markets especially in this face of technological growth in today's world.

2.2.4 Performance Expectancy (Independent Variable)

Performance expectancy refers to the extent to which an individual believes that using a particular information system or technology will enhance their efficiency and effectiveness in achieving desired outcomes which widely agreed by various studies such as Gunasinghe et al. (2019), Ashari and Zin (2023) and Priantinah et al. (2025). It reflects the perception that the system

contributes to improved performance and productivity (Wang & Ma, 2023). Mehra et al. (2022), Chao and Chen (2023) and Priantinah et al. (2025) explored that performance expectancy is a key factor influencing users' behavioral intention to adopt technology. According to Almetere et al. (2020), consumers are more likely to use technology when they perceive it as beneficial and capable of enhancing their performance. Therefore, for high-tech services to be considered valuable and effective, they must provide necessary function or economic benefits while ensuring convenience and a user-friendly experience (Ali et al., 2021). Similarly, when investors experienced positive user experience from the technology, they will be more inclined to adopt and continue to utilize it (Ks & Antony, 2024). Conversely, if the technology or service fails to meet user expectations, it may negatively impact consumers' willingness to adopt it (Zainavy et al., 2023).

The performance expectancy of investors for reshaping investment strategies is strongly reflected in the use of Financial Technology (FinTech). As an emerging industry, FinTech showcases the advancement of global technology by seamlessly integrating information technology with financial services to provide more efficient and effective financial solutions (Nainggolan & Handayani, 2023; Anand & Abhilash, 2022; Ashari & Zin, 2023; Cheong et al., 2023). Ali et al. (2021) highlighted that the growth of FinTech has fueled the expansion of technology-driven financial services, particularly investment trading applications. Anand and Abhilash (2022), Arfina et al. (2023) and Johri et al. (2023) declared that online trading application is included as one of the FinTech product and these applications have revolutionized how investors buy and sell assets, significantly enhancing trading efficiency and convenience. According to Nainggolan and Handayani (2023) an effective trading app should offer advanced features tailored to investors' needs. These include offering wide range of financial products, low trading fees, real-time financial information, detailed financial reports, algorithmic trading, charting tools for market analysis, automated order execution, fair value price computation, and

personalized product recommendations. Malhotra (2020) also declared that the key features of trading application had increased the number of retail investors to adopt it and investment analysis information is one of the important features that will influence investor intention to use trading app.

Stanley et al. (2024) and Johri et al. (2023) indicated that such trading application's features not only facilitate trading but also improve decision-making processes. Santur et al. (2022) study shows that trading application has promoted fundamental analysis which is an approach based on the ratio announced quarterly that enable investor to evaluate share prices with internal valuation methods. This had been supported by Bustani et al. (2021) and Sari et al. (2022) with further emphasize that fundamental analysis with financial ratios is crucial for investor as a main foundation to familiar with company's financial condition before determining investment decisions. Besides that, Gardi et al. (2021) also had declared that financial accounting report is major for corporate's management decision making by tracking all financial transaction. Bustani et al. (2021) and Gardi et al. (2021) showed that Earning Per Share (EPS), Price to Book Value (PBV), Dividend Payout Ratio (DPR), Price to Earnings ratio (P/E), and market Price-to-Book value (P/B) ratio are crucial index for fundamental analysis. Moreover, Sari et al. (2022) further demonstrated that fundamental analysis encompasses not only the examination of financial ratios but also an in-depth evaluation of a company's financial statements, earnings growth, cash flow, and overall business prospects. Furthermore, prospective investor with limited technical expertise is more likely to adopt trading platforms, as these features enhance their proficiency and enable more rational investment decisions (Bhatnagr & Rajesh, 2024). Besides, Ali et al. (2021) concluded that Fintech's benefits play an important role in motivating an user's intention to adopt the online trading application.

According to past studies, there are mixed results regarding the impact of performance expectancy on reshaping investment strategies. Priyadarshi et

al. (2024) stated that performance expectancy in FinTech applications has a largely beneficial influence on investor decision-making. The emergence of FinTech applications enhance decision-making processes and democratize investors' access to investment opportunities. Mascarenhas et al. (2021) also illustrated that when investor felt that trading platform providing benefit for them, they will continuously adopt FinTech application. Similarly, Esawe (2022) found that performance expectancy significantly influences consumers' behavioral intention to use FinTech products such as e-wallets, as they help save time and make transactions more efficient. This finding is supported by Anand and Abhilash (2022), who demonstrated a significant relationship between performance expectancy and investors' behavioral intention to use trading applications. Additionally, Chen et al. (2023) concluded that FinTech adoption and customers' intention to use it influence investor decision-making through theoretical analysis. Meanwhile, Shivani et al. (2022), Srivastav et al. (2024) and Sembel et al. (2024) also substantiate that there is significant impact of mobile stock investment application platforms on investment choice decision. In conclusion, when FinTech applications meet investor expectations, they are more likely to utilize the technology and leverage the information provided by these platforms to thoroughly evaluate their investment options before making a final decision.

However, some studies have presented differing views on the impact of performance expectancy on investor decision-making. Priantinah et al. (2025) study shows that performance expectancy is negative and insignificant impact on behavioural intention to use application due to users may not yet fully perceive the benefits of the application in improving their business performance. Besides that, Xu et al. (2022) also declared that performance expectation had less influence on intention to buy financial products as users may be no exposure and no experience to internet financial products. Furthermore, Raja and Thenmozhi (2020) and Nazim et al. (2021) concluded that the performance expectancy is insignificant to influence the

intention to adopt blockchain technology as unable to enhance the bankers' performance and productivity in their jobs.

In summary, there are inconsistent findings regarding the relationship between performance expectancy and reshape investment strategies. Some studies suggest that performance expectancy significantly influences the process of strategy reshaping, as investors who perceive trading applications as beneficial and informative are more likely to incorporate them into their investment decisions. Conversely, other studies argue that performance expectancy does not directly affect investment decisions, as not all users are able to fully utilize the features provided by FinTech, thereby limiting its direct impact on investor choices. Therefore, this study seek to further investigate this relationship to provide a clearer understanding of how performance expectancy influencing investors' decision in reshaping their investment strategies.

2.2.5 Personal Innovativeness in Information Technology (Independent Variable)

Personal innovativeness in Information Technology (IT) is an additional predictor in the extension of the UTAUT 2 model to UTAUT 3 (Farooq et al., 2017; Gunasinghe et al., 2020; Kamalasena & Sirisena, 2021; Awdziej et al., 2024). Personal innovativeness in IT refers to an individual's willingness to experiment with new Information Technology, as defined by Agarwal and Prasad (1998). This statement is in line with Amid and Din (2021) and Ciftci et al. (2021) who declared that personal innovativeness in IT domain also reflect one's tendency to explore and adopt with emerging new information technology developments or innovative tool. Unlike other UTAUT predictors, personal innovativeness in IT does not focus on the performance or benefits of the technology itself. Instead, it emphasizes the

user's intrinsic traits and openness to innovation. This perspective is declared by Farooq et al. (2017) who identified personal innovativeness as a stable personality trait that drives individuals to explore and adopt emerging technologies which had widely supported by various research such as Twum et al. (2022).

Individuals with higher levels of personal innovativeness in IT are more likely to develop an awareness of technological innovation and demonstrate a stronger intention to adopt new technologies (Flavián et al., 2022; Nguyen et al., 2021; Kandoth & Shekhar, 2022). This said as individuals possessing a higher degree of personal innovativeness in IT are less reliant on positive perceptions than those with lower innovativeness (Twum et al., 2022). This was support by Alkawsi et al. (2021) and provide further indication that individuals with higher innovativeness are better equipped to form positive attitudes toward the anticipated use of innovative technologies than their less innovative counterparts. Therefore, highly innovative investors, often categorized as early adopters, tend to be risk-takers who exhibit a strong willingness and enthusiasm to explore emerging technologies, even before they achieve widespread public adoption (Kandoth & Shekhar, 2022). Twum et al. (2022) further elaborate that innovative investor tend to be more capable of overcoming the technical complexities associated with new technologies compared to less innovative individuals. According to Salvi et al. (2024) and Sun et al. (2020) studies, both of them emphasized that an investor's proactiveness and openness to new experiences play a crucial role in investment decision-making. This said as investors with high personal innovativeness tend to have greater trust in technology, making them more willing to adopt emerging financial technologies and investment instruments to enjoy the advancement and meet market faster than others to enhance their competitiveness (Cheong et al., 2023; Eren 2023; Cao et al., 2025).

Investor personal innovativeness in IT for reshaping investment strategies could be strongly reflected in the use of robo-advisory. Robo-advisory, an AI-powered financial service which utilizes automated algorithms to provide investors with automated financial planning and investment management (Kumar, 2020; Tao et al., 2021). Yeh et al. (2023) demonstrated that robo-advisory had become the widely used by investors to assist investor in formulate efficiently diversified investment portfolios in this modern society. Omopariola and Aboaba (2021) and Eren (2023) support with encounter that robo-advisory as recent most up-to-date innovations in the financial world. This said as the financial investment service provided by robo-advisory has evolved into a fully automated advisor without human intervention (Cheong et al., 2023). Wang and Ma (2023) further defined robo-advisory as an intelligent investment advisor and highlighting its ability to offer data-driven investment recommendations. This was supported by Kumar (2020), Vangala (2024) and Onabowale (2024) which demonstrated that innovative investor are more trust and reliable in robo-advisory's algorithmic capabilities and its data-driven strategies and analytical approaches with data-backed recommendations tailored to investors' preferences. Eren (2023) further illustrated that innovative investor had greater trust on robo-advisory. Therefore, investors with higher personal innovativeness will leverage robo-advisory's automated investment advisory services, as these services rely on big data, artificial intelligence, and other modern technologies to optimize investment decisions (Bartram et al., 2020; Shen et al., 2025). Furthermore, robo-advisory are able tailored investment strategies with investor need and preferences, risk tolerance, financial goals, and investment horizon as well as any unique characteristic by providing personalized well diversified investment portfolio for investor (Kumar, 2020; Zhang et al., 2021; Khosravi, 2024; Vangala, 2024; Shen et al., 2025; Baboo & Imran, 2025).

According to past studies, the impact of personal innovativeness in Information Technology (IT) on reshaping investment strategies has produced mixed results. Salvi et al. (2024) found that an investor's degree

of IT innovativeness significantly influences individual investment decisions. This finding is further supported by Syed and Janamolla (2024), who highlighted that AI-driven robo-advisory services have a notable impact on investment decision-making and portfolio performance within the financial sector. Similarly, Flavián et al. (2022) emphasized that an investor's level of innovativeness and readiness to adopt technology play a crucial role in shaping their approach to investment analysis. Furthermore, Eren (2023) stated that trust in AI has a significant influence on investors' willingness to use robo-advisory services. Moreover, Ze and Loang (2025) asserted that an investor's awareness of technology and rate of innovative adoption significantly affect their investment strategies and consequently, their investment returns. In addition, Falsetti (2025) and Vangala (2024) noted that robo-advisory platforms have significantly reshape and enhanced investment strategies through its personalized features, which enable tailored investment planning and portfolio management based on investor preferences.

However, some studies have reported mixed findings. For example, Rydstrand and Reichard (2025) noted that although AI has rapidly developed and become increasingly prominent in the modern era, its impact and functionality in shaping investment strategies remain insignificant. Similarly, Liu et al. (2023) found no significant relationship between the use of robo-advisory services and investors' trading frequency. This suggests that robo-advisory may not substantially influence how frequently investors trade, thereby implying a limited role in reshaping overall investment strategies. Furthermore, a study by Otioma and MacNeil (2025) revealed that when the recommendations provided by robo-advisory closely align with investors' existing portfolios, investors may choose to maintain their current investment strategies without relying on robo-advisory services.

In summary, existing literature presents conflicting findings regarding the relationship between personal innovativeness in Information Technology

(IT) and the reshaping of investment strategies. Some studies suggest that investors with higher levels of IT innovativeness are more likely to adopt robo-advisory services for investment management and planning, due to their preference for data-driven decision-making support. However, other research offers contrasting perspectives, indicating that this relationship may not be as significant or consistent. Therefore, this study aims to further investigate how personal innovativeness in IT influences existing investors' tendency to reshape their investment strategies.

2.2.6 Market Sentiment

The overall attitude and collective outlook by all individual investors towards any financial securities or markets is known as market sentiment (Koratomaddi et al., 2021; Du et al., 2024). Market sentiment can be broadly classified in two sentiments which is bullish and bearish sentiment (Ustali et al., 2025). In early 1990s, finance scholars had proposed this classification based on patterns of rising or falling prices (Heydarian et al., 2024). As the sum of overall market expectations, sentiment reflects groups of individuals' thoughts, views, feelings, ideas, emotions, moods, beliefs, or even their future expectations. Under this broad definition, all of these factors may be considered sentiment, as they influence decision-making (Aggarwal, 2022). In finance, most measures of investor sentiment are derived from large-scale market and economic data, reflecting overall trends rather than individual opinions (Nyakurukwa & Seetharam, 2023).

Market sentiment plays a vital role in this context because it reflects the collective emotions of investors and often causes asset prices to deviate from their fundamental value (Rimsha & Javeed, 2024). Wang (2023) study mentioned that when bullish sentiment dominates, excessive optimism may lead to asset bubbles, while bearish sentiment can fuel panic selling, causing

market overreact and asset prices fall below their fundamental worth. This is supported by Wang et al. (2022) who further stated that in a bull market, optimistic investor sentiment drives more people to buy stocks, whereas in a bear market, optimism may lead investors to hold back from selling or even attempt to buy at lower prices. However, Oelschläger and Adam, (2021) stated that generally, equity investors seek to enter the market at the onset of bullish trends and divest their holdings before prices decline in bearish market. Therefore, during bullish markets, optimism dominates, leading to increase buying activity; during bearish markets, pessimism leads to selling pressure (Li et al., 2023). Wang et al. (2021) study illustrated that sentiment can be described as the aggregate of overall market expectations, reflecting groups of individuals' thoughts, views, or feelings. Therefore, understanding market sentiment is crucial as it directly impact investment decisions, shapes market trends and influence overall market stability.

Research conducted by Rimsha et al. (2024) in Pakistan revealed a positive relationship between bearish trends and investor sentiment, indicating that investor sentiment can contribute to the formation of bearish trends. Similarly, Yadav and Chakraborty (2022) demonstrated a positive relationship between market returns and investor sentiment in the context of the Indian stock market as positive sentiment encourages more buying, which pushes prices higher. According to Rawat (2023), investor sentiment plays a crucial role in decision-making, serving as a moderating factor that shapes the relationship between various determinants and investor behaviour, with statistically significant effects on both market sentiment and investment decisions. Not only that, Wang et al. (2022) conducted a scenario-based survey to examine the impact of market conditions on investor attitudes and the results showing that bull and bear markets significantly influence investors' perspective, as they tend to adjust their attitudes based on prevailing market conditions. The result conducted by Tariq and Valeed (2021) found that during periods of bearish sentiment, investors frequently search online for specific stocks to evaluate selling

decisions, which increases selling pressure and ultimately exerts a negative effect on excess stock returns.

In summary, although these studies employed different research methods, such as varying country contexts and analytical approaches, they consistently demonstrate that market sentiment significantly influences investor decision-making. This indicates that extensive research has been conducted on the relationship between investor sentiment, market performance, and decision-making. Therefore, building on these studies, this research introduces market sentiment as a moderating variable to examine its impact on the relationship between the independent and dependent variables.

2.2.7 Market Sentiment (Moderating Effect)

Table 2.1:

Market sentiment with significant moderating effect

Authors	Variables	Results
Filip & Pochea (2023)	Herding Effect	Significant
Messaoud & Amar (2024)		
Tham (2023)	Habit	Significant
Abakah et al. (2023)	Performance	Significant
Zeng et al. (2024)	expectancy	
Xia et al. (2023)	Personal innovativeness in IT	Significant

According to Table 2.1, it shows different results about how market sentiment is moderate toward other independent variables such as herding effect, habit, performance expectancy and personal innovativeness in IT. Filip and Pochea (2023) and Messaoud and Amar (2024) shows that market sentiment as a moderator has significant effects between herding behaviour and investment decision-making. Tham (2023) states that sentiment acts as a moderator in the relationship between how habit affect the decision making, the article said the bearish sentiment increase habit sensitively. Besides, Abakah et al. (2023) study demonstrated that market sentiment influences performance expectancy by shaping investors' perceived effectiveness of FinTech solutions. Bullish sentiment enhances trust and adoption, while bearish sentiment reduces confidence, leading to cautions investment strategies. Zeng et al. (2024) research also indicated that sentiment is a factor to affect the performance expectancy and investment strategies since a lot of investors incorporating sentiment into online technology. According to Xia et al. (2023), the study is showing that the market sentiment as a moderator has significantly affected the relationship between personal innovativeness in IT and reshape investment strategies.

2.2.8 Market Sentiment (No Moderating Effect)

Table 2.2:

Market sentiment with insignificant moderating effect

Authors	Variables	Results
Loang (2025)	Herding Effect	Insignificant
Kumari et al. (2025)		
Singhal (2023)	Habit	Insignificant

Ustali et al. (2025)	Personal innovativeness in IT	Insignificant
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Table 2.2 above shows opposite result regarding how market sentiment is moderating against independent variables. Loang (2025) and Kumari et al. (2025) had conclude that the moderator of market sentiment has an insignificant effect towards the relationship between herding effect and investment decision making. Besides, study by Singhal (2023) has found that the moderator effect between habit and investment decisions in market sentiment is proven to be insignificant. Furthermore, study by Ustali et al. (2025) also found that market sentiment has zero impact between personal innovativeness in IT and investors' investment decision.

2.3 Conceptual Framework

Figure 2.4 presented the conceptual framework of this study to investigate the financial awareness and technology growth in influencing investor to reshape investment strategies in Malaysia. The conceptual framework is developed to refer to the theoretical framework that was covered in the previous section.

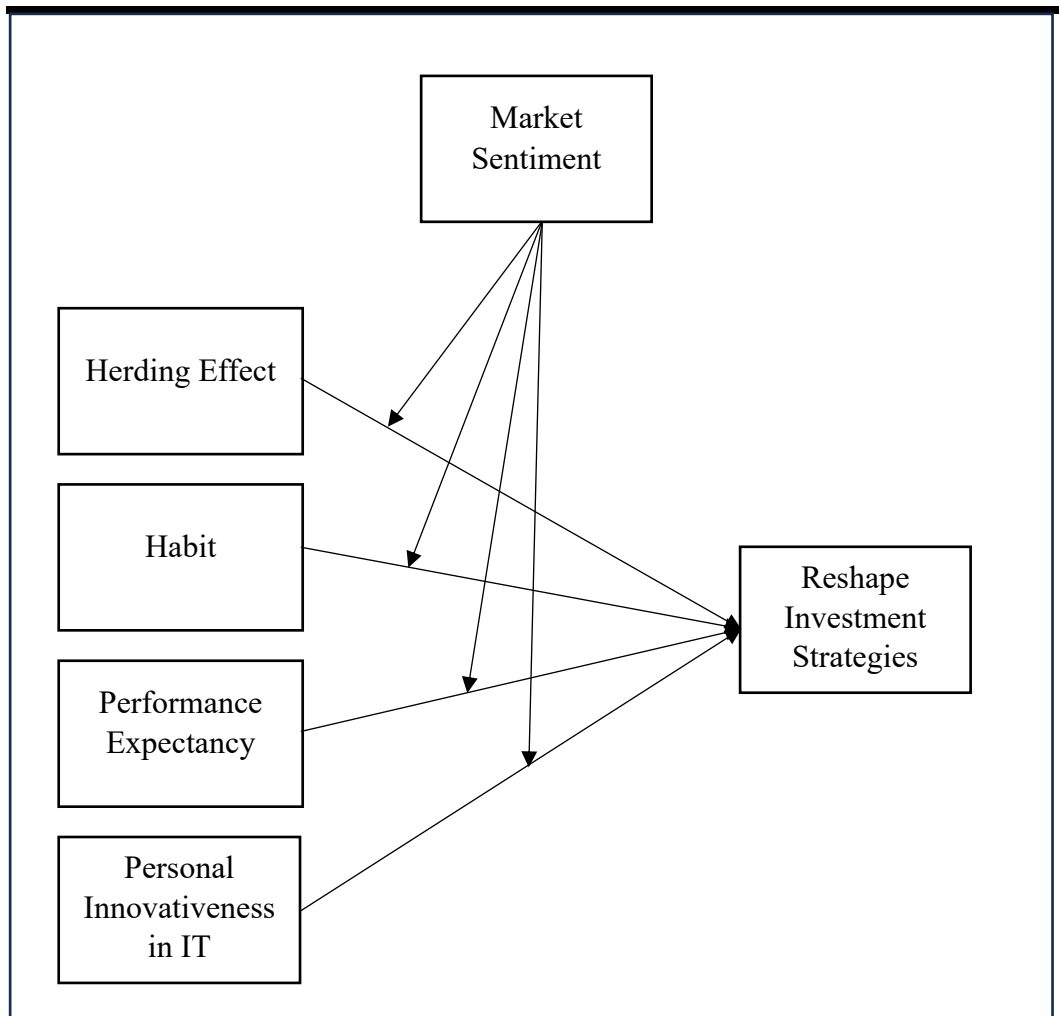


Figure 2.4 Conceptual Framework. Source: Developed by this study.

Figure 2.4 presents the conceptual framework of this study which comprises four independent variables, one moderator, and one dependent variable. Drawing upon prior research, Hirdinis (2021), Cao et al. (2021) and Rahayu et al. (2021) found that the herding effect significantly influence in investors' investment decision-making. In addition, Haasnoot et al. (2020), Sourirajan and Perumandla (2022), Sonkar et al. (2023) and Arsyianti et al. (2023) demonstrated that the variable habit had significant relationship with investors' decision. Besides, Chen et al. (2023), Priyadarshi et al. (2024) and Srivastav et al. (2024) have all concluded that performance expectancy have significance influence on investor's investment decision. Similarly, Flavián et al. (2022), Eren (2023), Salvi (2024) and Ze and Loang (2025) highlighted that investors' proactiveness and openness to adopting new technologies significantly affect the reshaping of investment strategies. With

respect to the moderator, Flip and Pochea (2023), Tham (2023), Abakah et al. (2023) and Xia et al. (2023) studies had demonstrated that market sentiment has significant impact on the relationship between each independent variables and reshape investment strategies. Overall, this framework serves to evaluate and enhance the accuracy of the study's outcomes.

2.4 Hypotheses Development

2.4.1 Herding Effect and Reshape Investment Strategies

Herding significantly influence investor decision-making. This is because a lot of studies shows that herding effect is pervasive and are not at all rare among institutional and individual investors in the capital market and is often identified as the primary cause of market volatility and instability (Komalasari, 2021; Mand et al., 2023). As well as herding effect refers to investors abandoning their own judgment, blindly following the market mainstream and imitating group behaviour (Ali & Amir, 2024). Prior research on the relationship between herding effect and investor decision making has found that herding effect is significant in several country such as study in Vietnam (Cao et al., 2021) and Indonesia stock market (Rahayu et al., 2020), suggested that the herding effect not only influences investment decision making but also positively impacts investor' relative investment performance and also indicates that under pressure, investors often ignore their own skills and follow the investment decision from the experts. Thus, the first hypothesis that was formulated for the research is:

H_1 : There is a significant relationship between market herding effect and reshaping investment strategies.

2.4.2 Habit and Reshape Investment Strategies

Besides, habit has also been found to significantly influence the investor decision making as it drives unconscious and automatic actions based on past experiences, making it a key predictor of technology adoption (Gunasinghe et al., 2019). As a growing trend of more fintech stakeholders in North America indicate that they have grown dependent on AI due to the development of financial technology, according to Ramadugu and Doddipatla (2022). This shows that as fintech evolves, investors also acquire habits and are used to relying on the usage towards these technologies. Investors' habits align with path dependency, where past decisions shape current choices (Simoens et al., 2022). The studies show that habit significantly drive investing behaviours, even when accounting for intentions and behavioural control (Sourirajan & Perumandla, 2022). Path dependency reinforces "investment lock-in," limiting flexibility and future adjustments due to psychological commitment (Haasnoot et al., 2020). Thus, the second hypothesis that was formulated for the research is:

H_2 : There is a significant relationship between habit and reshaping investment strategies.

2.4.3 Performance Expectancy and Reshape Investment Strategies

Moreover, performance expectancy can also significant influence the investor decision making. Performance expectancy reflects the perception

that the system contributes to improved performance and productivity (Wang & Ma, 2023). According to Almetere et al. (2020), investor is more preferred to use technology when they perceive it as beneficial and capable of enhancing their performance. For high-tech services must be functional, beneficial, and user-friendly to drive adoption to attract user use the high-tech services such as FinTech. If investor fail to meet expectation, users may hesitate to adopt those high-tech (Zainavy et al., 2023). Chen et al. (2023) concluded that there is indirect impact on investor decision between the FinTech and the willingness of the user. Shivani et al. (2022), Srivastav et al. (2024) and Sembel et al. (2024) also proven that FinTech significantly influences investors' decision making when it effectively meets the investor needs. Thus, the third hypothesis that formulated for the research is:

H₃: There is a significant relationship between performance expectancy and reshaping investment strategies.

2.4.4 Personal Innovativeness in IT and Reshape Investment Strategies

Personal innovativeness in IT is found to be significant influence investor decision making. Studies by Salvi et al. (2024) and Syed and Janmolla (2024) indicate that an investor's level of IT innovativeness, such as the adoption of AI-driven robo-advisory services, significantly influences decision-making processes and portfolio performance within the financial sector. Ze and Loang (2025) asserted that personal innovativeness in adopting technology plays a pivotal role in reshaping investment strategies and enhancing returns. Not only that, Vangala (2024) and Falsetti (2025) also noted that robo-advisory platforms have significantly reshape and enhance the investment strategies through personalized features that tailor

investment planning and portfolio management to investor preferences.

Thus, the fourth hypothesis that formulated for research is:

H_4 : There is a significant relationship between personal innovativeness in IT and reshaping investment strategies.

2.4.5 Moderating Effect of Market Sentiment on the relationship between Independent Variables and Reshape Investment Strategies

Market sentiment is studied through sentiment analysis which examines people's sentiment, attitudes, opinions, emotions, evaluations, and appraisals toward various entities such as events, topics, services and product, individuals, organizations, issues, and their attributes (Liu, 2022). Messaoud and Amar (2024) indicated that market sentiment plays a significant moderating role in the relationship between herding behaviour and investment decision making. Similarly, Tham (2022) highlighted that sentiment moderates the impact of habit on decision making. Based on Xia et al. (2023) and Asad et al. (2022), market sentiment is seen as an endogenous variable in performance expectancy, personal innovativeness in IT and investor decision making. Thus, the following continuous hypothesis generated for this investigation are:

H_5 : Market sentiment moderates the relationship between herding effect and reshaping investment strategies.

H_6 : Market sentiment moderates the relationship between habit and reshaping investment strategies.

H_7 : Market sentiment moderates the relationship between performance expectancy and reshaping investment strategies.

H_8 : Market sentiment moderates the relationship between personal innovativeness in IT and reshaping investment strategies.

2.5 Conclusion

This chapter provides a detailed examination of the factors influencing investor decision-making, supported by a review of existing literatures. The key variables discussed include herding effect, habit, performance expectancy, and personal innovativeness in IT, with market sentiment as a moderating variable. However, no prior studies have directly investigated the relationship between these variables and investor decision-making in the context of reshaping investment strategies. Therefore, this study builds on previous researches to explore how financial awareness and technological advancements influence investor decision-making to drive adjustments to investment strategies. Additionally, this chapter presents the theoretical frameworks from prior studies, leading to the development of a conceptual framework. The chapter concludes with the formulation of hypotheses based on the identified relationships.

CHAPTER 3: METHODOLOGY

3.0 Introduction

In this study, the main objective is to examine what factors that will affect investors to reshape their investment strategies in Malaysia. To achieve this objective, this chapter places a strong emphasis on the research methodology. It begins by outlining the research design, followed by a detailed explanation of the data collection methods. Subsequently, the sampling design, research instruments, and measurement scales employed in the study are discussed. Finally, the procedures for data processing and the analytical techniques applied are clearly described.

3.1 Research Design

Research design is defined as the collection of data within a research area to facilitate the interpretation and analysis of information designed to address a research question. Research designs can be categorized as qualitative, quantitative, and mixed designs. The quantitative research methodologies had applied in this study. Previous studies which related to strategy reshaping affected by market sentiment, financial awareness and technology also adopted quantitative research methods. Within the quantitative research framework, participants were constrained to a fixed range of predetermined response options, which restricted their ability to elaborate beyond the structured choices provided.

3.2 Sampling Design

3.2.1 Target respondents of the Study

The target respondent refers to an individual who fulfils the defined eligibility criteria and is considered suitable to participate in a particular research study. In this research, the target population consists of equity investors in Malaysia who are aged 18 and above. The focus on this age group is appropriate as individuals must be at least 18 years old to open a Central Depository System (CDS) account, which is required to participate in the equity market, according to the CDS Guide for Depositors issued by Bursa Malaysia in year 2025. Furthermore, the study specifically targets existing equity investors, as they are more likely to have relevant experience in the local investment environment, thereby enhancing the accuracy and relevance of the research findings.

3.2.2 Sampling Location

Based on Malaysian Retail Investor Insights (2024) which is an analysis done by Bursa Malaysia, the report shows that Malaysia's stock investors are primarily concentrated in economically robust states such as Selangor, Johor, and Penang. Therefore, the sampling locations for this study will focus on these key regions, as they represent a significant portion of the active investor population in Malaysia.

3.2.3 Sampling method

Non-probability sampling is a method where researchers select participants based on specific criteria or judgment, rather than using random selection.

It allows for targeted sampling, particularly valuable in qualitative research where contextual understanding and depth are prioritized (Tansey, 2009).

One common type of non-probability sampling is purposive sampling, in which participants are deliberately chosen for their relevance to the research topic. A purposive sampling method was employed in this study, with respondents selected based on relevance to the research objectives , specifically focusing on Malaysian investors. Samples were drawn from specific regions across Malaysia as stated above.

3.2.4 Sampling Techniques

In this study, data was collected through a questionnaire designed for individuals who have invested or are currently investing in equity market in Malaysia. Therefore, this study adopted a purposive sampling method and randomly selected investors from these three states such as Selangor, Johor, and Penang to participate in the survey. Purposive sampling was also used by Adiputra (2021) to gather information from Indonesian investors to understand how various factors influence their investment decision-making.

3.2.5 Sample Size of the Study

A sample refers to an investigation conducted on a smaller group of people selected from a larger population. Selecting an optimal sample size is crucial to minimize sampling errors and reduce research costs. Krejcie and Morgan (1970) proposed an approximate sample size based on the overall population, offering a practical framework for determining an appropriate sample size.

The sample sizes corresponding to different population sizes are outlined in the Table 3.1.

Table 3.1:

Determining Sample Size Based on Population

Population Range	Approximate Sample Size
8000	367
9000	368
10000	370
15000	375
20000	377
30000	379
40000	380
50000	381
75000	382
1000000	384

Source: Krejcie & Morgan (1970).

According to Malaysian Retail Investor Insights (2024) which is an analysis report done by Bursa Malaysia, it declared that the number of investors in the certificate depository system has exceeded two millions. Considering this population size, the recommended sample size for this study is 384 respondents. Therefore, this study will require a minimum of 384 respondents to ensure the sample is representative of the larger population.

3.3 Data Collections Methods

3.3.1 Data Collection

The research aim will be accomplished by the use of primary data in this study. Questionnaires were employed as the major data collection method from respondents. This method aligns with the approaches adopted in the studies conducted by Zhang et al. (2021) and Gill et al. (2018), both of which investigated similar research objectives and employed comparable methodologies.

3.3.2 Questionnaire

A questionnaire was employed as the primary research instrument to collect data from investors in Malaysia. As a method of primary data collection, the questionnaire is structured into three sections: Section A, Section B, and Section C. In total, there are 36 questions and statements, that respondents are required to complete. The researcher utilized a Google Forms-based online questionnaire to distribute and collect data for this study.

The purpose of Section A was to gather demographic information from respondents, 6 questions pertaining to demographic information were asked, including those concerning gender, age, ethnicity, state, occupation, and investment status. Section B then asked twenty five questions, five questions for herding effect, five questions for habit, five questions for performance expectancy, five questions for personal innovativeness in IT and five questions which represent market sentiment as a moderator between each independent and dependent variables in Malaysia. Section C, the final part of the study which consists of five questions. It presents respondent data to provide insights that reshape investors' investment strategies.

In both Sections B and C, a five-point Likert scale was employed as an ordinal level of measurement with corresponding numerical values to quantify respondents' degrees of agreement across various items. The response options, namely strongly agree, agree, neutral, disagree and strongly disagree, were systematically coded to facilitate analysis.

3.3.3 Pre-Test

The questionnaire was sent to two lecturers from Universiti Tunku Abdul Rahman for review purpose before being distributed to the investors in Malaysia.

3.3.4 Pilot Test

Conducting a pilot test is a critical step in research, as it assesses the effectiveness of the research instrument by identifying potential issues and areas that may require modifications (Teijlingen & Hundley, 2002). In this study, a pilot test will be conducted to assess both the reliability and validity of the questionnaire. Based on the recommendation by Viechtbauer et al. (2015), a sample size of 59 participants is deemed appropriate for pilot testing. This sample size ensures that any ambiguities related to the inclusion or exclusion criteria can be identified with a high level of confidence. Consequently, the online survey was distributed to 59 Malaysian investors aged 18 and above. The data collected from the pilot test will be analysed using SmartPLS 4.0 to evaluate the internal consistency and reliability of the questionnaire items.

Pilot test result as below:

3.3.4.1 Reliability Test

Table 3.2:

Cronbach's Alpha Reliability Analysis

No	Type of Variable	Name (Variable)	Number (Item)	Cronbach's Alpha	Reliability Test
1	Dependent Variable	Reshape Investment Strategies	5	0.848	Good
2	Independent Variable	Habit	5	0.871	Good
3	Independent Variable	Performance Expectancy	5	0.837	Good
4	Independent Variable	Personal Innovativeness in IT	5	0.826	Good
5	Independent Variable	Herding Effect	5	0.867	Good
6	Moderator	Market Sentiment	5	0.886	Good

Table 3.2 above indicates the pre-test results of reliability test of dependent variable, independent variables as well as moderator. Variables that have been tested with results indicating good reliability, suggesting Cronbach's alphas larger than 0.80 while lower than 0.90, includes reshape investment strategies with 0.848, habit with 0.871, performance expectancy with 0.837, personal innovativeness in IT with 0.826, herding effect with 0.867, and market sentiment with 0.886.

3.3.4.2 Measurement Model Assessment

In the pilot test of this research, outer loadings were examined to assess the reliability of the measurement items. Referring to Appendix 1, outer loading values greater than 0.70 indicate acceptable reliability and internal consistency of the variables, while values below 0.50 are typically considered for removal from the analysis. The results showed that all variables had outer loading values within the acceptable range of 0.70 to 0.90. Additionally, for the interaction terms, which include market sentiment multiplied by habit, herding effect, performance expectancy, and personal innovativeness in IT, each construct reported a single loading of 1.000. These findings confirm that all reflective constructs meet the minimum threshold for indicator reliability.

3.3.4.3 Validity and reliability

In PLS-SEM, composite reliability and average variance extracted (AVE) are essential indicators for evaluating the quality of the measurement model. It is generally recommended that the values of both composite reliability (ρ_A) and composite reliability (ρ_C) exceed 0.70 to indicate good

internal consistency. Convergent validity is assessed through the AVE, where values above the threshold of 0.50 demonstrate that a substantial portion of variance is captured by the indicators. According to Appendix 2, the measurement model evaluation of this pilot test showed that both rho_A and rho_C values for all reflective constructs were above 0.80, confirming strong internal consistency. The AVE values ranged from 0.591 to 0.684, supporting acceptable convergent validity for all constructs. These results indicate that the measurement model is both reliable and valid, thereby justifying its application in the structural model analysis.

3.3.4.4 Multicollinearity Test

The results indicate that all variance inflation factor (VIF) values are presented in Appendix 3 which all values are below the critical threshold of 5, suggesting that multicollinearity is not a significant issue in this study. For the direct predictors of reshape investment strategies, all independent variables recorded VIF values below 5. Regarding the interaction terms, market sentiment multiplied by personal innovativeness in IT showed the highest VIF value at 4.895, which is close to the threshold. This may be attributed to the limited sample size. Nevertheless, all interaction terms remain below the cut-off point of 5.0. Therefore, it can be concluded that multicollinearity does not pose a concern for the constructs in this model.

3.3.4.5 Discriminant Validity

Appendix 4 presents the heterotrait-monotrait ratio (HTMT) results for each construct obtained from the pilot test, which was used to assess discriminant validity. All HTMT values are below the recommended threshold of 0.90,

indicating that each construct is empirically distinct from the others (Hair et al., 2019). As shown in the table, HTMT values in the model range from 0.032 to 0.898. The highest value, 0.898, is observed between herding effect and reshape investment strategies, while the lowest value, 0.032, is found between habit and the interaction term of market sentiment multiplied by habit. These results confirm that the model demonstrates satisfactory discriminant validity, as all values fall below the threshold of 0.90.

3.3.4.6 Structural Model Assessment

Refer to Appendix 5, it presents the structural model of the pilot test using the PLS-SEM structural model. All measurement items show strong outer loadings above the recommended threshold of 0.70, indicating good indicator reliability. The path coefficients illustrate the relationships among the constructs, with market sentiment exhibiting both positive and negative moderating effects. A positive moderation is observed with personal innovativeness in IT, while negative moderating effects are evident in the relationships involving habit, performance expectancy, and herding effect. The R^2 value for reshaped investment strategies is 0.831, suggesting that the model explains 83.1% of the variance in the dependent variable, which indicates strong explanatory power. Overall, the pilot model demonstrates satisfactory reliability, validity, and predictive relevance.

3.3.4.7 Coefficient of Determination (R^2)

Referring to Appendix 6, the R^2 value for reshape investment strategies is 0.831 which indicating that 81.30% of the total variance in the dependent

variable is explained by habit, herding effect, performance expectancy, personal innovativeness in IT and market sentiment in pilot test.

3.3.5 Nominal Scale

Idika et al. (2023) declared that nominal scale is a qualitative measurement scale used to label or classify data into distinct categories based on shared characteristics. It involves assigning respondents into different groups or categories, such as gender, nationality, or blood type, for identification and classification purposes only. The nominal scale will be used to indicate questionnaire of Section A which named demographic data which included gender, age, ethnicity, state, occupation, and investment status.

3.3.6 Ordinal Scale

The ordinal scale is a level of measurement that categorizes variables into distinct groups with a meaningful order or rank. It is often used in questionnaires where responses are recoded into ordinal diagnoses like high, medium, or low. The ordinal scale will be used in Section B by using Linkert Scale of 5-point ordinal scale.

3.3.7 Origin of Construct

Table 3.3:

Origin of Construct

Variables	Adapted From	Items	Scale
Dependent Variable: Reshape Investment Strategies	Gill et al. (2018)	4 items	Strongly Agree (5) to Strongly Disagree (1)
	Waweru et al. (2008)	1 item	Disagree (1)
Independent Variable: Herding Effect	Nareswari et al. (2021)	2 items	Strongly Agree (5) to Strongly Disagree (1)
	Cao et al. (2021)	3 items	Disagree (1)
Habit	Hossain & Siddiqua (2024)	1 item	
	Antony & Joseph (2017)	1 item	Strongly Agree (5) to Strongly Disagree (1)
	Almansour & Arabyat (2017)	2 items	Disagree (1)
	Cao et al. (2021)	1 item	
Performance Expectancy	Nair et al. (2023)	3 items	Strongly Agree (5) to Strongly Disagree (1)
	Belanche et al. (2019)	1 item	Disagree (1)
	Guo & Barnes (2012)	1 item	
Personal Innovativeness in IT	Zhang et al. (2021)	1 item	Strongly Agree (5) to Strongly Disagree (1)
	Farooq (2017)	1 item	Disagree (1)

Moderator Variable: Market Sentiment	Lee (2009)	1 item	Strongly Agree (5) to Strongly Disagree (1)
	Schütz et al. (2023)	2 items	
	Bialowolski & Biolowolska (2014)	1 item	
	Sudirman et al. (2023)	1 item	
	Xia et al. (2025)	1 item	
	Bhatia et al. (2021)	1 item	
	Nareswari et al. (2021)	1 item	

3.3.8 Questionnaire Design

3.3.8.1 Section A

Section A is used for collecting demographic data of respondent. There are six questions included in this section to be answered by respondents which included gender, age, ethnicity, state, occupation, and investment status.

3.3.8.2 Section B

3.3.8.2.1 Herding Effect

Herding Effect within Behavioral Finance Theory refers to the specified scenario whereby investors give up on their convictions and instead choose to “move with the market” or to “follow the general market trend”, believing that this action will obtain access profits (Almansour et al., 2023).

Herding effect was totally measured using five items, two items were adapted from Nareswari et al. (2021), “I feel comfortable in making same investment decisions with the majority of investors.”, “My investment decisions will influenced by the financial instrument’s price movements.”, and three items adapted from Cao et al. (2021), “I tend to invest in trendy financial instrument.”, “Financial instrument’s bid and ask volume will influences my investment choice.” and “I make swift investment decision in respond to market change.”

HE1. I feel comfortable in making same investment decisions with the majority of investors.

HE2. My investment decisions will influenced by the financial instrument’s price movements.

HE3. I tend to invest in trendy financial instrument.

HE4. Financial instrument’s bid and ask volume will influences my investment choice.

HE5. I make swift investment decision in respond to market change.

3.3.8.2.2 Habit

Habit is the degree to which one acts in an unconscious and automated manner due to accumulations of past experiences (Gunasinghe et al., 2020).

Habit was totally measured using five items. One item is adapted from Hossain and Siddiqua (2024), “I sense more assurance in my own investment views over others”, one item is adapted from Antony and Joseph (2017), “I have my own specific skills and experience about investment.”, two items adapted from Almansour and Arabyat (2017), “I tend to invest in the same type of assets I am familiar with.”, “I believe the returns are higher for investments that I am familiar with.” And the last item is adapted from Cao et al. (2021), “I usually repeat the same investment actions based on my past experience.”

HB1. I sense more assurance in my own investment views over others.

HB2. I have my own specific skills and experience about investment.

HB3. I tend to invest in the same type of assets I am familiar with.

HB4. I believe the returns are higher for investments that I am familiar with.

HB5. I usually repeat the same investment actions based on my past experience.

3.3.8.2.3 Performance Expectancy

Performance expectancy refers to the extent to which an individual believes that using a particular information system or technology will enhance their efficiency and effectiveness in achieving desired outcomes (Priantinah et al., 2025).

Performance expectancy was measured by employing five items which included three items adapted from Nair et al. (2023), “I believe that using trading platform will improve my performance in stock trading.”, “I believe that investing through trading platform would enable to make profit more quickly.”, “I feel that using trading platform is useful for reshape my investment strategies.”, and one item adapted from Belanche (2019), “Investing in the stock through trading platform will enhance my investment effectively.”, and another one item is adapted from Guo and Barnes (2012), “I utilize trading platforms to track virtual item prices and market news, enabling me to reshape my trading strategy in a timely manner.”

PE1. I believe that using trading platform will improve my performance in stock trading.

PE2. Investing in the stock through trading platform will enhance my investment effectively.

PE3. I believe that investing through trading platform would enable to make profit more quickly.

PE4. I utilize trading platforms to track virtual item prices and market news, enabling me to reshape my trading strategy in a timely manner.

PE5. I feel that using trading platform is useful for reshape my investment strategies.

3.3.8.2.4 Personal Innovativeness in Information Technology

Personal Innovativeness in Information Technology was measured by employing five items which included one item adapted from Zhang et al. (2021), “Among my peers, I am usually the first to try out new information technologies like robo-advisory.”, and one item adapted from Farooq et al.

(2017), “I like to experiment new features and advancements in information technologies.”, and another one item adapted from Lee (2009), “I think that I would be able to use new technologies well for reshaping my investment strategy.” and the last two items adapted from Schütz et al. (2023), “I believe that robo-advisor performs its role of providing investment recommendations successfully.”, “I believe robo-advisor is making recommendations in my best interest, helping reshape my investment strategy.”

PI1. Among my peers, I am usually the first to try out new information technologies like robo advisory.

PI2. I like to experiment new features and advancements in information technologies.

PI3. I think that I would be able to use new technologies well for reshaping my investment strategy.

PI4. I believe that robo advisor performs its role of providing investment recommendations successfully.

PI5. I believe robo advisor is making recommendations in my best interest, helping reshape my investment strategy.

3.3.8.2.5 Market Sentiment as a Moderator Between Independent and Dependent Variables

Market sentiment reflects investor reactions towards different market conditions. It could be defined as the aggregate of overall market expectations which reflect groups of investors’ thought and views (Wang et al. 2021).

The moderating effect of market sentiment on the relationship between the independent variables and the dependent variable was assessed using five

items, with each item corresponding to one of the independent variables. One item adapted from Bialowolski and Biolowolska (2014), “I believe that changes in interest rates influence the overall market mood, which affects my investment decisions.”; one item was adapted from Sudirman et al. (2023), “I tend to rely on my habits even in different market conditions when making investment decisions.”; one item was adapted from Xia et al. (2025), “I believe that using an efficient trading platform enhances my confidence in different market sentiment and reshape my investment strategies.”; one item was adapted from Bhatia et al. (2021), “I trust robot-advisors more than traditional financial advisors during high market volatility because of the rationality of robot-advisory systems.”; one item was adapted from Nareswari et al. (2021), “I am not confident in making different decisions than the majority of investors when market sentiment is volatile.”

MS1. I believe that changes in interest rates influence the overall market mood, which affects my investment decisions.

MS2. I tend to rely on my habit even in different market conditions when making investment decisions.

MS3. I believe that using an efficient trading platform enhances my confidence in different market sentiment and reshape my investment strategies.

MS4. I trust robot-advisors more than traditional financial advisors during high market volatility because of the rationality of robot-advisory systems.

MS5. I am not confident in making different decisions than the majority of investors when market sentiment is volatile.

3.3.8.3 Section C

3.3.8.3.1 Reshape Investment Strategies

Reshaping investment strategies defined as the process by which investors modify or adjust their existing approaches (Ali, 2024).

Reshape investment strategies was measured by employing five items which included one item adapted from Waweru (2008), “When the stock price changes, I will be willing to reshape my investment based on the suggestion provided by AI to make a profit maximize.”, four items adapted from Gill et al. (2018), “I adjust my investment strategy based on the level of risk associated with different stocks.”, “I change my holding period to realize profits early when there are quick gains in stock price.”, “I ensure that my investment in stock has a high degree of safety investment by reshaping investment strategy.”, “When international markets become volatile, I switch my investment focus to local stocks to maintain portfolio stability.”.

- RI1. When the stock price changes, I will be willing to reshape my investment based on the suggestion provided by AI to make a profit maximize.
- RI2. I adjust my investment strategy based on the level of risk associated with different stocks.
- RI3. I change my holding period to realize profits early when there are quick gains in stock price.
- RI4. I ensure that my investment in stock has a high degree of safety investment by reshaping investment strategy.
- RI5. When international markets become volatile, I switch my investment focus to local stocks to maintain portfolio stability.

3.3.9 Data Checking, Filtering and Coding

In this study, data screening was conducted by filtering out responses that did not meet the required criteria. This included respondents who selected the same answer across all items on the 5-point Likert scale and those who indicated "not an investor" in the initial screening question. Furthermore, during the data coding process, numeric values were assigned to responses and entered into SmartPLS 4.0. Responses were coded on a scale from 1 to 5, while any missing values were represented with a code of 0.

Table 3.4:

Section A Code

Q1	Gender	"Male" = 1 "Female" = 0
Q2	Age	"18 – 30" = 1 "31 – 40" = 2 "41 – 50" = 3 "51 – 60" = 4 "Above 60" = 5
Q3	Ethnicity	"Malay" = 1 "Chinese" = 2 "Indian" = 3 "Others" = 4
Q4	State	"Selangor" = 1 "Johor" = 2 "Penang" = 3 "Others" = 4
Q5	Occupation	"Student" = 1 "Employee" = 2 "Employer" = 3 "Unemployment" = 4
Q6	Are you currently an investor?	"Yes" = 1 "No" = 0

In Section B and C, each question is encoded according to the 5-point Likert scale as follows:

- The code for "Strongly Agree (SA)" is 5.
- The code for "Agree (A)" is 4.
- The code for "Neutral (N)" is 3.
- The code for "Disagree (D)" is 2.
- The code for "Strongly Disagree (SD)" is 1.

3.4 Proposed Data Analysis Tool

Descriptive data analysis includes measures for distribution shape, dispersion, and central tendency. Descriptive analysis also contains frequency statistics. Tables were created to display crucial information such as mean, standard deviation, frequency, and percentage of responses.

3.4.1 Reliability test

3.4.1.1 Internal consistency test

In this study, internal consistency was evaluated using both Cronbach's alpha coefficient and composite reliability. A threshold value of 0.70 or higher for each independent variable was considered acceptable to demonstrate adequate reliability. The interpretation guidelines for Cronbach's alpha are summarized in Table 3.5.

Table 3.5:

Cronbach's Alpha Rule of Thumbs

Cronbach's Alpha	Level of Reliability
$\alpha > 0.9$	Excellent
$0.9 > \alpha > 0.8$	Good
$0.8 > \alpha > 0.7$	Acceptable
$0.7 > \alpha > 0.6$	Questionable
$0.6 > \alpha > 0.5$	Poor
α Less than 0.5	Unacceptable

Source: Schrepp (2020).

3.4.1.2 Validity test

The validity assessment consisted of three tests include convergent validity, factor loading, and discriminant validity. Convergent validity was deemed acceptable when each independent variable achieved a value of at least 0.7. For discriminant validity, the factor loading and heterotrait-monotrait ratio (HTMT) for each variable must be less than 0.9 (Hair et al., 2019).

3.4.2 Preliminary Data Screening

3.4.2.1 Multicollinearity

In this study, VIF was calculated with SmartPLS 4.0. The VIF is a tool to measure and quantify how much the variance is inflated. A variance inflation factors greater than 5 indicates significant multicollinearity among independent variables (Daoud, 2017).

3.4.3 Inferential analysis

By using the sample data of investor form different urbans areas in Malaysia, it is possible to determine how market sentiment, technology growth and financial awareness affect the investor to reshape their investment strategies in Malaysia. Inferential data in this study were analysed using partial least squares-structural equation modelling (PLS-SEM).

3.4.3.1 Partial Least Square (PLS) Structural Equation Modelling

In this study, Partial Least Squares Structural Equation Modelling (PLS-SEM) was utilized to perform regression analysis on the collected data. This study also measured how independent variables including herding effect, habit, performance expectancy and personal innovativeness in IT reshape investment strategies in Malaysia, with the moderating effect of market sentiment. The software SmartPLS 4.0 was used in this study. SmartPLS version 4.0 was utilized to conduct the analysis. The relationships between each independent and dependent variables were assessed through path coefficient significance, which included the beta values, standard errors, t-values, and p-values. Moreover, the significance of the moderating effect of market sentiment on the interaction terms was tested using the bootstrapping procedure, with a resampling size of 395. Additionally, the model's explanatory power (R^2) and effect size (f^2) were evaluated.

3.5 Conclusion

In conclusion, the research methods employed in this study are detailed in Chapter 3. This study adopted a quantitative research approach. Prior to data collection, both pre-tests and pilot tests were conducted to ensure the questionnaire was free from bias. During the actual data collection phase, a total of 395 Malaysian investors participated by completing the questionnaire. The collected data was subsequently analysed using SmartPLS 4.0 for both descriptive analysis and inferential statistical analysis purpose.

CHAPTER 4: DATA ANALYSIS

4.0 Introduction

Data analysis would be performed for this chapter, consisting of the showcasing of data results as well as the explanation of them. This chapter begins with a descriptive analysis, followed by reliability test with the purpose of testing and justifying the scales' dependability, then preliminary data screening to see if issues of multicollinearity and non-normality exist, and lastly finishes with an analysis of multiple linear regression. The analysis included within this chapter is completed using SmartPLS 4.1.1.4.

4.1 Descriptive Analysis

To help with the understanding and interpretation of the data collected, a descriptive analysis would first be performed. Demographic information of the participants collected in Section A of the questionnaire would first be analysed, then followed by data collected on variables and moderator from Section B and C.

4.1.1 Respondents' Demographic Profile

In this study, six demographic data were collected from the respondents including gender, age, ethnicity, state, occupation, and investment status. Each data will be analyzed, discussed and presented independently.

4.1.1.1 Gender

The frequency and percentage distribution of respondents by gender are presented in Table and Figure 4.1 below.

Table 4.1:

Gender

	Frequency	Percentage (%)	Cumulative Frequency	Cumulative Percentage (%)
Male	252	63.8	252	63.8
Female	143	36.2	395	100

Sources: Develop for this study

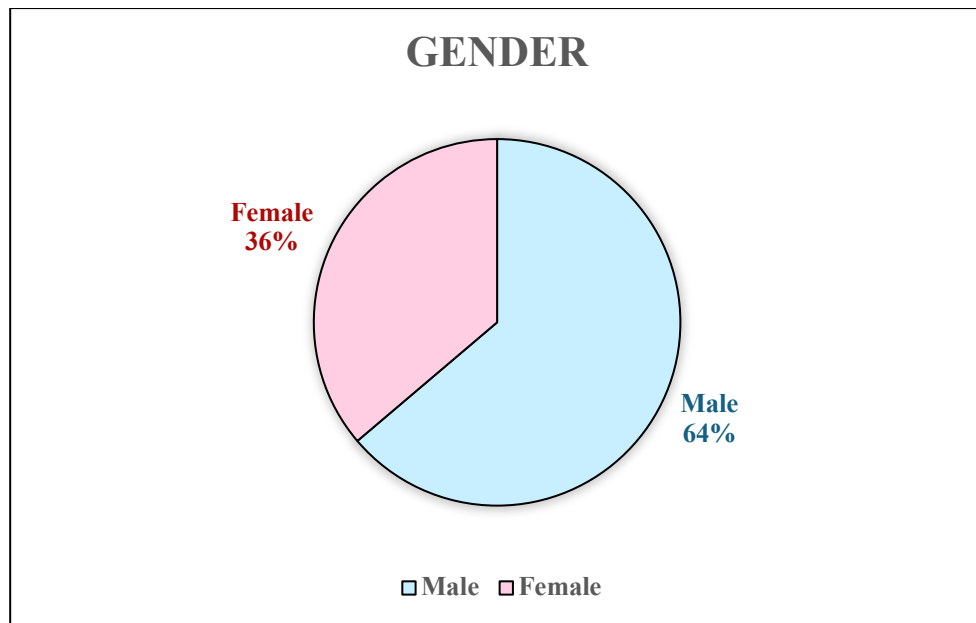


Figure 4.1 Descriptive Analysis – Gender. Source: Develop for this study.

Table 4.1 and Figure 4.1 above show that among the 395 respondents, 252 of the respondents are male, making up for 63.8% of the total respondents. On the other hand, female respondents only take up 36.2% of the respondents with a lesser 143 individuals.

4.1.1.2 Age

Table and Figure 4.2 presents the frequency and percentage distribution of respondents according to age.

Table 4.2:

Age

	Frequency	Percentage (%)	Cumulative Frequency	Cumulative Percentage (%)
18 – 30	225	57	225	57
31 – 40	128	32.4	353	89.4
41 – 50	34	8.6	387	98
51 – 60	8	2	395	100

Sources: Develop for this study

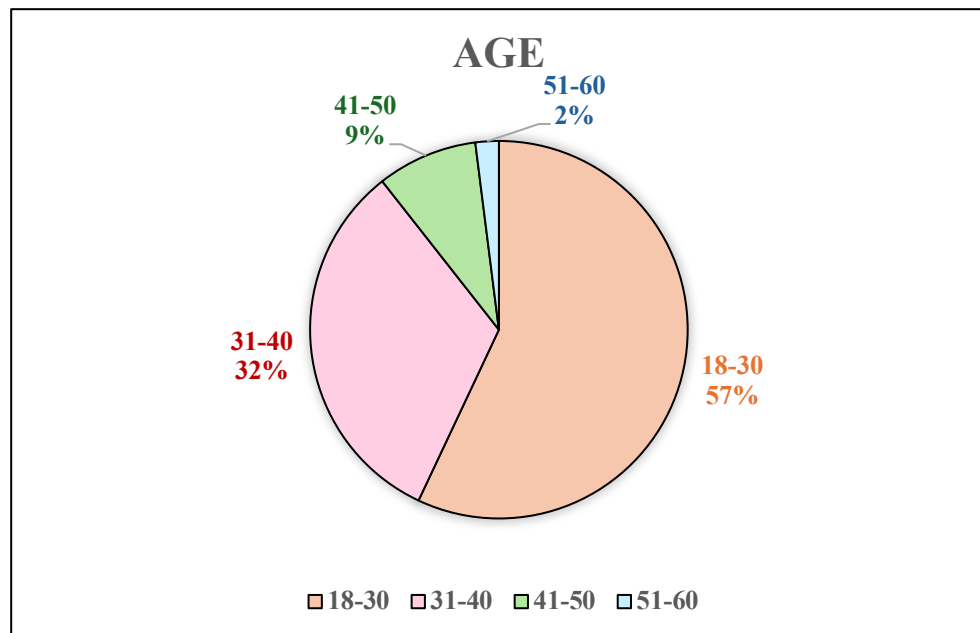


Figure 4.2 Descriptive Analysis – Age. Sources: Develop for this study.

The questionnaire had collected a total of 395 responses, among which 57% which translates to 225 of the respondents are within the age range of 18 – 30 years of age, follow by 32.4% which translates to 128 of the respondents aged within 31 – 40 years old, 8.6% which translates to 34 respondents are of age within 41 – 50 years old, and lastly with 2% which translates to 8 respondents within the age of 51 – 60.

4.1.1.3 Ethnicity

The ethnicity of the participants of this study is displayed in the following table and figure.

Table 4.3:

Ethnicity

	Frequency	Percentage (%)	Cumulative Frequency	Cumulative Percentage (%)
Malay	0	0	0	0
Chinese	364	92.2	364	92.2
Indian	31	7.8	395	100

Sources: Develop for this study

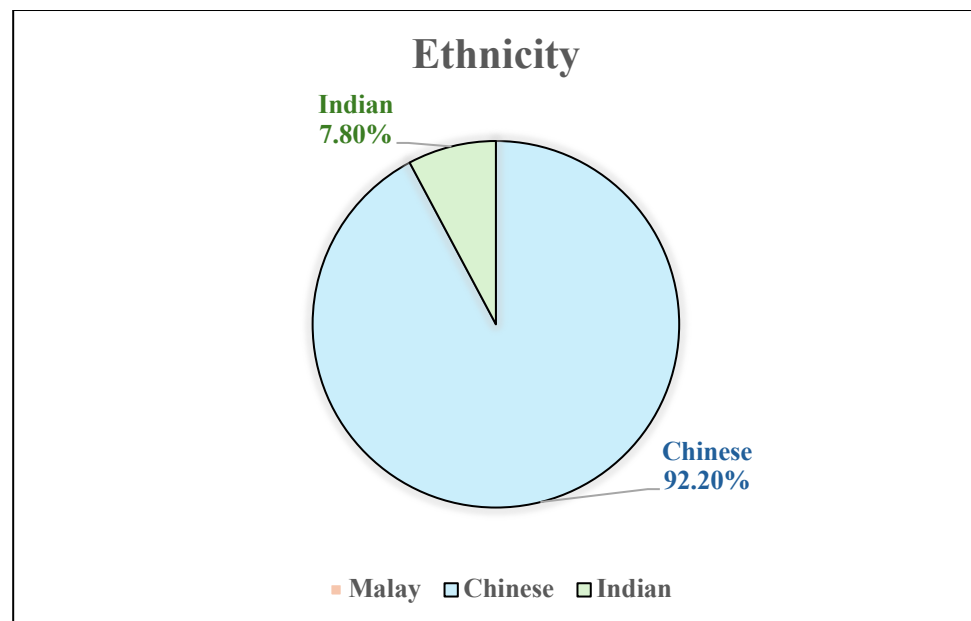


Figure 4.3 Descriptive Analysis – Ethnicity. Sources: Develop for this study.

As presented in the table above, a significant portion of the respondents among the sample size is Chinese, taking up for 92.2% of responses with 364 individuals. Indian respondents take up for 7.8% of the responses with 31 respondents. However, there are absence of Malay.

4.1.1.4 State

The number of respondents contributed by each of the listed state are displayed in the table and figure below.

Table 4.4:

State

	Frequency	Percentage (%)	Cumulative Frequency	Cumulative Percentage (%)
Selangor	168	42.5	168	42.4
Johor	133	33.7	301	71.2
Penang	94	23.8	395	100

Sources: Develop for this study

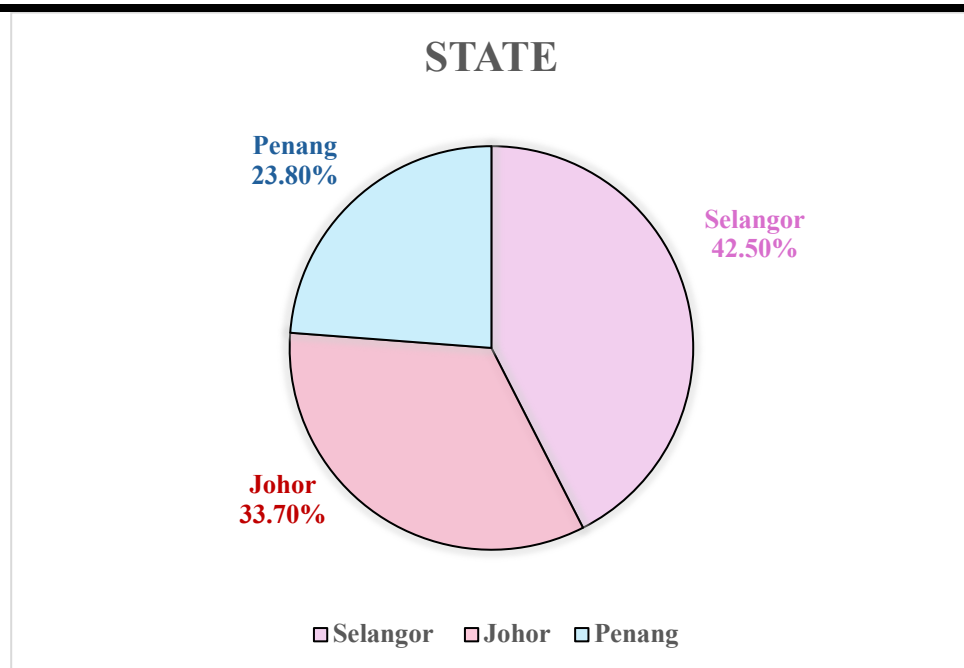


Figure 4.4 Descriptive Analysis – State. Sources: Develop for this study.

The table above shows that the responses collected are from three different states. The majority of the respondents are from Selangor, with 42.5%, which is equivalent to 168 respondents, being from there. The state with the second greatest number of participants is Johor, taking up 33.7% of the responses, which is equivalent to 113 respondents. Lastly, Penang contributed 23.8% of the responses, which translates to 94 respondents.

4.1.1.5 Occupation

The occupation of the study respondents is shown in the following Table and Figure 4.5.

Table 4.5:

Occupation

	Frequency	Percentage (%)	Cumulative Frequency	Cumulative Percentage (%)
Student	88	22.3	88	22.3
Employee	227	57.5	315	79.8
Employer	53	13.4	368	93.2
Unemployment	27	6.8	395	100

Sources: Develop for this study

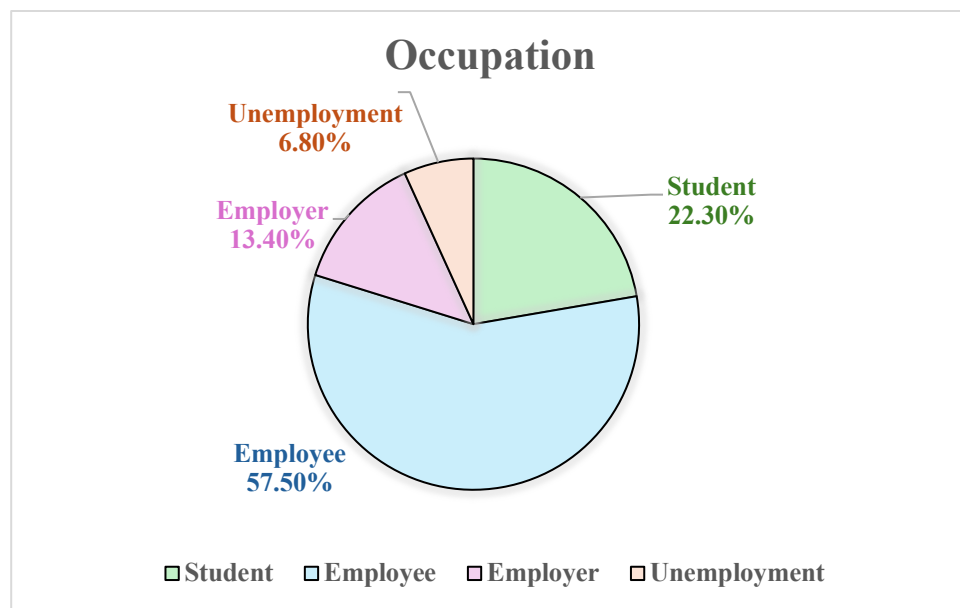


Figure 4.5 Descriptive Analysis – Occupation. Sources: Develop for this study.

In terms of occupation, employees are the most significant proportion of the participants, accounting for up to 57.5% of the responses with 227 respondents. The second most significant proportion of the participants would be students, with 88 respondents, accounting for up to 22.3% of the responses. The third most significant proportion of the participants would be employers, contributing 13.4% of the responses with 53 respondents. Lastly, 27 respondents, or 6.8% of the respondents, are unemployed.

4.1.1.6 Investment Status

The proportion of investors among the respondents is presented in the table below.

Table 4.6:

Investment Status

	Frequency	Percentage (%)	Cumulative Frequency	Cumulative Percentage (%)
Yes	395	100	395	100
No	0	0	395	100

Source: Develop for this study

According to Table 4.6, 100% of the responses collected from the questionnaire were contributed by investors in the equity market. This indicates that all respondents met the selection criteria, as they are actively involved in equity investments. As a result, this strengthens the accuracy and credibility of the research findings, ensuring the data is both relevant and reliable for the study's objectives.

4.1.2 Central Tendencies and Dispersion Measurement of Constructs

In this section, questions regarding the independent variables, moderator, and dependent variable in the questionnaire would be evaluated. The

evaluation revolves around the means and standard deviation of each variable independently.

4.1.2.1 Reshape Investment Strategies

Table 4.7 below is presented with the questions adopted for the questionnaire in this study, along with the respective mean, mean ranking, standard deviation, and the standard deviation ranking. RI1 represents the first question on reshape investment strategies in the Google Form, RI2 represents the second question, and the same naming convention applies to RI3, RI4, and RI5.

Table 4.7:

Central Tendencies Measurement – Reshape Investment Strategies

	Statement	Sample Size, N	Mean	Standard Deviation	Mean Ranking	Standard Deviation Ranking
RI1	When the stock price changes, I will be willing to reshape my investment based on the suggestion provided by AI to make a profit maximize.	395	4.144	0.855	5	4
RI2	I adjust my investment strategy based on the level of risk	395	4.190	0.784	3	5

	associated with different stocks.						
RI3	I change my holding period to realize profits early when there are quick gains in stock price.	395	4.238	0.877	1	3	
RI4	I ensure that my investment in stock has a high degree of safety investment by reshaping investment strategy.	395	4.147	0.911	4	2	
RI5	When international markets become volatile, I switch my investment focus to local stocks to maintain portfolio stability.	395	4.220	0.944	2	1	

**Note: RI – Reshape Investment Strategies

The dependent variable would be investigated. Based on the table above, RI3 has the greatest mean of 4.238 and the third greatest standard deviation of 0.877, suggesting that most responses are within 0.877 points of “Agree”. Following this, RI5 has the second largest mean of 4.220 and the largest standard deviation of 0.944, suggesting that most responses are within 0.944 points of “Agree”. On the other hand, RI2 has the third highest mean of 4.190 and the smallest standard deviation of 0.784, suggesting that most

responses are within 0.784 points of “Agree”. RI4 has the fourth largest mean of 4.147 and the second highest standard deviation of 0.911, suggesting that most responses are within 0.911 points of “Agree”. Lastly, RI1 has the smallest mean of 4.114 and the second lowest standard deviation of 0.855, suggesting that most responses are within 0.855 points of “Agree”.

4.1.2.2 Herding Effect

Table 4.8 below is presented with the questions adopted for the questionnaire in this study, along with the respective mean, mean ranking, standard deviation, and the standard deviation ranking. HE1 represents the first question on herding effect in the Google Form, HE2 represents the second question, and the same naming convention applies to HE3, HE4, and HE5.

Table 4.8:

Central Tendencies Measurement – Herding Effect

	Statement	Sample Size	Mean	Standard Deviation	Mean Ranking	Standard Deviation Ranking
HE1	I feel comfortable in making same investment decisions with the majority of investors.	395	3.970	0.911	5	4
HE2	My investment decisions will be influenced by the financial	395	4.180	0.845	2	5

	instrument's price movements.					
HE3	I tend to invest in trendy financial instrument.	395	4.099	1.000	3	1
HE4	Financial instrument's bid and ask volume will influences my investment choice.	395	4.081	0.959	4	3
HE5	I make swift investment decision in respond to market change.	395	4.261	0.960	1	2

**Note: HE – Herding Effect

For herding effect, HE5 has the largest mean of 4.261 alongside with the second highest standard deviation of 0.960, suggesting that most responses are within 0.960 points of 4.261, closer to “Agree”. HE2 follows up next with the second greatest mean of 4.180 as well as the smallest standard deviation of 0.845, suggesting that most responses are within 0.845 points of 4.180, closer to “Agree”. On the other hand, HE3 has the third highest mean of 4.099 as well as the largest standard deviation of 1, suggesting that most responses are within 1 point of 4.099, closer to “Agree”. HE4 follows with the second smallest mean of 4.081 and the third largest standard deviation of 0.959, suggesting that most responses are within 0.959 points of 4.081, closer to “Agree”. Lastly, HE1 has the lowest mean of 3.97 with the second smallest standard deviation of 0.911, suggesting that most responses are within 0.911 points of 3.97, closer to “Agree”.

4.1.2.3 Habit

Table 4.9 is presented with the questions adopted for the questionnaire in this study, along with the respective mean, mean ranking, standard deviation, and the standard deviation ranking. HB1 represents the first question on habit in the Google Form, HB2 represents the second question, and the same naming convention applies to HB3, HB4, and HB5.

Table 4.9:

Central Tendencies Measurement – Habit

	Statement	Sample Size, N	Mean	Standard Deviation	Mean Ranking	Standard Deviation Ranking
HB1	I sense more assurance in my own investment views over others.	395	4.278	0.788	1	5
HB2	I have my own specific skills and experience about investment.	395	4.058	0.954	3	3
HB3	I tend to invest in the same type of assets I am familiar with.	395	4.008	1.010	4	2
HB4	I believe the returns are higher for investments that I am familiar with.	395	3.990	1.016	5	1

HB5	I usually repeat	395	4.081	0.894	2	4
	the same					
	investment					
	actions based on					
	my past					
	experience.					

**Note: HB – Habit

The analysis of habit begins with HB1. HB1 has the highest mean of 4.278 but the lowest standard deviation of 0.788, suggesting that most responses are within 0.788 points of 4.278, closer to “Agree”. HB5 follows with the second largest mean of 4.081 and the second lowest standard deviation of 0.894, suggesting that most responses are within 0.894 points of 4.081, closer to “Agree”. HB2 follows with the third highest in both mean of 4.058 and standard deviation of 0.954, suggesting that most responses are within 0.954 points of 4.058, closer to “Agree”. Next would be HB3 with the fourth highest mean of 4.008 but the second largest standard deviation of 1.010, suggesting that most responses are within 1.010 points of 4.008, closer to “Agree”. Lastly, HB4 would have the smallest mean of 3.990 but largest standard deviation of 1.016, suggesting that most responses are within 1.016 points of 3.990, closer to “Agree”.

4.1.2.4 Performance Expectancy

Table 4.10 is presented with the questions adopted for the questionnaire in this study, along with the respective mean, mean ranking, standard deviation, and the standard deviation ranking. PE1 represents the first question on performance expectancy in the Google Form, PE2 represents the second question, and the same naming convention applies to PE3, PE4, and PE5.

Table 4.10:

Central Tendencies Measurement – Performance Expectancy

	Statement	Sample Size, N	Mean	Standard Deviation	Mean Ranking	Standard Deviation Ranking
PE1	I believe that using trading platform will improve my performance in stock trading.	395	4.068	0.873	3	4
PE2	Investing in the stock through trading platform will enhance my investment effectively.	395	3.782	0.967	5	3
PE3	I believe that investing through trading platform would enable to make profit more quickly.	395	3.949	1.059	4	2
PE4	I utilize trading platforms to track virtual item prices and market news, enabling me to reshape my trading strategy in a timely manner.	395	4.091	0.867	1	5
PE5	I feel that using trading platform is useful for reshape	395	4.081	1.074	2	1

my investment
strategies.

****Note:** PE – Performance Expectancy

For the third variable, performance expectancy would be look into. PE4 possesses the same highest mean of 4.091 but the lowest standard deviation of 0.867, suggesting that most responses are within 0.867 points of “Agree”. Moving to PE5, with the second highest mean of 4.081 and the largest standard deviation of 1.074, suggesting that most responses are within 1.074 of “Agree”. PE1 would be the following with the third highest mean of 4.068 and fourth highest standard deviation of 0.873, suggesting that most responses are within 0.873 points of “Agree”. Moving on to PE3 with the fourth highest mean of 3.949 and second highest standard deviation of 1.059, suggesting that most responses are within 1.059 points of 3.949, closer to “Agree”. Lastly, PE2 have the lowest mean of 3.782 and the third highest standard deviation of 0.967. This suggests that most responses are within 0.967 points of 3.782, closer to “Agree”.

4.1.2.5 Personal Innovativeness in IT

Table 4.11 is presented with the questions adopted for the questionnaire in this study, along with the respective mean, mean ranking, standard deviation, and the standard deviation ranking. PI1 represents the first question on personal innovativeness in IT in the Google Form, PI2 represents the second question, and the same naming convention applies to PI3, PI4, and PI5.

Table 4.11:

Central Tendencies Measurement – Personal Innovativeness in IT

	Statement	Sample Size	Mean	Standard Deviation	Mean Ranking	Standard Deviation Ranking
PI1	Among my peers, I am usually the first to try out new information technologies like robo advisory.	395	3.747	0.948	1	4
PI2	I like to experiment new features and advancements in information technologies.	395	3.742	0.919	2	5
PI3	I think that I would be able to use new technologies well for reshaping my investment strategy.	395	3.706	0.976	3	3
PI4	I believe that robo advisor performs its role of providing investment recommendations successfully.	395	3.691	1.058	5	2
PI5	I believe robo advisor is making recommendations in my best	395	3.704	1.082	4	1

interest, helping
reshape my
investment
strategy.

****Note:** PI – Personal Innovativeness in IT

For personal innovativeness in IT, PI1 has the highest mean 3.747 of but the second lowest standard deviation of 0.948, suggesting that most responses are within 0.948 points of 3.747, closer to “Agree”. Followed by PI2 with the second highest mean of 3.742 and lowest standard deviation of 0.919, suggesting that most responses are within 0.919 points of 3.742, closer to “Agree”. PI3 would be next with the third highest mean and standard deviation of 3.706 and 0.976 respectively, suggesting that most responses are within 0.976 points of 3.706, closer to “Agree”. Up next would be PI5 with the fourth highest mean of 3.704 and the largest standard deviation of 1.082, suggesting that most responses are within 1.082 points of 3.704, closer to “Agree”. Lastly, PI4 has the smallest mean of 3.691 and the second highest standard deviation of 1.058, suggesting that most responses are within 1.058 points of 3.691, closer to “Agree”.

4.1.2.6 Market Sentiment

Table 4.12 is presented with the questions adopted for the questionnaire in this study, along with the respective mean, mean ranking, standard deviation, and the standard deviation ranking. MS1 represents the first question on market sentiment in the Google Form, MS2 represents the second question, and the same naming convention applies to MS3, MS4, and MS5.

Table 4.12:

Central Tendencies Measurement – Market Sentiment

	Statement	Sample Size	Mean	Standard Deviation	Mean Raking	Standard Deviation Ranking
MS1	I believe that changes in interest rates influence the overall market mood, which affects my investment decisions.	395	3.615	0.913	5	5
MS2	I tend to rely on my habits even in different market conditions when making investment decisions.	395	3.648	1.112	4	1
MS3	I believe that using an efficient trading platform enhances my confidence in different market sentiment and reshape my investment strategies.	395	3.722	0.943	3	4
MS4	I trust robo-advisors more than traditional financial advisors during high	395	4.033	1.068	1	2

	market volatility					
	because of the					
	rationality of					
	robo-advisory					
	systems.					
MS5	I am not confident	395	3.952	0.955	2	3
	in making					
	different decisions					
	than the majority					
	of investors when					
	market sentiment					
	is volatile.					

**Note: MS – Market Sentiment

According to Table 4.12 above, MS4 would have the highest mean of 4.033 and the second highest standard deviation of 1.068, suggesting that most responses are within 1.068 points of 4.033, closer to “Agree”. Next, MS5 would have the second highest mean of 3.952 and the third largest standard deviation of 0.955, suggesting that most responses are within 0.955 points of 3.952, closer to “Agree”. MS3 has the third highest mean of 3.722 and the second lowest standard deviation of 0.943, suggesting that most responses are within 0.943 points of 3.722, closer to “Agree”. Coming in at the fourth place of highest mean would be MS2 with mean of 3.648 and the largest standard deviation of 1.112, suggesting that most responses are within 1.112 points of 3.648, closer to “Agree”. Lastly, MS1 has both the smallest mean and standard deviation of 3.615 and 0.913 respectively, suggesting that most responses are within 0.913 points of 3.615, closer to “Agree”.

4.2 Scale Measurement

4.2.1 Reliability Test

Table 4.13:

Cronbach's Alpha Reliability Analysis

No	Type of Variable	Name (Variable)	Number (Item)	Cronbach's Alpha	Reliability Test
1	Dependent Variable	Reshape Investment Strategies	5	0.824	Good
2	Independent Variable	Habit	5	0.811	Good
3	Independent Variable	Performance Expectancy	5	0.783	Acceptable
4	Independent Variable	Personal Innovativeness in IT	5	0.806	Good
5	Independent Variable	Herding Effect	5	0.859	Good
6	Moderator	Market Sentiment	5	0.788	Acceptable

Table 4.13 above indicates the results of reliability test of all independent variables, dependent variable as well as moderator. Variables that have been tested with results indicating good reliability, suggesting Cronbach's alphas larger than 0.80 while lower than 0.90, includes reshape investment strategies with 0.824, habit with 0.811, personal innovativeness in IT with 0.806, and herding effect with 0.859. For the variable performance expectancy and market sentiment, reliability test results suggest that these

two variables have achieved acceptable dependability with Cronbach's alphas of 0.783 and 0.788 respectively.

4.3 Preliminary Data Screening

To ensure the credibility and robustness of the study's findings, a series of preliminary data screening procedures were conducted prior to hypothesis testing. Initial data screening included the outer loading matrix, multicollinearity assessment, validity and reliability tests, and the heterotrait-monotrait ratio (HTMT) to ensure the data's suitability for hypothesis testing.

4.3.1 Measurement Model Assessment

Table 4.14:

Factor Loadings

	HB	HE	MS	PE	PI	RI	MS x HB	MS x HE	MS x PE	MS x PI
HB1	0.758									
HB2	0.748									
HB3	0.751									
HB4	0.748									
HB5	0.765									
HE1		0.793								
HE2		0.813								
HE3		0.785								
HE4		0.818								
HE5		0.785								

MS1	0.724	
MS2	0.721	
MS3	0.722	
MS4	0.773	
MS5	0.715	
PE1	0.737	
PE2	0.729	
PE3	0.720	
PE4	0.716	
PE5	0.752	
PI1	0.724	
PI2	0.741	
PI3	0.782	
PI4	0.721	
PI5	0.775	
RI1	0.760	
RI2	0.748	
RI3	0.775	
RI4	0.738	
RI5	0.808	
MS x HB	1.000	
MS x HE	1.000	
MS x PE	1.000	
MS x PI	1.000	

**Note: HB – Habit; HE – Herding effect; MS – Market Sentiment; PE – Performance Expectancy; PI – Personal Innovativeness in IT; RI – Reshape Investment Strategies

The measurement model was evaluated using indicator loadings to assess item reliability. As Hair et al. (2021) indicator outer loadings should ideally be above 0.70, indicating that the observed variables adequately reflect their respective latent constructs. As presented in Table 4.14, all items measuring their respective constructs exhibit outer loadings greater than 0.70, ranging

from 0.715 to 0.818. This confirms that each indicator contributes substantially to its corresponding construct, thereby satisfying the threshold for indicator reliability.

For the construct habit, all five items (HB1 to HB5) show loadings between 0.748 and 0.765. Similarly, the construct herding effect demonstrates strong loadings from HE1 to HE5, ranging from 0.785 to 0.818. The constructs market sentiment, performance expectancy, and personal innovativeness in IT also meet the loading criteria, with all items loading between approximately 0.716 and 0.782. Lastly, the construct reshape investment strategies is supported by five indicators, with outer loadings between 0.738 and 0.808, further confirming its internal consistency. Regarding the interaction terms, namely market sentiment multiplied by habit, herding effect, performance expectancy, and personal innovativeness in IT, all four constructs exhibit a single loading of 1.000. This is typical when interaction terms are generated using the product indicator approach or the two-stage approach in SmartPLS. These values are not interpreted in the same manner as reflective indicators, but their inclusion supports the structural model in conducting moderation analysis.

In summary, all reflective constructs demonstrate satisfactory indicator reliability, with outer loadings exceeding the minimum requirement. The results confirm that the measurement model is both reliable and appropriately specified for subsequent structural analysis.

4.3.2 Validity and reliability

Table 4.15:

Construct Validity and Reliability

	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
HB	0.814	0.868	0.569
HE	0.864	0.898	0.638
MS	0.804	0.852	0.535
PE	0.785	0.851	0.534
PI	0.812	0.865	0.561
RI	0.825	0.877	0.587

****Note:** HB – Habit; HE – Herding effect; MS – Market Sentiment; PE – Performance Expectancy; PI – Personal Innovativeness in IT; RI – Reshape Investment Strategies

In PLS-SEM, composite reliability and average variance extracted (AVE) are key indicators for assessing the quality of the measurement model. Composite reliability, reported as reliability coefficient (rho_A) and composite reliability (rho_C), evaluates the internal consistency of each construct. The results of the measurement model evaluation show that both rho_A and rho_C values for all reflective constructs are above 0.70. Additionally, convergent validity is established through the AVE, with all constructs exceeding the minimum threshold of 0.50, thereby confirming that a substantial portion of the variance is captured by the indicators (Hair et al., 2019). All constructs have reliability coefficient (rho_A) and composite reliability (rho_C) are above 0.70, confirming good internal consistency. The AVE values range from 0.534 to 0.638, all exceeding the minimum threshold of 0.50, thereby supporting acceptable convergent validity for all constructs. This indicates that the measurement model is both reliable and valid, justifying its use in the structural model analysis.

4.3.3 Multicollinearity Test

Table 4.16:

Collinearity (VIF)

	RI
HB	2.571
HE	2.053
MS	1.353
PE	1.667
PI	1.233
RI	
MS x PI	1.332
MS x HB	2.258
MS x HE	2.141
MS x PE	1.776

**Note: HB – Habit; HE – Herding effect; MS – Market Sentiment; PE – Performance Expectancy; PI – Personal Innovativeness in IT; RI – Reshape Investment Strategies

The results indicate that all variance inflation factor (VIF) values are below the critical threshold of 5, suggesting that multicollinearity is not a significant concern in this study. For the direct predictors of reshape investment strategies, the lowest variance inflation factor value is recorded for personal innovativeness in IT at 1.233, while the highest is habit at 2.571. Regarding the interaction terms, the values range from 1.332 for market sentiment multiplied by personal innovativeness in IT to 2.258 for market sentiment multiplied by habit. Since all values are well below the standard threshold of 5.0, it can be concluded that there is no evidence of multicollinearity among the constructs. This implies that the predictor variables are sufficiently independent, ensuring the stability and reliability of the structural model estimates.

4.3.4 Discriminant Validity

Table 4.17:

Heterotrait-Monotrait Ratio (HTMT) Output

	HB	HE	MS	PE	PI	RI	MS x PI	MS x HB	MS x HE	MS x PE
HB										
HE	0.681									
MS	0.471	0.325								
PE	0.644	0.708	0.321							
PI	0.391	0.292	0.099	0.221						
RI	0.838	0.875	0.435	0.759	0.432					
MS x PI	0.186	0.181	0.1	0.086	0.049	0.22				
MS x HB	0.528	0.16	0.224	0.177	0.138	0.293	0.364			
MS x HE	0.193	0.267	0.136	0.165	0.158	0.227	0.368	0.542		
MS x PE	0.225	0.179	0.164	0.124	0.082	0.169	0.185	0.515	0.614	

****Note:** HB – Habit; HE – Herding effect; MS – Market Sentiment; PE – Performance Expectancy; PI – Personal Innovativeness in IT; RI – Reshape Investment Strategies

The Table 4.17 above presents the HTMT (Heterotrait-Monotrait) ratio results for each construct in the study, which were used to evaluate discriminant validity. As shown in table, all HTMT values in the model range from 0.049 to 0.875. The highest value, 0.875, is observed between herding effect and reshape investment strategies. Although this value is relatively high, it remains below the 0.90 threshold, indicating that discriminant validity is still maintained. The lowest HTMT value is 0.049, observed between personal innovativeness in IT and the interaction term market sentiment multiplied by personal innovativeness in IT, suggesting minimal overlap between these constructs. Overall, all HTMT values fall

below the recommended threshold of 0.90, as suggested by Hair et al. (2019), indicating that each construct is empirically distinct from the others. Therefore, the model demonstrates satisfactory discriminant validity and confirms that discriminant validity has been adequately established.

4.4 Inferential Analysis

4.4.1 Structural Model Assessment

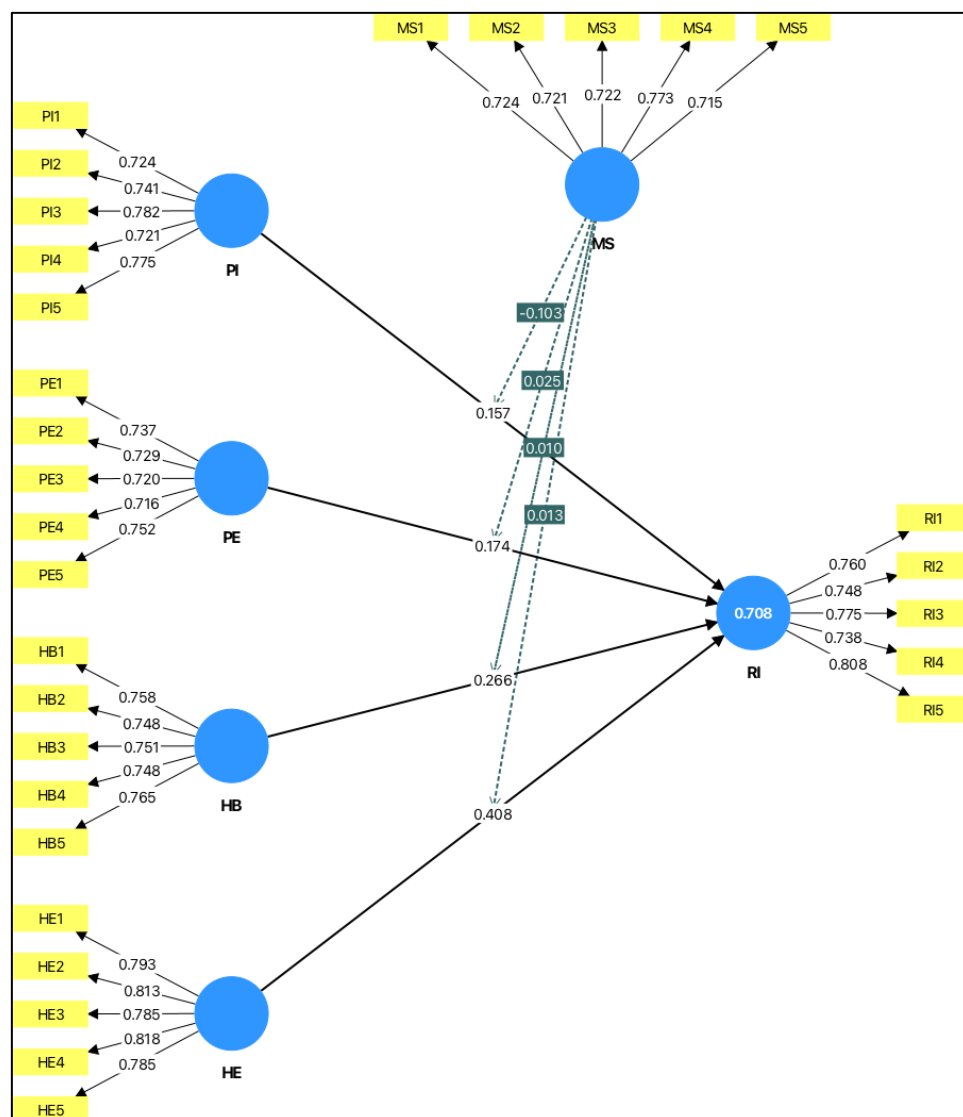


Figure 4.6 Structural Model Assessment.

The Figure 4.6 presents the structural model output generated using SmartPLS, covering both the measurement and structural components. Each latent construct, including habit, herding effect, performance expectancy, personal innovativeness in IT, market sentiment and reshape investment strategies, is measured by multiple reflective indicators with loadings above 0.70, indicating acceptable reliability. The R square value for reshape investment strategies is 0.708, suggesting that 70.8% of its variance is explained by the five predictor constructs. Herding effect has the strongest influence with a path coefficient of 0.408, followed by habit, performance expectancy, and personal innovativeness in IT. The moderating effects of market sentiment on the relationships with habit, herding effect, performance expectancy, and personal innovativeness in IT show path coefficients of 0.010, 0.013, 0.025, and 0.103 respectively. The strongest effect is the interaction with personal innovativeness in IT, showing that higher market sentiment will weaken its influence on reshape investment strategies. Overall, the model demonstrates strong explanatory power and highlights how psychological and technological factors reshape investment strategies.

4.4.2 Assess Path Coefficients

Table 4.18:

Path Coefficient, Standard Error, T-Value, P-Value and Hypotheses Testing

Hypotheses	Description	Beta Value	Standard Error	T- Value	P- Value	Decision
H1	HE -> RI	0.408	0.058	7.003	0.000	H1 accepted
H2	HB -> RI	0.266	0.069	3.843	0.000	H2 accepted

H3	PE -> RI	0.174	0.046	3.751	0.000	H3 accepted
H4	PI -> RI	0.157	0.036	4.379	0.000	H4 accepted

****Note:** HB – Habit; HE – Herding effect; MS – Market Sentiment; PE – Performance Expectancy; PI – Personal Innovativeness in IT; RI – Reshape Investment Strategies

The results of the direct effect hypothesis testing are displayed in the table above. The dependent variable, reshape investment strategies, is directly influenced by the independent variables such as herding effect, habit, performance expectancy, and personal innovativeness in IT. At the significance level of $\alpha = 0.05$, all four independent variables show statistically significant results, indicating that each has a direct relationship with reshape investment strategies (Hypothesis 1, 2, 3 and 4 accepted).

4.4.3 Analysis of Moderating effect

Table 4.19:

Path Coefficient, Standard Error, T-Value, P-Value and Hypotheses Testing (Moderating)

Hypotheses	Description	Beta Value	Standard Error	T-Value	P-Value	Decision
H5	MS x HE -> RI	0.013	0.052	0.253	0.800	Reject H5
H6	MS x HB -> RI	0.01	0.046	0.219	0.827	Reject H6
H7	MS x PE -> RI	0.025	0.044	0.574	0.566	Reject H7

H8	MS x PI -> RI	-0.103	0.032	3.234	0.001	Accept H8
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****Note:** HB – Habit; HE – Herding effect; MS – Market Sentiment; PE – Performance Expectancy; PI – Personal Innovativeness in IT; RI – Reshape Investment Strategies

In this study, market sentiment acts as a moderator that influences the relationship between the independent variables, including herding effect, habit, performance expectancy, personal innovativeness in IT, and the dependent variable, reshape investment strategies.

The results in Table 4.19 provide compelling evidence supporting Hypothesis 8, indicating that the relationship between personal innovativeness in IT and reshape investment strategies is significantly moderated by market sentiment. Specifically, market sentiment exerts a statistically significant moderating influence on the relationship between personal innovativeness in IT and the dependent variable, as demonstrated by a p-value below the 0.05 threshold. In contrast, market sentiment does not exhibit a significant moderating effect on the relationships involving habit, herding effect and performance expectancy, as the p-values are greater than 0.05. Therefore, hypotheses 5, 6 and 7 are rejected.

4.4.4 Coefficient of Determination (R^2)

Table 4.20:

Determination of co-efficient (R^2)

	R-square	R-square adjusted
RI	0.708	0.701

****** RI – Reshape Investment Strategies

The R^2 value for reshape investment strategies is 0.708, indicating that 70.8% of the total variance in the dependent variable is explained by herding effect, habit, performance expectancy, personal innovativeness in IT and market sentiment.

4.4.5 Assess Effect Size f^2

Table 4.21:

Determination of effect size (f^2)

	RI
HB	0.094
HE	0.277
MS	0.039
PE	0.062
PI	0.069
RI	

****Note:** HB – Habit; HE – Herding effect; MS – Market Sentiment; PE – Performance Expectancy; PI – Personal Innovativeness in IT; RI – Reshape Investment Strategies

According to Hair et al. (2019), the assessment criteria for effect size (f^2) suggest that a value higher 0.02 indicates a small effect, values between 0.15 and 0.35 represent a medium effect, and values exceeding 0.35 reflect a large effect.

Based on the Table 4.21, herding effect demonstrates the strongest influence on the dependent variable, which is reshape investment strategies. In

contrast, market sentiment exhibits the weakest effect size on the same dependent variable, followed by performance expectancy, habit, and personal innovativeness in IT.

4.5 Conclusion

SmartPLS version 4.0 is used to conduct the data analysis for this study. The reliability assessment confirmed that the measurement scales applied in the questionnaire demonstrated adequate internal consistency. Additionally, the dataset fulfilled all preliminary data screening requirements, including the evaluation of construct validity and reliability, multicollinearity test, the heterotrait-monotrait ratio (HTMT), and the outer loading matrix. The results of the structural model indicated that the independent variables, namely herding effect, habit, performance expectancy and personal innovativeness in IT, significantly influenced in reshape investment strategies. In the moderation analysis, market sentiment was identified as a significant moderator only in the relationship between personal innovativeness in IT and reshape investment strategies.

CHAPTER 5: DISCUSSION, CONCLUSION AND IMPLICATIONS

5.0 Introduction

In this chapter, a detailed exploration of the results and findings will be presented. Firstly, a summary of the statistical analyses will be provided in table form to offer

a concise overview. This will be followed by a discussion of the factors contributing to these results, supported by relevant findings from previous studies. In addition, practical recommendations based on the findings will be proposed to demonstrate their applicability and relevance to different target groups in real-world contexts. Finally, the chapter outlines the limitations of the study and suggests directions for future research.

5.1 Statistical Analysis Summary

To provide a comprehensive overview of the data analysis, a statistical analysis summary table will be constructed. This table aims to offer a clearer and more organized presentation of the research findings, allowing for easier interpretation and comparison of results. The t-values and p-values for each independent variable, obtained from the SmartPLS Structural Equation Modeling (SEM) analysis, will be systematically reported. By evaluating these values, the study can identify which variables have a statistically significant impact on the outcome of interest.

Table 5.1:

Statistical Analysis Summary

Independent Variable	T - value	P - value	Findings
Herding Effect	7.003	0.000	Significant
Habit	3.843	0.000	Significant
Performance Expectancy	3.751	0.000	Significant
Personal Innovativeness in IT	4.379	0.000	Significant
Moderating Effect of market sentiment towards herding effect	0.253	0.800	Insignificant

Moderating Effect of market sentiment towards habit	0.219	0.827	Insignificant
Moderating Effect of market sentiment towards performance expectancy	0.574	0.566	Insignificant
Moderating Effect of market sentiment towards personal innovativeness in IT	3.234	0.001	Significant

According to Table 5.1, the findings indicate that independent variables with p-values below 0.05 are statistically significant. These variables include herding effect, habit, performance expectancy, personal innovativeness in IT, as well as the moderating effect of market sentiment towards personal innovativeness in IT. This suggests that these factors have a significant relationship with the dependent variable of this study which is reshape investment strategies.

On the other hand, the moderating effect of market sentiment towards herding effect, habit, and performance expectancy was found to be statistically insignificant. This indicates that market sentiment does not moderate the relationship between these independent variables and the dependent variable respectively. In other words, the influence of herding effect, habit, and performance expectancy on reshape investment strategies remains unaffected by market sentiment.

5.2 Discussions of Major Findings

5.2.1 Herding Effect

Based on the results obtained, herding effect is found to be significant in influencing the reshape of investment strategies, of which is tally with the result from Hirdinis (2021), Cao et al. (2021), Rahayu et al. (2021), and Pham et al. (2023).

Hirdinis (2021) analyzed the impact of herding effect on investment decision making on Indonesia Stock Exchange and the results shows that there is positive correlation between the herding effect with the investment decisions by investors in the Jakarta area, suggesting that herding is in fact an encouraging factor for investors. Similarly, another study by Rahayu et al. (2021) done in Indonesia suggests that investors often ignore their own capabilities and rather believe in others whom they believe to be skillful, proving that herding is significant in investment.

This can be explained as Zhang et al. (2021) suggested that as financial market develops and technologic growth, it often requires investors to respond quickly and requires fast investment decision making to avoid losing profitable opportunities but not necessarily allowing them to gather all the information they require to make sound investment decisions. But as limited information is available to be taken into consideration (Alhadri & Hamid, 2024), as well as the shortening of timespan available for the decision making (Linn et al., 2024), these factors could act as catalysts for the occurrence of herding effect among investors. Similar results have also been suggested by Cao et al. (2021), that herding is a significant factor in the generating of investment decision making, therefore showcasing the significance relationship between the factors. Similarly, Pham et al. (2023) also suggests investors tend to be affected by the opinions of those around them. In conclusion, this study's results illustrates that investors' decision in investment strategies in Malaysia is impacted by other individuals around them and showing a significant relationship between herding effect and reshape investment strategies.

5.2.2 Habit

According to the results obtained, habit was found to be significant in influencing the reshaping of investment strategies, which is consistent with the results suggested by the studies conducted by Haasnoot et al. (2020), Sourirajan and Perumandla (2022), Sonkar et al. (2023) and Arsyianti et al. (2023).

In today's ever-changing financial markets, investors are constantly being bombarded with news and information, overwhelming them with the challenge of processing and evaluating all available inputs (Bernales et al., 2024). Furthermore, with the popularization of mobile devices and social media, news and information are being shared, transmitted, and reviewed by a growing number of investors within increasingly shorter time spans, thereby intensifying the risk of news overload (Zhang et al., 2022). Due to this nature of the market, news overload has been suggested to be fatiguing and capable of reducing investors' ability to fully understand, analyse, and interpret available information (Eissa et al., 2024). However, when investors utilize fintech such as robo-advisors, the discomfort and psychological burden of potential financial loss are eased (Back et al., 2021). Therefore, when investors build habituation on dependence upon fintech, their strategy follows (Kumar, 2020). All Haasnoot et al. (2020), Sourirajan and Perumandla (2022), Sonkar et al. (2023) and Arsyianti et al. (2023) highlighted that there is indeed a significant relationship between the habit of investors and the reshaping of their investment strategies.

This study therefore concludes that the phenomenon is observable in the Malaysian context as well, where personal habit plays a substantial role in

shaping and reshaping investors' strategies decisions. The findings emphasize that, even amidst technological progress and volatile market conditions, habitual behavior continues to exert a powerful and consistent influence on how investors navigate their financial choices.

5.2.3 Performance Expectancy

Based on the result obtained, the performance expectancy was found to be influencing investor to reshaping their investment strategies. The result is found to be aligned with the study conducted by Srivastav et al. (2024), Priyadarshi et al. (2024) and Stanley et al. (2024).

Srivastav et al. (2024) found that FinTech plays a crucial role in investor decision making when it effectively meets users' needs by providing valuable insights and facilitating well-informed choices, ultimately leading to improved investment performance. Besides that, Priyadarshi et al. (2024) also stated that performance expectancy in FinTech applications has a largely beneficial influence on investor decision-making as the emergence of FinTech applications enhance decision-making processes and democratize investors' access to investment opportunities.

Bustani et al. (2021) indicated that this is particularly evident in the use of trading platforms, which provide structured and comprehensive fundamental analysis that investors can rely on when evaluating their preferred stocks. This observation is further supported by the findings of Sari et al. (2022) which demonstrated that fundamental analysis would affect investors' investment decision as around 70% of investors rely fundamental analysis as main foundation in choosing stocks. Instead, these tools deliver readily accessible and organized financial information. As a

result, according to findings from Stanley et al. (2024) the features offered by trading platforms not only support informed investment decisions but also assist investors in reshaping their investment strategies. By integrating real-time data, analysis tools, and user-friendly interfaces, these platforms empower investors to respond more strategically and efficiently to changing market conditions and personal financial goals (Nainggolan & Handayani 2023; Bhatnagr & Rajesh, 2024).

5.2.4 Personal Innovativeness in Information Technology

According to the result obtained, the personal innovativeness in IT was found to be influencing investor to reshaping their investment strategies. This result is aligned with previous studies Salvi et al. (2024) and Syed and Janamolla (2024).

Salvi et al. (2024) demonstrated that an investor's degree of innovativeness influences individual investment decisions, particularly among those who perceive themselves as highly innovative, as they are more willing to experiment with new technologies. Furthermore, Syed and Janamolla (2024) stated that the integration of AI-driven robo-advisors has revolutionized the investment decision-making process by offering numerous benefits, including personalization, boost efficiency, and enhance performance. Therefore, these findings were aligned with our result suggesting that individuals with a high level of personal innovativeness are more likely to adopt new emerging technologies, such as robo-advisory (Kandoth & Shekhar, 2022) which in turn facilitates the reshaping of their investment strategies.

Zheng et al. (2025) and Cheong et al. (2023) indicated that highly innovative investors tend to place greater trust in AI-powered robo-advisory platforms, as they believe that data-driven strategies and analytical approaches are more reliable. Unlike manual evaluations, Onabowale (2024) and Kumar (2020) stated that robo-advisory can promptly respond to market changes by providing instantaneous adjustments to investment strategies and data-backed recommendations tailored to investors' preferences. Therefore, innovative investors are able to reshape their investment strategies more swiftly based on the advice provided by robo-advisory in a timely manner (Shen et al., 2025). Furthermore, when seeking to explore new investment opportunities or diversify their portfolios, innovative investors can rely on the robo-advisory's algorithmic capabilities to generate personalized, well-balanced investment plans aligned with their risk tolerance, financial goals, and investment horizon as well as any unique characteristic (Kumar, 2020; Khosravi, 2024; Baboo & Imran, 2025). As a result, innovative investor can follow the recommended strategies to diversify their portfolios and manage risks more effectively, thereby reshaping their investment strategies in a more systematic and technology-driven manner as well as bias-free.

5.2.5 Moderating effect of market sentiment towards herding effect and reshape investment strategies

According to the results obtained, the data suggests that there is no moderating effect of market sentiment towards herding effect and the reshaping of investors' investment strategies. This outcome is tally with Loang (2025) and Kumari et al. (2025).

According to Loang (2025), it has been shown to prove that market sentiment and news sentiment are both insignificant on herding effect in Asia, suggesting that in terms of their impact, both have limited and

constrained effects against herding effect. Loang (2025) further suggested that the findings may varies from market regions due to varieties of factors that are driving the effect of herding behaviours, such as the structure of market and investor behaviour. This study aligned with the findings of Loang (2025) and Kumari et al. (2025), proving that investors in Malaysia will be impacted by herding effect, on whether or not to reshape their investment strategies, no matter the market sentiment of bullish or bearish. The occurrence of such phenomenon can be explained as market sentiment that it will last up a period of consistent trend, either upwards or downwards, for a significant amount of time (Chan et al., 2024). But herding effect does not possess the characteristics of lasting for a span of time (Ng et al., 2022).

According to Loang and Ahamd (2021), the herding of investments are in fact due to volatility. Due to this nature, herding might occur in within any market sentiment and does not necessarily has any impact on the herding effect in the reshaping of investment strategies. Therefore, no matter bullish or bearish, herding effect have the possibility of occurrence, showing insignificance in relationship between market sentiment and the relationship between herding effect and the reshaping of investment strategies. This study therefore concludes that there is no impact of sentiment against the relationship between herding effect and reshape investment strategies.

5.2.6 Moderating effect of market sentiment towards habit and reshape investment strategies

According to the results obtained, the data suggests that there is no moderating effect of market sentiment towards habit and the reshaping of investors' investment strategies. The outcome of this study is tally with the results obtained by Singhal (2023).

The results suggest that regardless of the market sentiment, bullish or bearish, habit of using fintech for investment strategy will be significant in affecting how investors reshape investment strategies. Due to habituation from past experience and pre-conceived ideas, investors' investment decisions and strategies do not necessarily change along with the market cycles but rather follow the recommendations from fintech platforms that they are accustomed to utilizing. According to Singhal (2023), when investors have been exposed to financial crises in the past, this experience builds a habit that they fail to change even during "booms" in the market, thereby causing them to miss potential opportunities for higher returns. Therefore, Singhal (2023) results suggest that investors follow their preconceived habits, even when market sentiment has shifted. This result aligns with this study, suggesting that there is no moderating effect of market sentiment towards habit and the reshaping of investment strategies.

In addition, according to Friedman (2023), the formation of habits in its very nature is to help minimize cognitive effort in making decisions, ensuring quicker, easier, and more consistent choices. Therefore, this study obtained results that aligned with Singhal (2023), showing that in Malaysia, investors' strategies are structured and rigid based on personal past experience and path-dependency preferences. They tend to stay the same no matter the prevailing market condition. Whether bullish or bearish, sentiment does not exert any effect on the relationship between investors' habit and the reshaping of their investment strategies, highlighting the enduring strength of habitual behaviour in shaping investment decision-making.

5.2.7 Moderating effect of market sentiment towards performance expectancy and reshape investment strategies

Moreover, the results of this study indicate that market sentiment does not have a moderating effect on the relationship between performance expectancy and reshaping investment strategies. This finding contradicts the results of Abakah et al. (2023) and Zeng et al. (2024) who found that during market sentiment such as fear in bearish market or overconfidence in bullish market can cause investors to rely more on intuition rather than data-driven analysis. Such behavior was shown to diminish performance expectancy toward trading applications, as investors may disregard the tools and insights offered by trading platforms during emotionally charged market conditions.

However, based on our result, market sentiment appears to have no significant influence on performance expectancy and investor to reshape their investment strategies. This result implies that regardless of whether market conditions are bullish or bearish, investors remain focused on the intrinsic value and functionality of FinTech applications, particularly trading platform (Almetere et al., 2020; Ali et al., 2021; Bhatnagr & Rajesh, 2024). Investors tend to consistently rely on performance-related features, such as real-time analytics, detailed financial reports, charting tools for market analysis, automated order execution, fair value price computation, and data-driven recommendations such as buy, hold, or sell signals to guide them in reshaping more rational and informed investment strategies (Malhotra, 2020; Nainggolan & Handayani, 2023). In addition, one possible explanation for this divergence could be the growing familiarity with and trust in trading tools. In today's technology-driven era, investors are increasingly reliant on trading platforms to undergo their investments.

Anand and Abhilash (2022) and Arfina et al. (2023) indicated that trading platform offers a convenient and accessible medium for investors to buy and sell shares directly from their smartphones, while simultaneously providing real-time information that supports investor reshaping investment strategies on time. For instance, access to firsthand news, the latest annual reports, and

up-to-date financial analysis (Gardi et al., 2021; Santur et al., 2022). As such, regardless of whether the market is bullish or bearish, these conditions do not appear to significantly influence investors' use of trading platforms for their trading activities. This suggests that trading platforms may help buffer investors' emotional responses to market fluctuations. Consequently, market sentiment does not substantially alter the effect of performance expectancy, as investors tend to prioritize the technological utility and functional benefits of FinTech when reshaping their investment strategies (Stanley et al., 2024).

5.2.8 Moderating effect of market sentiment towards personal innovativeness in IT and reshape investment strategies

Moreover, the results of this study indicate that market sentiment have a moderating effect on the relationship between personal innovativeness in IT and reshape investment strategies. This result is aligned with study from Xia et al. (2023).

Xia et al. (2023) demonstrated that investor sentiment has significant impact on the willingness to use robo-advisory, thereby influencing investor investment decisions. Their study highlights that emotionally driven investors particularly those experiencing optimism or enthusiasm during favourable market conditions are more inclined to adopt robo-advisory services. Therefore, Xia et al. (2023) further reveals that positive emotions make investors more receptive to new technologies and reduce resistance to automation in investment decision-making. In contrast, during bearish markets, heightened fear or scepticism may decrease investors' willingness to rely on robo-advisory. As such, market sentiment plays a critical role that

affecting investor's personal innovativeness in IT as according to Eren (2023) and Cao et al. (2025) individuals in a positive emotional state are more likely to place trust in robo-advisory services and embrace technological solutions to reshape their investment strategies. This is because when a bullish market occurs, it indicates that the overall market is experiencing an upward trend, providing investors with more confidence and numerous stock selection opportunities (Gopane et al., 2024; Zakamulin, 2024).

However, identifying which stocks best align with an investor's individual preferences and risk tolerance can be challenging and time costing (Zhang et al., 2021). To address this, robo-advisory platforms offer a practical and efficient solution by providing comprehensive, personalized investment portfolio (Tao et al., 2021; Saivasan, 2024; Bartram et al., 2020). These platforms leverage algorithms to match investors with the most suitable assets and diversification based on their financial goals, risk profiles, and personal financial status, thereby supporting more informed and tailored investment strategies during bullish periods (Zhang et al., 2021; Shen et al., 2025).

As a result, the empirical findings of this study reveal that all four independent variables exhibit significant relationships with the dependent variable. Specifically, the herding effect reflects the dimension of financial awareness, whereas habit, performance expectancy, and personal innovativeness in IT collectively represent technological growth. These results collectively indicate that both financial awareness and technological advancement play pivotal roles in influencing investors to reshape their investment strategies. This conclusion is consistent with and further validates insights from prior studies that underscore the importance of behavioural and technological factors in reshaping investor strategies processes. For instance, Hirdinis (2021), Almansour et al. (2023), Ghimire and Dahal (2024), and

Saini et al. (2025) substantiate that investors' financial awareness significantly influences their ability to reshape investment strategies in order to safeguard and enhance their future financial security. On the other hand, studies by Ze and Loang (2025), Singh (2024), Hasan et al. (2024), and Ansari and Bansal (2024) demonstrate that technological advancement and innovation assist investors in reshaping their existing strategies by providing easier access to clearer insights into changing market trends and investor preferences. Therefore, financial awareness and technological advancement play a significant role in influencing investors to restructure and reshape their investment strategies.

5.3 Implications of the Study

This study investigates the influence of financial awareness and technology growth on the reshaping of investment strategies under varying market sentiment conditions in Malaysia. Given the central focus on how financial awareness and technological advancements drive changes in investment strategies, the study holds significant relevance for individual investors, corporate entities, government agencies, and future researchers. Their involvement is essential in understanding and applying the findings to enhance strategic investment decisions.

The findings of this study hold significant implications for individual investors, particularly in light of the increasing complexity and volatility of financial markets. It emphasizes the importance of enhancing financial awareness and critical thinking to support more rational and independent investment decisions. By understanding how market perception and behavioural biases influence their choices, investors can better avoid the pitfalls of emotionally driven or trend-following strategies. The study encourages investors to take a more informed and analytical approach by making use of reliable financial information and technological tools such as FinTech and robo-advisory while maintaining a strong foundation in fundamental investment principles. Such improvements not only help to reduce the likelihood of

financial losses but also empower investors to align their strategies with long-term financial goals.

For corporations, particularly those seeking to attract and retain investors in an increasingly digital investment landscape, this study highlights the importance of enhancing transparency, credibility, and digital responsiveness. As investors increasingly rely on online platforms to assess company performance, corporations that meet high expectations for information accessibility and usefulness are more likely to gain investor trust, reflecting the influence of performance expectancy in shaping engagement. The study also suggests that investor behaviour is shaped by habit, as individuals tend to rely on familiar sources and consistent patterns when making investment decisions. Therefore, corporations can benefit from maintaining continuity in how they present and communicate financial information across digital channels. Additionally, the concept of path dependency underscores the strategic value of learning from successful past practices. Companies that adopt approaches already proven effective in attracting investors, such as integrating sustainability initiatives or enhancing financial communication strategies, are better positioned to align with investor expectations. By responding to these behavioural patterns and continuously refining their digital presence, corporations can strengthen their competitiveness and build more enduring investor relationships.

The findings of this study offer valuable implications for government and regulatory authorities in maintaining financial market stability. The significant role of the herding effect in reshaping investment strategies indicates that many investors are prone to following collective market behaviour rather than making independent, rational decisions, especially during times of uncertainty. To mitigate the potential risks of panic-driven trading and excessive volatility, the government should continue to enforce or enhance protective mechanisms such as circuit breakers, which temporarily halt trading when stock prices fall beyond a certain threshold. These measures allow time for market participants to reassess information and reduce emotional reactions. Furthermore, the government can play a crucial role in promoting financial literacy and awareness through public education campaigns.

By encouraging more informed and rational investment behaviour, such efforts contribute to the development of a more stable, transparent, and resilient investment environment in Malaysia.

This study offers valuable insights for future researchers examining the evolving patterns of investor behaviour, particularly among individuals with a high level of personal innovativeness in Information Technology. As financial technology continues to advance, an increasing number of investors, especially those from younger demographics, are relying on digital tools such as robo-advisory platforms to support their investment decisions. These investors are generally more receptive to adopting new technologies and are more willing to engage with innovative financial solutions. Accordingly, future research may focus on exploring the differences in technology adoption among investor groups with diverse backgrounds, including factors such as educational attainment, trustiness on technology and risk tolerance. A deeper understanding of these variations can contribute to the development of more targeted and personalized financial technology products, thereby enhancing the effectiveness and reach of technological integration within investment practices.

5.4 Limitations of the Study

First and foremost, this study primarily targets investors in Malaysia, covering a wide range of occupational backgrounds such as students, employees, employers, and individuals without formal employment. However, the classification of unemployed respondents in this study was not sufficiently detailed, which may influence the accuracy of the findings. Within the unemployed category, there are distinct groups such as full-time traders, retirees, and housewives, each potentially demonstrating different investment behaviours and levels of familiarity with financial technology. Treating these diverse groups as a single category may have resulted in the loss of important insights regarding how different types of investors

reshape their investment strategies based on financial awareness, technology adoption, and market sentiment.

Secondly, the results presented that the respondents in this study consisted only of individuals from Chinese and Indian ethnic backgrounds. There were no Malay participants captured in the data. The absence of Malay respondents limits the generalizability of the findings across all major ethnic groups in Malaysia. This might reduce the inclusiveness of the dataset and narrows the scope of perspectives considered in the analysis. As a result, the findings may not be entirely generalizable to the wider Malaysian population, since the views and investment behaviours of one of the major ethnic groups are missing. The limitation highlights that the outcomes of this study are more aligned with the perspectives of Chinese and Indian respondents, thereby restricting the extent to which the conclusions can be extended across all ethnic communities in the country.

Thirdly, this study adopts the Unified Theory of Acceptance and Use of Technology (UTAUT 3) as one of its theoretical foundations. UTAUT 3 outlines eight key factors that influence technology acceptance, namely performance expectancy, effort expectancy, social influence, hedonic motivation, price value, facilitating conditions, habit, and personal innovativeness in IT. However, this research only focuses on three of these variables, which are performance expectancy, habit, and personal innovativeness in IT. The exclusion of the remaining factors may limit the comprehensive application of the UTAUT 3 framework and restrict a fuller understanding of how various dimensions of technology acceptance influence the reshaping of investment strategies.

In this study, market sentiment was examined as a moderator influencing the relationship between each independent variables with the dependent variable. However, the results presented in Table 4.19 indicate that market sentiment only significant moderating one relationship which is personal innovativeness in IT and the reshape investment strategies. In contrast, no significant moderating effect was

observed for the relationships involving herding effect, performance expectancy, and habit. This limitation may be attributed to the questionnaire design, in which the items related to market sentiment may not have been developed with sufficient depth or precision to effectively capture its interaction with the examined variables. As a result, the insignificant outcomes for these constructs may reflect constraints in measurement rather than the absence of a potential moderating effect.

Lastly, while this study highlights personal innovativeness in IT as a significant factor influencing the reshaping of investment strategies, the practical application of innovative tools such as robo-advisory platforms remain underexplored. Although many investors, particularly younger ones, exhibit a high degree of openness to new technologies, the actual impact and effectiveness of robo-advisory services on individual investment decision-making have not been thoroughly investigated. The current trend toward adopting these tools may reflect market enthusiasm rather than proven reliability or objectivity. As such, there is a limitation in understanding whether robo-advisory platforms are genuinely useful and trustworthy in guiding investors or whether their popularity is driven more by technological trends than by practical value.

5.5 Recommendations for Future Research

Future research is recommended to adopt a more detailed classification of investor profiles, particularly among respondents without formal employment. Instead of grouping all unemployed individuals together, future studies should distinguish between subgroups such as full-time traders, retirees, and housewives, as each group may possess unique investment behaviours, financial goals, and levels of engagement with financial technology. A more granular categorization would allow for deeper analysis and more accurate interpretations of how different types of investors reshape their investment strategies in response to financial awareness, technological growth, and market sentiment. This approach would enhance the

richness and relevance of the findings and support more targeted recommendations for different investor segments.

Furthermore, future research should aim to include more diverse ethnic representation, particularly by incorporating Malay respondents, to improve the generalizability of findings across Malaysia's multi-ethnic population. Ensuring the inclusion of Malay respondents, alongside Chinese and Indian participants, would allow for a more balanced dataset that better reflects the country's demographic composition. This broader representation would enhance the generalizability of the findings and provide a more comprehensive understanding of investment behaviours across different ethnic communities. A more inclusive sampling approach would also make it possible to identify potential variations in the patterns of reshaped investment strategies that may be influenced by cultural or social backgrounds. Such insights could enrich the literature by offering a deeper and more holistic view of investor behaviour in the Malaysian context.

In addition, future research is also encouraged to adopt a more comprehensive approach in applying the UTAUT 3 framework by including suitable core constructs. Future researchers could explore motivational factors such as facilitating conditions to examine how the presence of technical infrastructure supports investors in reshaping their investment strategies by using technology. Furthermore, effort expectancy also represents a suitable independent variable, as it evaluates whether the perceived ease of using technology influences investors in modifying their strategies. By incorporating these constructs, future studies can provide deeper insights into how infrastructural support and user-friendliness drive the adaptation of investment approaches in a technological context. Not only that, but a broader application of the framework would also allow research to capture more nuanced relationships between technological and investor strategies, leading to more robust and generalizable insights into how technology reshapes investments strategies across different investor groups.

Besides that, future research could consider incorporating market sentiment as moderating variable particularly within the context of the investment sector. A more granular examination of these contrasting market sentiment could provide deeper and more nuanced insights into the dynamics under investigation. By analysing the effects of market sentiment separately under bullish and bearish scenarios, future scholars may be able to uncover variations in behavioural responses, strategic adjustments, and outcome patterns that might otherwise remain obscured in aggregate analyses. Such distinctions could enrich the understanding of how market conditions shape the interplay between key variables, thereby contributing to more robust theoretical development and practical investment implications.

In addition, greater attention should be given to the design and development of questionnaire items that measure market sentiment to ensure they are sufficiently robust to capture its moderating role in future research. More nuanced and context-specific items may provide a clearer understanding of how market sentiment interacts with constructs such as herding effect, habit, performance expectancy and personal innovativeness in IT. Future researchers should place greater attention on ensuring that the questions used are more suitable, particularly by carefully reviewing prior literature that align more closely with the constructs under investigation. Additionally, employing mixed methods, such as combining quantitative surveys with qualitative interviews, may help validate whether insignificant results are due to measurement constraints or reflect actual weak relationships. By adopting these approaches, future studies can generate more comprehensive insights into the moderating role of market sentiment across different investor behaviours.

Last but not least, future research should explore more actual effectiveness and reliability of robo-advisory platforms in shaping individual investment strategies. Although their growing use reflects a trend toward technological innovation, it remains unclear whether these tools offer genuine value or are simply driven by market enthusiasm. Empirical studies focusing on their performance and impact, especially among younger and more innovative investors, would provide clearer

insights into their practical role in investment strategy development. This could also help determine whether such robo-advisory contribute to more informed reshape investment strategies or merely reinforce existing behavioural biases.

5.6 Conclusion

The primary objective of this study is to examine the factors influencing the reshaping of investment strategies among Malaysian investors, with a particular focus on financial awareness and technology growth, and the moderating effect of market sentiment. Data were collected through a questionnaire and analyzed using SmartPLS 4.0. Based on the analysis of the direct hypotheses between the independent variables and the dependent variable, all hypotheses were accepted. This clearly indicates that all independent variables including herding effect (H1), habit (H2), performance expectancy (H3), and personal innovativeness in IT (H4) have a significant direct influence on the dependent variable, which is the reshape investment strategies.

However, the results regarding the moderating role of market sentiment are mixed. Only H8 was supported, showing that market sentiment significantly moderates the relationship between personal innovativeness in IT and the reshaping of investment strategies. This suggests that under the influence of market sentiment, an investor's level of innovativeness in IT is more strongly expressed, thereby influencing how they adjust their investment strategies. On the other hand, market sentiment did not exhibit a significant moderating effect on the remaining variables. This may be attributed to the relatively stable and internal nature of those behavioral constructs, which are less affected by external emotional or perceptual shifts in the market environment.

In addition, the limitations of the current research are duly acknowledged. To strengthen the robustness and generalizability of future studies, this research offers a clear direction for conducting more in-depth and detailed investigations. Key recommendations include the improvement of sampling techniques, the expansion of the variable scope, and the refinement of methodological design. It is suggested that future research should diversify the questionnaire distribution to include all ethnic groups in Malaysia, in order to ensure that responses from the entire population are adequately represented. Moreover, when collecting demographic data, researchers are encouraged to adopt more refined classifications particularly in employment status such as specific categories of unemployment, as well as detailed income levels. This approach could yield deeper insights into how socio-economic factors influence investors' behavioral tendencies and reshaping their investment strategies. As a result, this study may serve as a valuable reference for future researchers in terms of respondent selection, data collection design, and variable identification, contributing to the development of more comprehensive and contextually relevant research frameworks.

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Appendix

Appendix 1: *Factor Loadings*

	HB	HE	MS	PE	PI	RI	MS x HB	MS x HE	MS x PE	MS x PI
HB1	0.702									
HB2	0.797									
HB3	0.784									
HB4	0.864									
HB5	0.835									
HE1		0.858								
HE2		0.774								
HE3		0.839								
HE4		0.83								
HE5		0.734								
MS1			0.843							
MS2			0.785							
MS3			0.829							
MS4			0.844							
MS5			0.833							
PE1				0.762						
PE2				0.804						
PE3				0.703						
PE4				0.790						
PE5				0.827						
PI1					0.843					
PI2					0.785					
PI3					0.729					
PI4					0.713					
PI5					0.767					
RI1						0.826				
RI2						0.767				

RI3	0.72
RI4	0.824
RI5	0.805
MS x HB	1.000
MS x HE	1.000
MS x PE	1.000
MS x PI	1.000

****Note:** HB – Habit; HE – Herding effect; MS – Market Sentiment; PE – Performance Expectancy; PI – Personal Innovativeness in IT; RI – Reshape Investment Strategies

Appendix 2: Construct Validity and Reliability

	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
HB	0.985	0.897	0.637
HE	0.871	0.904	0.653
MS	0.907	0.915	0.684
PE	0.847	0.885	0.606
PI	0.834	0.878	0.591
RI	0.848	0.892	0.623

****Note:** HB – Habit; HE – Herding effect; MS – Market Sentiment; PE – Performance Expectancy; PI – Personal Innovativeness in IT; RI – Reshape Investment Strategies

Appendix 3: Collinearity (VIF)

	RI
HB	1.596
HE	1.844
MS	1.282

PE	1.807
PI	2.41
RI	
MS x HB	1.73
MS x HE	2.403
MS x PE	4.257
MS x PI	4.895

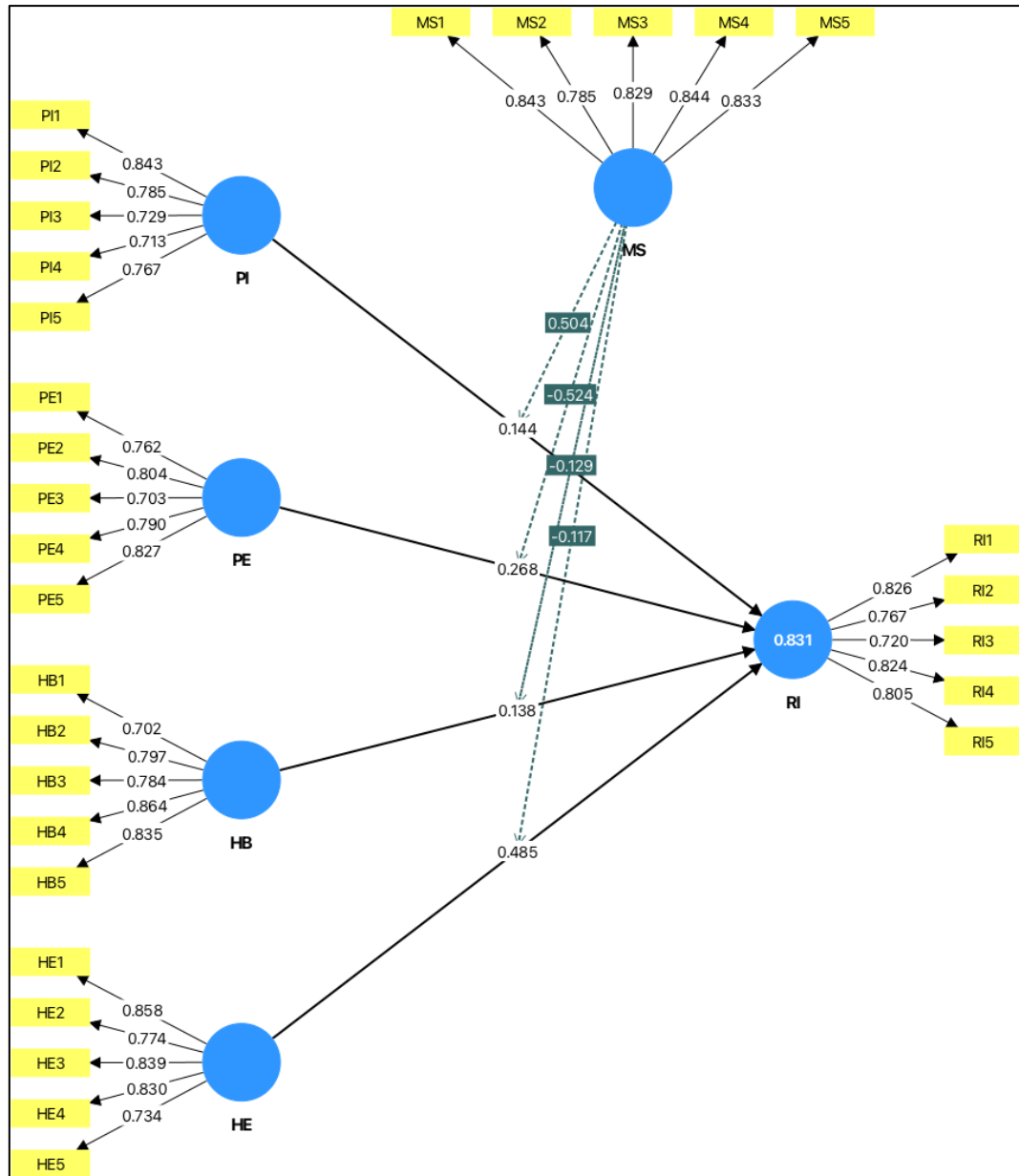
****Note:** HB – Habit; HE – Herding effect; MS – Market Sentiment; PE – Performance Expectancy; PI – Personal Innovativeness in IT; RI – Reshape Investment Strategies

Appendix 4: *Heterotrait-Monotrait Ratio (HTMT) Output*

	HB	HE	MS	PE	PI	RI	MS x HB	MS x HE	MS x PE	MS x PI
HB										
HE	0.396									
MS	0.269	0.337								
PE	0.388	0.617	0.287							
PI	0.563	0.704	0.35	0.658						
RI	0.483	0.898	0.466	0.706	0.825					
MS x HB	0.032	0.072	0.245	0.121	0.178	0.178				
MS x HE	0.067	0.134	0.066	0.2	0.318	0.299	0.297			
MS x PE	0.116	0.167	0.061	0.115	0.352	0.391	0.462	0.717		
MS x PI	0.149	0.239	0.061	0.314	0.424	0.314	0.561	0.686	0.835	

****Note:** HB – Habit; HE – Herding effect; MS – Market Sentiment; PE – Performance Expectancy; PI – Personal Innovativeness in IT; RI – Reshape Investment Strategies

Appendix 5: *Structural Model*



Appendix 6: *Determination of co-efficient (R^2)*

	R-square	R-square adjusted
RI	0.831	0.800

** RI – Reshape Investment Strategies