TECH-SAVVY INVESTORS: ADOPTION OF WEALTH TECH FOR WEALTH MANAGEMENT IN MALAYSIA

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A final year project submitted in partial fulfillment of the
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DECLARATION

We hereby declare that:

(1) This undergraduate FYP is the end result of our own work and that due acknowledgement has been given in the references to ALL sources of information be they printed, electronic, or personal.
(2) No portion of this FYP has been submitted in support of any application for any other degree or qualification of this or any other university, or other institutes of learning.
(3) Equal contribution has been made by each group member in completing the FYP.
(4) The word count of this research report is 27533.

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DEDICATION

We dedicate this research project to our esteemed supervisor, Ms. Nik Nuraisyah binti Nik Azmi, whose unwavering support, insightful guidance, and continuous encouragement have been instrumental throughout every stage of this research. Her dedication to our academic development has been a source of inspiration, and we are truly grateful for the opportunity to work under her supervision.

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PREFACE

Financial technology evolves rapidly resulting in Wealth Tech digital platforms. These technological advances have transformed how people manage their wealth by introducing features that improve convenience and accessibility. The number of Wealth Tech solutions available in Malaysia has experienced rapid growth while investor adoption shows varied speeds. The present research "Tech Savvy Investors: Adoption of Wealth Tech for Wealth Management in Malaysia" emerged because of this observation.

The study took shape because the research topic fascinates researcher both academically and personally how finance meets technology. The experience in Banking and Finance education has shown digital transformation has gained vital importance in financial services including new development patterns for investment platforms. The desire to explore Wealth Tech adoption systematically emerged from personal peer interactions together with observed market trends and genuine interest in clarifying why people use Wealth Tech services when others seem hesitant. Extensive local research about Wealth Tech adoption in the Malaysian context fails to exist which makes this investigation necessary.

ABSTRACT

The rapid advancement of financial technology has revolutionised the wealth management industry, leading to the rise of digital-only banks. This research examines the key factors influencing the adoption of Wealth Technology, including performance expectancy, effort expectancy, social influence, facilitating conditions and technology readiness. The research integrates the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Technology Readiness Index (TRI) to develop a comprehensive theoretical framework. A quantitative research approach was employed, utilizing survey-based primary data collection from 384 Malaysians across different genders, age groups, highest educational levels, races, employment status, net income levels and regions. Statistical analysis was conducted to determine the significance of these factors in shaping user adoption behavior. The findings reveal that performance expectancy and effort expectancy, while social influence and facilitating conditions also play a significant role. Additionally, technology readiness contributes to user behavioural intention to adopt Wealth Tech in Malaysia. These insights provide valuable implications for financial institutions aiming to enhance user trust and engagement in digital banking services. This research contributes to the growing literature on fintech adoption and offers strategic insights for financial institutions and policymakers to enhance digital wealth management services.

Keywords:

Digital Wealth Management, Wealth Tech, Technology Adoption, Behavioural Intention, Unified Theory of Acceptance and Use of Technology (UTAUT), Technology Readiness Index (TRI), Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Condition, Technology Readiness

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

AI	Artificial Intelligence
AUM	Asset Under Management
AVE	Average Variance Extracted
BI	Behavioural Intention
CAGR	Compound Annual Growth Rate
CCID	Commercial Crime Investigation Department
C-TAM-TPB	Combined Model of TAM and TPB
DOI	Diffusion of Innovation Theory
DOSM	Department of Statistics Malaysia
EE	Effort Expectancy
ETF	Exchange-Traded Fund
FC	Facilitating Conditions
HNWI	High-Net-Worth Individual
IDT	Innovation Diffusion Theory
IWM	Internet Wealth Management
MCMC	Malaysian Communications and Multimedia Commission
MCO	Movement Control Operations

MM	Motivational Model
MPCU	Model of PC Utilisation
NSRC	National Scam Response Centre
PE	Performance Expectancy
PC	Personal Computer
SCM	Securities Commission Malaysia
SCT	Social Cognitive Theory
SI	Social Influence
SPSS	Statistical Package for Social Sciences
TAM2	Technology Acceptance Model 2
TPB	Theory of Planned Behaviour
TR	Technology Readiness
TRA	Theory of Reasoned Action
TRI	Technology Readiness Index
UTAUT	Unified Theory of Acceptance and Use of Technology
VC	Venture Capital
VIF	Variance Inflation Factor

LIST OF APPENDICES

CHAPTER 1 INTRODUCTION

1.0 Introduction

This chapter starts by discussing the research's background. The research problem will be highlighted in the problem statement. Additionally, research objectives and research questions are listed correspondingly. The importance of conducting this research is then discussed. The essential concepts from Chapter 1 are summarised in the conclusion.

1.1 Research Background

Fintech

Fintech is a term combining "finance" and "technology" to describe the confluence between financial services and information technology (Roh et al., 2023). In the big picture, the Fintech ecosystem includes a complex network of interactions between Fintech companies, investors, regulators, government, and skilled institutions who share a mutual interest in the Fintech startup environment. Fintech provides its customers with automated platforms so they can manage their assets on their own while these platforms are operated by specific algorithms and involve robo-advisors (Gabor & Brooks, 2016). As of 2023, it is reported that approximately 5400 million people worldwide have internet access (Figure 1.1) while this amount is equivalent to 67.1% of the global population, representing a significant rise from ten years ago, when only 35% had internet access (Petrosyan, 2024) which this is perceived in the way which it would have contributed to the growth of Fintech. Based on Statista (2024d), 71% of Malaysians were actually aware of Fintech, proving that rising internet accessibility enhances individuals' awareness of Fintech. Nowadays, it even comes to an argument that wealth and asset managers have now been overtaken by these automated systems (Goldstein et al., 2019). This is said so as small start-ups that aided banks with their creative approaches at the beginning of financial technology eventually grew into the latter, forming alliances with banks to fortify the entire financial services ecosystem.

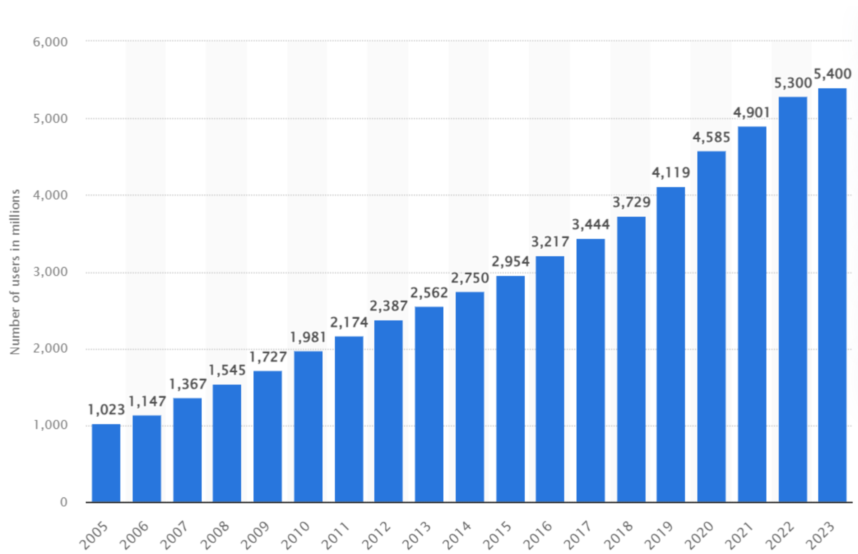


Figure 1.1. Global internet access. Adapted from Petrosyan, A. (2024, May 22). *Number of internet users worldwide from 2005 to 2023*. Statista; Statista. https://www.statista.com/statistics/273018/number-of-internet-users-worldwide/

Wealth Management

In recent years, there has been a dramatic change in the financial services industry, driven by rapid technological advancements and changing consumer preferences. On the contrary, traditional banking and wealth management paradigms are being challenged by innovative digital solutions that promise greater efficiency, accessibility, and personalisation. This evolution is particularly evident in the realm of digital wealth management. Wealth management is the latest financial sector affected by technology disruption in terms of opportunities and difficulties. Moreover, wealth management is the process of overseeing an investor's assets through a particular financial plan and strategy, as well as putting that strategy into effect with variable degrees of customer contact. To name a few, essential wealth management services include retirement planning, offshore services, investment management, tax planning, and tax preparation (Panda et al, 2023). North America, Western Europe, Latin America, the Middle East, and other regions have increased personal wealth from 1999 to 2019. Moreover, global personal wealth has been increasing by nearly 1.7% from 1999 to 2019 (Figure 1.2). Global wealth has increased fourfold in the last 20 years, from 80 trillion USD in 1999 to 226 trillion USD in 2019 (Zakrzewski et al., 2020). It can be concluded that global personal wealth has been increasing consistently despite several obstacles that have affected global wealth, such as the COVID-19 epidemic and the financial crisis in 2008.

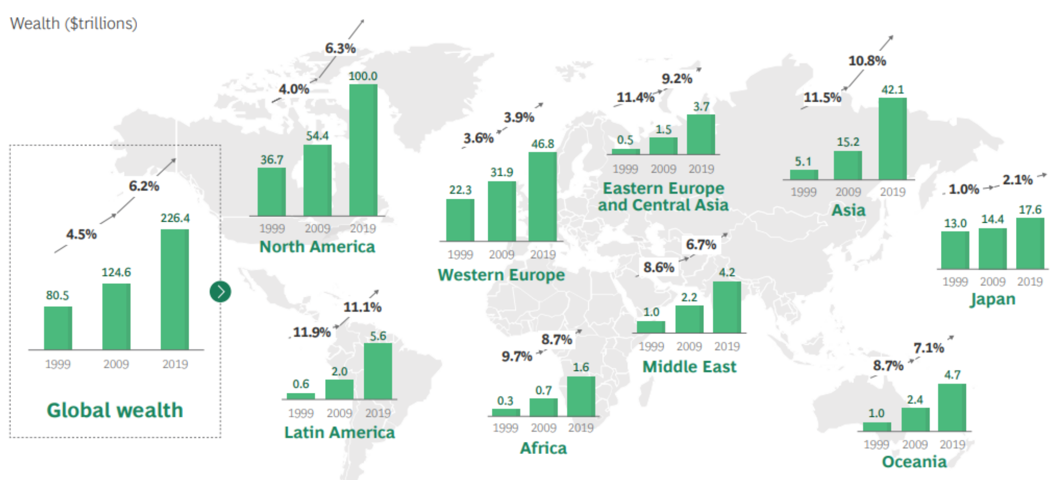


Figure 1.2. Increasing number of personal wealth. Adapted from Zakrzewski, A., Carrubba, J., Frankle, D., Hardie, A., Kahlich, M., Kessler, D., Mende, M., Tang, T., & Xavier, A. (2020). The future of wealth management—a CEO agenda. In *Boston Consulting Group* (pp. 5–11). https://www.bcg.com/publications/2020/global-wealth-future-of-wealth-management-ceo-agenda

Digital Wealth Management

Headlines with an appealing message, like "Traditional wealth management is gone," this emphasise how a formerly hidden sector is changing (Ong, 2018). The technological advancements in the banking industry have redefined the financial services experience for its consumers throughout the world (Ahmed & Sur, 2021; Chauhan et al., 2022). As digital wealth management is recognised as a sub-sector of Fintech, however, its main emphasis is on managing customer portfolios and investments through the use of digital technologies and customized products and services., such as robo-advisory and digital brokerage.

Innovations in technology have transformed the field of wealth management. In modern times, technology puts the client first and enhances the investor's experience of receiving financial advice. Digitalization also increases clients' trust, involvement, awareness, and confidence by emphasising human connection and plain-language financial education. Leveraged low-cost Exchange-Traded Funds (ETFs) and stock indexing aids in portfolio diversification at reduced costs with a transparent fee structure compared to traditional methods and digital advancements (Lopez et al., 2015).

These robo-advisors use algorithms based on their customer's investment characteristics and preferences to recommend a portfolio of assets to invest in. This business model benefits from low or no investment minimums due to appealing unit economics, a straightforward and clear fee structure, and shifting consumer behaviour and demographics that favour automated and passive investing strategies (Jung et al., 2019).

The wealth management industry faces more challenges than in the past. Along with external variables like Big Tech entry threats, continuous generation wealth transfer, fast-changing consumer profiles, and industry trends like rapid digitization and increasing emphasis on cost control, this industry is shaped in part by external factors, including threats of an economic downturn, environmental disasters like pandemics, and political stability. Therefore, Wealth Tech has been growing and appears to solve a number of the major issues facing the wealth management sector as a whole (Dziawgo, 2021).

Wealth Tech

Wealth Tech is one of the Fintech service trends that have evolved as the global financial system has become more digitalised. Chishti and Puschmann (2018) define Wealth Tech as the impact of technology on the worldwide investing and wealth managing industry, which Wealth Tech services include robo-advisory, robo-retirement, digital brokerage, micro-investments, algorithmic trading, and B2B software (Dziawgo, 2021). Wealth Tech aims to "democratize the financial service" by providing readily available, cost-effective, and efficient wealth management services to underserved market groups (Li et al., 2020). However, the rapid growth of Wealth Tech and personal financial portfolio management products and services in recent years has been attributed to increased financial market automation and technical developments that make it easier to do activities like automated trading, small capital investments, automated asset management, and retail investing (Dziawgo, 2021). As a result, KPMG (2022) reported that the global venture capital (VC) investment into Wealth Tech companies grew more than threefold between the years 2017 to 2021, demonstrating a doubling of investment value in 2020 and a triple from 2017. In 2021, it is even observed that venture funding reached a 125% year-on-year basis increase, reaching the figure of 8.8 billion USD (Figure 1.3).

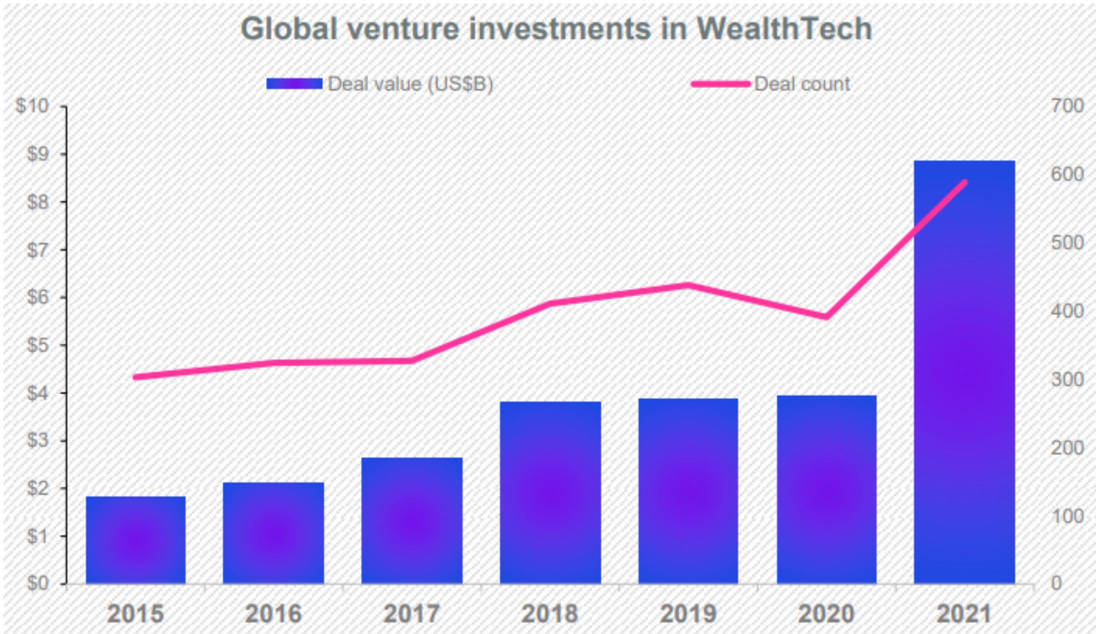


Figure 1.3. Global venture capital investment in Wealth Tech. Adapted from KPMG. (2022). *WealthTech: Looking ahead Exploring the growth, trends and future of WealthTech*. https://assets.kpmg.com/content/dam/kpmg/sg/pdf/2022/09/wealthtech-looking-ahead-report.pdf

The Rise of Wealth Tech

Wealth Tech encompasses a diverse array of digital solutions designed to improve the wealth management process. The rise of Wealth Tech might be due to several factors. Firstly, the integration of artificial intelligence, machine learning, big data analytics, and blockchain technology into wealth management enhances operational efficiency and democratises access to complicated financial tools and strategies (Dziawgo, 2021). Secondly, the changing investor demographics. As the population of High-Net-Worth Individuals (HNWIs) grows, the younger generation who are tech-savvy and digitally native expect customised banking and wealth management solutions to meet their financial demands (KPMG, 2021). Thirdly, strong regulatory support. In July 2022, the Securities Commission Malaysia (SCM) allowed the trading of digital assets and currencies on regulated exchange platforms, promoting the development and investment in digital assets. Currently, the commission approved the trading platforms including Luno, Tokeinze, and SINEGY to operate in Malaysia (Onieno, 2022). Moreover, the financial industry is among many others whose digital transformation has been expedited by the COVID-19 pandemic. During the pandemic, social restrictions measures and Movement Control Operations (MCO) have brought awareness to how crucial digital channels are for monitoring investments and completing financial transactions (Le et al., 2022).

Wealth Tech in Malaysia

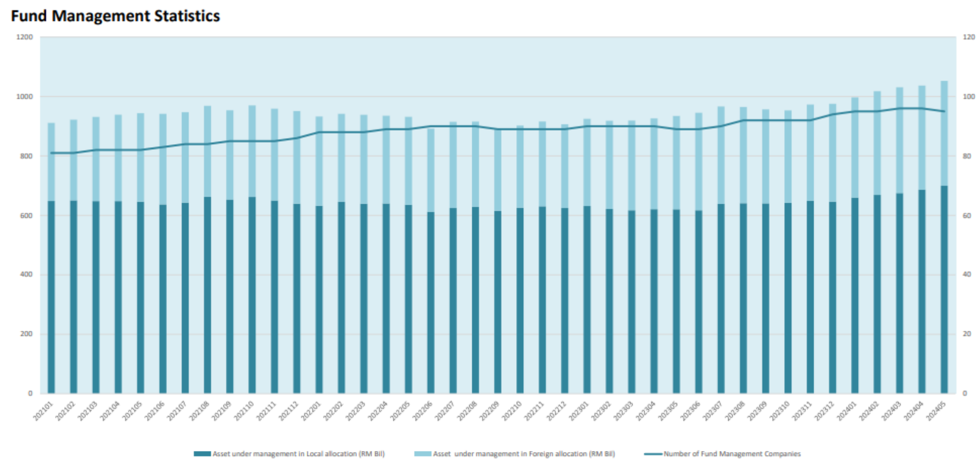
There is growing digital banking adoption and HNWIs with a strong internet penetration. According to Huawei (2020), Malaysia scored highly in terms of internet and smartphone penetration, placing it at rank 34th in the 2020 Global Connectivity Index. High penetration rates have been fueled by improvements in internet pricing, speed, and overall accessibility. Approximately 96% of all internet users, or 25.9 million people, accessed the internet using their mobile devices in 2019 (Kemp, 2020).

Besides, Malaysian banks have invested more in technology to improve their digital capabilities in recent years. The average percentage of technology spending in overall expenses climbed from 4.1% in 2016 to 6.4% in 2018 (Figure 1.4). CIMB and Hong Leong Bank increased their technology spending from 5% in 2016 to 9% and 8% in 2018, accordingly (Washington, 2020). This surge in spending is explained by the increased competitive from market new players, especially innovative new businesses, which has compelled Malaysia's established financial institutions to step up their efforts to go digital. KDI Invest, Versa, Stashaway, and Akru are a few examples of Fintech that handle wealth (RinggitPlus, 2024).

Figure 1.4. Wealth Tech landscape in Malaysia. Adapted from Fintech News

Malaysia. (2023, October 11). *Malaysia fintech report 2023*. Fintech News Malaysia. https://fintechnews.my/malaysia-fintech-report-2023/

Generally, the wealth management sector in Malaysia has observed a significant increase in number over the years. Measured in terms of numbers of total Asset Under Management (AUM) by SCM, initiating from 2022 with the count of RM906.46 billion, it then undergoes 7.61% growth to the figure of RM975.48 billion in 2023. As of May 2024, the number has reached RM1052.35 billion (Figure 1.5). The drastic rise of AUM counts is even projected to reach US$ 21.53 billion by the end of 2024. It is further observed that financial advisory is now serving as a dominant segment of the market with a projected market volume of US$ 19.35 billion by 2024 (Statista, 2024d). This demonstrates that Malaysians necessitate a high demand for expert financial advice and services in the nation's wealth management industry. Looking from a broader perspective, the AUM is forecasted to expand stably (CAGR 2024-2028) at 0.85%. This development trajectory is expected to result in a market volume of US$ 22.27 billion by 2028. Meanwhile, all these figures suggest a bright future for Malaysia's wealth management business, offering prospects for both investors and financial institutions.



1. Asset Allocation for Overall Fund Management

Year	Month	AUM (RM Bil) Equities	Fixed Income Securities	Money Market Placement	Unit Trust Funds	Private Equity / Unquoted Stocks	Others	Total
2021		467.87	209.73	146.52	52.69	14.27	59.97	951.05
2022		431.42	210.78	134.23	48.26	14.56	67.20	906.46
2023		474.53	223.87	130.00	54.19	16.66	76.23	975.48
2024	**Jan 2024**	494.22	224.05	127.10	55.38	17.07	79.19	997.00
	Feb 2024	509.98	226.58	127.14	57.07	17.12	79.85	1017.74
	Mar 2024	519.69	228.56	124.77	58.20	17.10	82.82	1031.14
	Apr 2024	521.13	227.66	129.25	58.34	17.27	83.19	1036.84
	May 2024	534.60	232.43	127.92	58.86	16.94	81.60	1052.35

Figure 1.5. Asset under management statistics. Adapted from Securities Commissions Malaysia. (2024). *Fund Management Statistics*. https://www.sc.com.my/api/documentms/download.ashx?id=4ae39256-e369-4cf4-b080-2411d38425a0

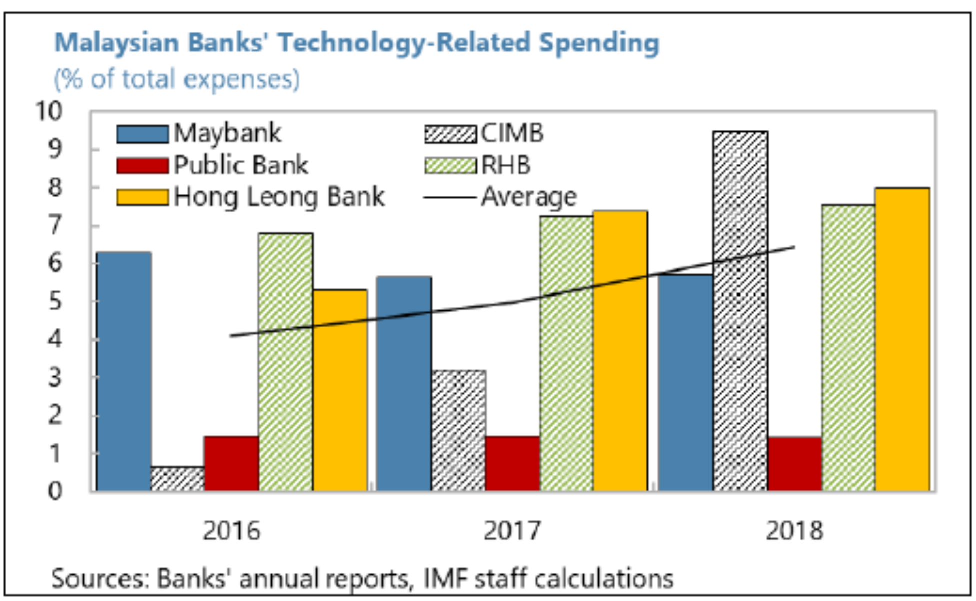


Figure 1.6. Technology spending. Adapted from Washington, D. (2020). *Malaysia Selected Issues International Monetary Fund*. https://www.imf.org/~/media/Files/Publications/CR/2020/English/1MYSEA2020002.ashx

1.2 Problem Statement

Due to the rapid expansion of financial technologies, particularly Wealth Tech, it has been said to transform the financial services landscape globally, including in Malaysia. It is witnessed that the Digital Assets with AUM of Malaysia are expected to achieve 470 million USD by the year 2024. It might show a significant number, but it remains low compared to neighbouring countries like Singapore (540.90 million USD) and Indonesia (869.30 billion USD) (Statista, 2024a; Statista, 2024b; Statista, 2024c). Therefore, as a subset of Fintech in the digital wealth management industry, it is found that Malaysia's Fintech adoption is considered low when compared across comparison over other countries. Compared to neighbouring country, Singapore, which is ranked as the world's top 10 countries with the highest rate of Fintech adoption, it can simply be derived that Fintech in Malaysia needs a greater exposure to further expand into the Wealth Tech sector. Tipalti (2023) has conducted research on the list of countries with the highest rate of fintech adoption, and concluded that China and India ranked first by having 87% of their population being digitally active, followed by South Africa with 82% and Columbia 76% as of 2019 (Figure 1.7).

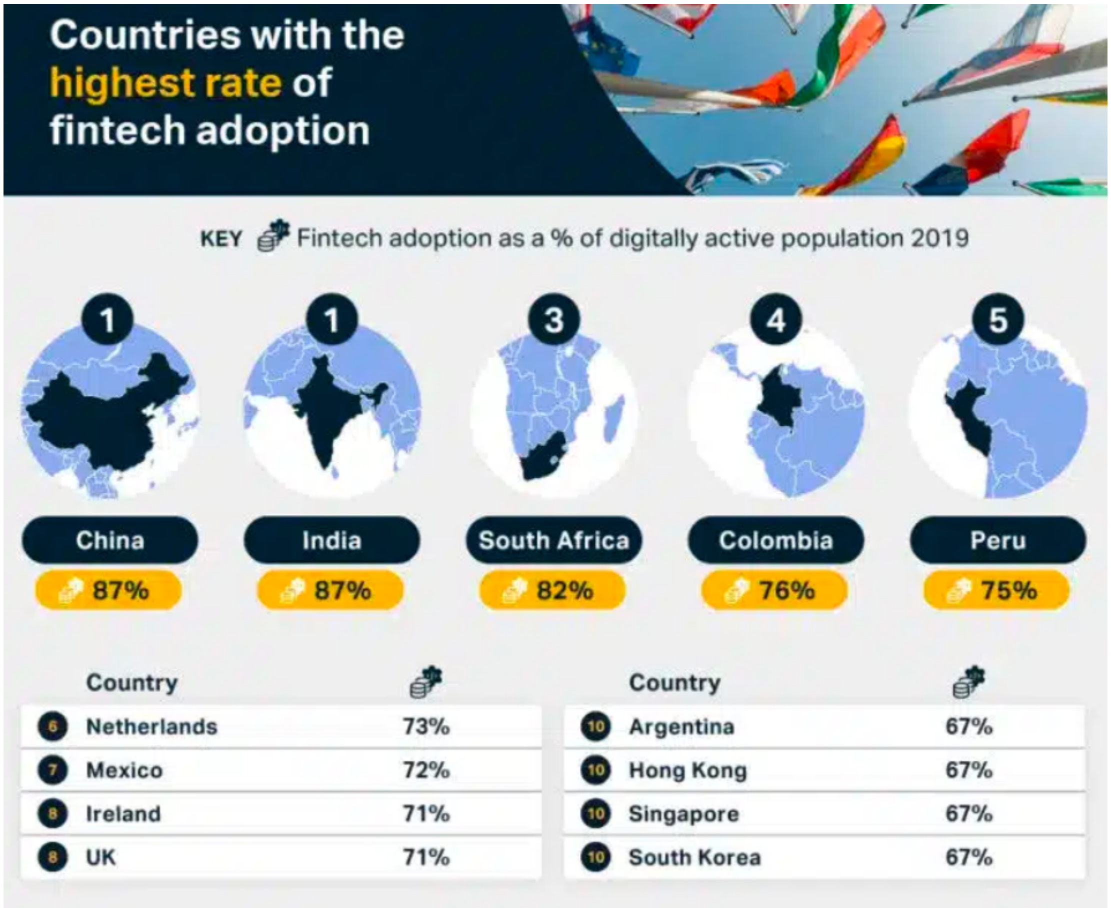


Figure 1.7. Countries with the highest rate of Fintech adoption. Adapted from Tipalti. (2023). Fintech Adoption Hotspots. *Tipalti*. https://tipalti.com/guide/fintech-adoption-hotspots/#:~:text=1.,China&text=China%20and%20India%2C%20leading%20the,adopted%20the%20use%20of%20fintech.

While having the big brother, United States and Europe helping to lead the way for Wealth Tech, the industry is also rapidly expanding in other parts of the world. In the meantime, Jhaxell (2024) studied that Southeast Asia is expected to have the highest potential of Wealth Tech expansion. With the expectation that the Asia-Pacific Countries have the potential to emerge as the world's largest Fintech market, Fintech revenue in the region is expected to expand eight times between 2021 and 2030 to reach 600 billion USD, according to a recent estimate by Boston Consulting Group (Jhaxell, 2024). However, among Southeast Asia countries, it is said that Malaysia is less likely to be declared successful or fast adopters of Wealth Tech. Nations like Indonesia, Thailand, Malaysia, and the Philippines are maturing in their Wealth Tech uptake at radically different rates from Singapore, which is leading the world in wealth management technology innovation and best practices. Indeed, Wealth Tech in the region is facing its greatest challenges and opportunities currently (Aite Novarica, 2017). Therefore, despite the potential benefits of Wealth Tech, such as increased financial inclusion and improved investment management, its adoption in Malaysia remains relatively low compared to other regions. Referring to Singapore, it has successfully positioned itself as a main wealth management hub regionally and globally by accounting for approximately 7% of the total VCs in 2021, presenting a 605% growth compared to Singapore's VC investment in Wealth Tech in 2017 (Figure 1.8) (KPMG, 2022). Although it is recognized that Wealth Tech in Malaysia is advancing by having over 175 thousand new digital investment management accounts opened in 2020, as reported by Fintech News Malaysia (2021), however, it has to be admitted that comparing to other countries across the globe, like Singapore and Indonesia mentioned, Wealth Tech in Malaysia is still at a infancy stage though it possess a huge potential for embedded investing.

Asia and Singapore venture investments in WealthTech, 2017 and 2021

	2017	2021	% Growth
▸ Asia	US$1,143M	US$2,208M	93%
▸ Singapore	US$23M	US$161M	605%
▸ Singapore as a % of Asia	2%	7%	

Figure 1.8. Comparison: Asia and Singapore venture capital investment in Wealth Tech. Adapted from KPMG. (2022). *WealthTech: Looking ahead Exploring the growth, trends and future of WealthTech*. https://assets.kpmg.com/content/dam/kpmg/sg/pdf/2022/09/wealthtech-looking-ahead-report.pdf

To analyse the possible cause of low and slow Wealth Tech adoption in Malaysia, it is concerned that many potential users are worried about the confidentially and security of their financial data on digital platforms. Far as Fintech solutions are IT-based, the biggest problems are always associated with technological glitches and cyber risks. This makes the users vulnerable to losing their data and may not know how their data has been used. Siddiqui and Rivera (2022) even highlighted this issue as a major threat towards the development of the industry. According to the Royal Malaysian Police (PDRM) Commercial Crime Investigation Department, it is stated RM2.23 billion losses incurred due to the occurrence of 67,552 cybercrime cases between 2017 and 2021. The investment scam is recorded as 6,273 cases of the total as people are susceptible to the lower risk investment scheme that promises high returns (Basyir, 2021). Accordingly, the cases increased by 12,092 cases resulting from cyber-criminal activities with RM 414.8 million losses in 2022 (Mardhiah, 2023). Moreover, the National Scam Response Centre (NSRC) further underscored the severity of the issue by reporting a total loss of RM27 million due to cybercrime as of February 2023 (Hanif, 2023). The Director of Bukit Aman's Commercial Crime Investigation Department (CCID), Datuk Seri Ramli Mohamed Youssuf, claimed that there was 95.2% alarming escalation in cybercrime cases over five years in 2023. Hence, the development of cutting-edge technologies that are incorporated into various financial services would have made crime tactics even more challenging (Mahari, 2024). Besides that, CyberSecurity Malaysia also echoed this alarming trend by documenting 4,741 cyber threats and 456 fraud cases in the same year. Thus, there is no doubt that user's concerns over cybersecurity breaches and the protection of sensitive information could have deter individuals from adopting the services, thereby indicating low Wealth Tech adoption among Malaysians.

Secondly, it is found that there remains a lack of awareness and exposure of Wealth Tech towards Malaysians. Many potential users are stated to have a substantial knowledge gap about the advantages and functions of digital wealth management products. This can be seen while the tech-savvy users might easily accept the concept of the nature of Fintech, but older generations might find it hard to understand the

Fintech services (Diniyya et al., 2021). According to the Institute for Capital Market Research Malaysia (2023) report, Malaysia's financial literacy is considered poor though a majority of people feel confident in their own financial ability, however, just 39% of respondents can accurately answer four to five fundamental financial literacy questions (Figure 1.9). Hence, the lack of awareness and comprehension of basic financial knowledge of how they might help with personal financial management could restrict Malaysia's ability to fully comprehend and adapt to Wealth Tech services.

Table 2:
Financial Literacy score

Financial literacy score	% of respondents
0% - 20%	24%
40% - 60%	37%
80% - 100%	**39%**

Figure 15:
Financial confidence rate

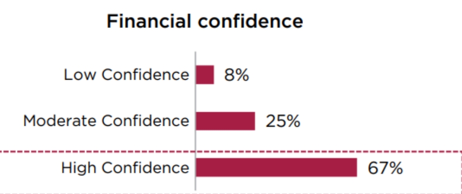


Figure 16:
Financial literacy score against financial confidence

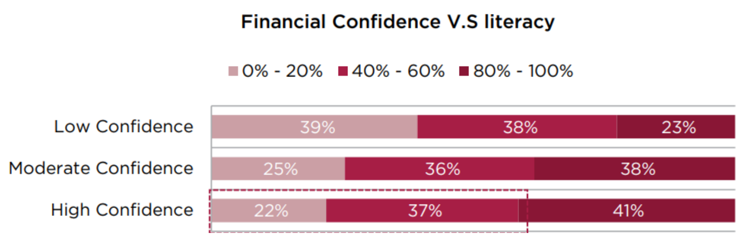


Figure 1.9. Financial literacy. Adapted from Institute for Institute for Capital Market Research Malaysia. (2023). *New age vulnerabilities: Understanding investor vulnerability within the malaysian context* (pp. 53–70). https://www.icmr.my/wp-content/uploads/2023/04/New-Age-Vulnerabilities-Understanding-Investor-Vulnerability-Within-the-Malaysian-Context.pdf

Furthermore, the increasing integration of technology in financial services has led to the emergence of Wealth Tech, a sector that leverages digital tools to optimise wealth management and investment processes. In Malaysia, Wealth Tech adoption is growing, but not without challenges. Particularly, one critical factor influencing this adoption is digital readiness, which is also often conceptualised as technological readiness. Far as it encompasses the extent to which individuals and businesses are prepared to adopt and utilise digital technologies effectively, it includes not only access to technology but also the necessary skills, attitudes, and infrastructure to support the effective use of these technologies. Malaysian Communications and Multimedia Commission (MCMC) in 2019 further showed the comparison of household internet usage in Malaysia between urban and rural areas with urban communities figured 70% and rural communities accounting for 30% as per data in 2018 (Samsuddin et al., 2021). Referring to Amanda (2024), Malaysia scored a digital readiness index of 0.46 out of 2.5 in 2021, indicating an accelerated stage of digital readiness. In terms of digital competitiveness, Malaysia dropped to 32nd place globally in 2023 (Lim, 2023). The IMD World Digital Competitiveness Ranking, which is comparable to the digital readiness index, assesses how well nations adopt and investigate digital technologies that have the potential to revolutionise corporate practices, governmental procedures, and society at large. As strong digital readiness enables people to discern credible sources from fraudulent information, critically evaluate web content, and use digital communication platforms in an appropriate manner, this digital divide suggests that while some segments of the population are well-equipped to adopt Wealth Tech, others may face significant barriers due to lower levels of digital readiness, thereby serving as a factor hindering Wealth Tech adoption in Malaysia.

Apart from that, ineffective customer service is also a considered an essential problem since it indirectly reflects the soundness of the Wealth Tech environment in which the users think they would have perceived throughout their access to the Wealth Tech platforms. Customer service in the context of Wealth Tech refers to the support provided to users in understanding, using, and troubleshooting Wealth Tech platforms and applications. Upon examining multiple Wealth Tech organisations, it has been observed that the worst evaluations in Wealth Tech are caused by disengaged customer service. A lack of response to support requests, calls, or chats, as well as the frequent use of automated advisors, were issues raised by users (Danielle, 2023). In Malaysia, where digital literacy and familiarity with advanced financial technologies may vary, the availability of effective customer service can be a decisive factor in whether individuals choose to adopt and continue using Wealth Tech services. In Malaysia, the significance of customer service is amplified by the country's demographic and socio-economic diversity. According to the Muller (2021), Malaysia's internet penetration rate reached 91.21% in 2021, but there remains a substantial segment of the population that lacks advanced digital skills, particularly among older adults and those in rural areas. For these groups, access to responsive and effective customer service could mitigate barriers to Wealth Tech adoption, making it easier for them to understand and trust these digital financial solutions. Furthermore, research by Wong et al. (2019) on the adoption of digital banking in Malaysia highlights that customers who received prompt and helpful support were more likely to continue using digital financial services, suggesting a similar trend could be expected in Wealth Tech adoption. Therefore, the consideration of perceived customer service by the Wealth Tech user is particularly relevant for Malaysia, where the competitive landscape of Wealth Tech is still evolving, and providers that offer superior customer support may gain a significant advantage in attracting and retaining users.

Similarly, in this fast-paced world, word-of-mouth referrals can be extremely important to the success of a financial firm, therefore it is imperative to respond to client issues promptly and with care. In investing services, the personal element is still crucial. Although it can be challenging, providing a personalised services without significantly raising costs is essential for attracting and keeping customers. Therefore, Fintech must better address customer expectations by providing greater accessibility, convenience, and customised goods, since Generation X and Y clients are increasingly tech-savvy. With the inclusion of Fintech-based channels, having an integrated client service management system will become increasingly crucial (Lee & Shin, 2018). Therefore, considering the increasing competition of the Fintech market, word-of-mouth referral could be a dominant contributor to affect Wealth Tech adoption among Malaysians as a subset of the Fintech market.

1.3 Research Questions

1. Is there any relationship between Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions towards Behavioural Intention to adopt Wealth Tech?
2. Is there any relationship between Technology Readiness towards Performance Expectancy and Effort Expectancy?

1.4 Research Objectives

1. To examine the relationship between Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions towards Behavioural Intentions to adopt Wealth Tech.
2. To examine the relationship between Technology Readiness towards Performance Expectancy and Effort Expectancy.

1.5 Significance of Research

The main objective of this research is to present readers a comprehensive overview of the Wealth Tech scene in Malaysia by highlighting the major variables driving its uptake, the difficulties industry participants confront, and the prospects for future expansion. The research incorporates technology readiness in the research to enhance comprehension of user preparedness to embrace Wealth Tech platforms and in which ways the technology users are more confident to utilise and benefit from the technology. The research intends to investigate the factors driving the adoption of digital wealth management solutions, including changing investor demographics, technology improvements, and economic and social issues, through an analysis of market trends. Comprehending these patterns is essential to pinpoint the factors influencing the Wealth Tech industry and projecting its future course. It is important to pinpoint the factors as companies or developers in the Wealth Tech industry can make more informed decisions about product and system development. By aligning the development with the key factors driving adoption, it can benefit the long-term sustainability of the Wealth Tech development.

Evaluating consumer behaviour is one of the research's other main objectives. It aims to comprehend Malaysian investors' preferences, actions, and perspectives about digital wealth management platforms. Performance expectancy, effort expectancy, facilitating conditions, social influences and technology readiness are all evaluated in this process. Through a thorough analysis of these variables, the research seeks to identify the elements that promote or hinder Wealth Tech adoption, offering valuable perspectives on how digital platforms may more effectively address the demands and anticipations of investors. The research seeks to express the outcomes in which the technology users better match to the tailored user experience. It is also to gain an insight for better segmentation of users based on their technological maturity, whereas distinct versions of Wealth Tech solutions, such as user-friendly and effectiveness might optimise the satisfaction of potential technology users.

Another significant objective is to identify and profile the major participants in the Malaysian Wealth Tech industry. Through the provision of comprehensive profiles that encompass the business models, service offerings, and market strategies of prominent Wealth Tech firms, the research endeavours to underscore the inventive methodologies and distinct competitive advantages that set these entities apart. A more comprehensive understanding of Wealth Tech's entire contribution to the financial sector, as well as its impact on investor behaviour and industry trends, will be possible through an evaluation of its market impact. For instance, it guides innovation on Wealth Tech solutions to equip with advanced features that appeal to tech-savvy users, otherwise providing better support to ensure each level of technological accessibility for the users be able to access Wealth Tech solutions.

Lastly, the research paper focuses on Malaysia's Wealth Tech industry's potential in the future. This entails examining the possible effects of developing technology, spotting business expansion prospects, and talking about potential difficulties. The research strives to assure sustainable growth and set up a supportive regulatory framework that supports innovation and preserves investor interests. It does this by offering techniques for minimising these issues and policy recommendations. This all-encompassing strategy will provide insightful information to investors, industry participants, and policymakers, directing the future growth of Wealth Tech in Malaysia.

1.6 Conclusion

In summary, Chapter 1 introduces the research by laying the foundation for understanding the intersection of Fintech and digital wealth management, particularly within the Malaysian context. The chapter discusses the rapid digitalization of financial services, the rise of Wealth Tech, and the challenges faced in its adoption. Key objectives are highlighted, focusing on evaluating consumer behaviour, regulatory influences, and market trends in the Wealth Tech industry. The chapter underscores the significance of addressing cybersecurity, financial literacy, and competition, setting the stage for the research's in-depth exploration of the factors influencing Wealth Tech adoption and its potential for growth in Malaysia.

CHAPTER 2 LITERATURE REVIEW

2.0 Introduction

In this chapter, the foundational theories utilized in this research will be further explored. The second half of this chapter will include studies on the dependent and independent variables, which have been thoroughly evaluated in highly recognised articles and publications. This chapter's third section introduces a conceptual framework to clarify the links between dependent and independent variables. Chapter 2 concludes with the establishment of hypotheses for behavioural intention of Wealth Tech adoption in Malaysia, demonstrating the relationships between variables.

2.1 Review of Variables

2.1.1 Behavioural Intention to Adopt Wealth Tech

The standard definition of behavioural intention is the degree to which a person has formulated conscious plans to perform or not perform some specific future behaviour (Warshaw & Davis, 1985). In line with previous research, we define and measure users' intents to use wealth tech as the probability that they will do so. People behave in certain ways depending on their state of mind at the time of an action. Behavioural intention is the psychological expression of an individual's readiness to act as a preceding behavioural element (Ajzen, 2011; Ajzen, 2020; Chen & Chang, 2013). In the research, behavioural intentions to adopt Wealth Tech in Malaysia are determined by various variables including performance expectancy, effort expectancy, facilitating conditions, social influences and technology readiness. According to Khalilzadeh et al. (2017), Unified theory of acceptance and use of technology (UTAUT) defines an individual's attitude toward a target behaviour as their willingness to carry out that action in a suitable manner. Since the UTAUT assumption has been widely utilised in a variety of technological contexts involving computerised equipment, it is anticipated that it can be applied to the setting of Wealth Tech. However, the development of the four UTAUT antecedents was predicated on the idea that attitudes acted as the primary mediating factor in the formation of predictors and behavioural intentionsm (Kelly et al., 2022). Behavioural intention is the probability that users will participate in an action (Ajzen, 2002). Higher behavioural intentions may lead to increased use of technology (Thoti, 2024 ; Tseng, 2025). For instance, individuals are more likely to accept digital wealth management systems if they believe they can help them achieve better financial outcomes and are simple to use (Mahdzan et al., 2022).

2.1.2 Performance Expectancy

Yeoh and Chin (2022) defined the term '*performance expectancy*' (PE) as the degree to which an individual believes that using the system will help him or her to attain gains in job performance. In the context of digital wealth management, performance expectancy can be understood as the extent to which potential users perceive that Wealth Tech tools and platforms will enhance their financial management, decision-making, and investment outcomes. These Wealth Tech solutions range from robo-advisors and algorithmic trading platforms to AI-driven financial planning tools. With the rapid digitalization of the financial services industry, the role of Wealth Tech has become pivotal in providing personalised, efficient, and accessible financial management solutions (Prabhakaran, 2025).

The concept of performance expectancy includes the construct of perceived usefulness, intrinsic drives, work fit, comparative advantage, and anticipated results. This aspect is recognized as the strongest predictor of technology usage intention as it is significant in both required and optional settings (Duan & Dong, 2025; Lai et al., 2024)

Several studies have validated its importance in diverse settings, such as Alamoudi et al. (2025) studied performance expectancy construct in Fintech services and Pranata (2025) researched performance expectancy in the mobile banking sector. The term "performance expectancy" in this research describes people's degree of confidence that adopting online wealth management platforms will benefit them. According to studies on Wealth Tech and Fintech adoption, users are more inclined to accept digital platforms if they perceive they provide real benefits such as higher financial returns, better investment management, and time savings (Jisham et al., 2024). For example, robo-advisors are becoming more popular because customers trust automated platforms to give optimal investment plans without much manual participation.

Lee and Shin (2018) claimed that Wealth Tech is emerging in various capital market areas, including investing, trading, managing risks, and researching. The automated trading tools enable real-time communication between investors and traders, including the ability to share knowledge, make orders, and analyse risks (Todorović et al., 2019).

Users' expectation that Wealth Tech services would result in better investing outcomes has a substantial impact on adoption. According to research, customers are attracted to digital wealth management tools because they believe they provide superior financial insights, automated decision-making, and improved portfolio performance (Ryu, 2018).

Furthermore, convenience is mentioned as one of the obvious advantages of technology adoption in wealth management, which stems from accessibility and immediate access (Arkorful et al., 2022). Besides, the transaction process of Wealth Tech is also considered by investors. The Wealth Tech process describes the advantages of utilising technology-driven wealth services, such as automated advisors, investment apps, and online brokerage services (Belanche et al., 2019). It is important to have a seamless transaction, which provides benefits that allow customers to conduct and manage their financial transactions easily. Through seamless transactions, customers can boost the transaction speed and financial transaction efficiency in comparison to traditional financial transactions (Ryu, 2018; Dewi & Rahadi, 2020). The application of AI and big data in Wealth Tech enables personalised financial planning and predictive analytics, which users see as adding significant value (Cao et al., 2021).

Consequently, if consumers believed that technology-driven services would help them, they intend to utilise wealth tech more frequently. Understanding some degree of self-benefit is an intention to people before starting to adopt financial technology. In a similar vein, the degree to which a person realises that employing wealth technology like robo-advisors would improve their wealth management is considered as performance expectancy (Bajunaied et al., 2023; Belanche et al., 2019).

2.1.3 Effort Expectancy

Effort Expectancy (EE) is defined as "the degree of ease associated with the use of technology" in the UTAUT model proposed by Venkatesh et al. (2003). Perceived ease of use and complexity are the building blocks of effort expectancy. Users believe technology is more beneficial when it is easier to use, which is why effort expectancy is associated (Mehta et al., 2019). The effort expectation refers to the ease of connecting the customer's actions to the product system. If users expect that using the technology requires a lot of effort, this can affect their decision to accept or reject the new technological product; If users find it simple to use and quick to pick up, this can encourage them to use the products (Thusi & Maduku, 2020; Twum et al., 2021).

A person's propensity to use a system is directly impacted by its ease of use. Prior research has demonstrated that a person's attitude about utilising new technology is influenced by how simple a system is to use (Chen & Chang, 2013). Moreover, expectation theory-based research by Rahi et al. (2019) demonstrated that effort expectancy modifies has a major impact on users' intents to adopt new technologies. Fedorko et al. (2021) also discovered that effort expectancy influences users' intentions significantly to utilise Internet banking services using electronic banking as a sample. Therefore, this research defines effort expectancy as the level of ease associated with using wealth tech in accordance with definitions from the UTAUT model and earlier literature.

As a result, in this research, effort expectancy has been linked to customers' expectations of Wealth Tech services' ease of use and has been regarded as a predictor of their inclination to adopt technology (Kilani et al., 2023). Customers must have access to a computer or a mobile device to use Wealth Tech services. The degree of platform compatibility and user interface friendliness may therefore influence customers' ease of use, which in turn may influence their intention to use Wealth Tech services (Le et al, 2022).

2.1.4 Social Influence

According to Venkatesh et al. (2003), social influence (SI) is the degree to which a person considers the significance of other people's opinions about why they should adopt the new system. Social influence indicates that people's behaviour is modified in response to how others see them, which is related to the subjective norms, social variables, and image constructs derived from the Theory of Planned Behaviour (TPB) and the Theory of Reasoned Action (TRA), Technology Acceptance Model Two (TAM2), a combined model of TAM and TPB (C-TAM-TPB), Model of PC Utilisation (MPCU), Innovation Diffusion Theory (IDT). Considering people's growing reliance on social media, social influence is predicted to be one of the key elements influencing Wealth Tech adoption in this research (Benevento et al., 2025; Sumadevi, 2023). Social influence refers to how much a user's close friends and family believe they embrace new technology, which can impact their decision (Cao et al., 2024). The researchers found that as technology gets more widely used, people tend to use it for social interactions, regardless of personal preferences (Senyo & Osabutey, 2020).

Through social media platforms, they can now get voluntary or involuntary feedback from friends, family, and strangers in this digital age. Furthermore, PricewaterhouseCoopers (2024) discovered a substantial correlation between an individual's attitude toward Wealth Tech and social influence. To put it in another way, if someone important or close to them suggests Wealth Tech, there's a good chance that others will view it favourably. Scholars have determined that this aspect has the potential to impact both the overall and specific adoption of technology by customers. Supported by studies from Graf-Vlachy et al. (2018), it is mentioned that peer influence, family, and societal norms could have significantly impacted technology adoption decisions. Social influence in this research refers to the users' perception of important others who motivate them to use wealth tech services (Le et al, 2022).

Using the Internet Wealth Management (IWM) platform, if people are unable to comprehend how IWM services can be applied because of limitations in terms of time, knowledge, or other variables, a reasonable alternative solution is to mimic the behaviour of others (Shao et al., 2022). Anybody who has an influence on the customer's life, including friends, family, coworkers, and relatives, might be considered in their social ties. It is believed that consumers frequently base their decision to buy a particular product on the recommendations of influential people, social network recommendations and the degree of usage displayed by those in their immediate vicinity (Melnyk et al., 2021).

Social influence can be conceptualised based on different types of social norms. For example, subjective norms, injunctive norms, and descriptive norms (Ajzen & Fishbein, 1972; Cialdini et al., 1990). Subjective norms are the perceived societal pressures or expectations of an individual to perform or refrain from a specific activity. Furthermore, subjective norms affect individuals by informing them about their closed ones' expectations on their behavioural decision, which is social pressure (Joa & Magsamen-Conrad, 2021: Irimia-Diéguez et al., 2023). Injunctive norms are social approbation or the perceived generality of positive or negative attitudes towards a specific behaviour. This norm will influence people's views towards technology by educating them of the socially popular attitude towards technology. Furthermore, injunctive norms influence adopters' intentions on how to use the technology (Panek et al., 2025).

Furthermore, descriptive norms refer to the popularity or perceived predominance of a specific behaviour. In terms of new technology adoption, descriptive norms have been shown to have a pretty large influence on adoption behaviour. The higher the apparent prevalence, the more likely potential users will regard such activity as usual. As a result, individuals are motivated to adhere to the social norms surrounding technology (Cialdini et al., 1990).

2.1.5 Facilitating Conditions

Facilitating conditions (FC) reflect the degree to which people understand the organisational and information-technology infrastructure that may assist them in adopting new technologies (Venkatesh et al., 2003). The concept of facilitating conditions is derived from TPB, C-TAM-TPB, MPCU, and IDT models, together with compatibility and perceived behavioural control. It indicates that when clients feel completely at ease regarding the security of their personal information, transaction processes, and technological methods when using a product, their trust in it will reach the maximum level (Venkatesh et al., 2012).

Using technological innovation involves resources such as gadgets, software, Internet connectivity, and specific skill sets. Without connectivity barriers, adoption rates in Malaysian Wealth Tech can be greatly influenced by the availability of strong digital infrastructure and regulatory support. For example, regarding digital mutual funds, the terms of facilitating conditions to the extent that users perceive the application to be supported by a well-trained help desk and a proficient team with a strong infrastructure (Dewi & Rahadi, 2020). However, the adoption of technology was still expected to be inhibited by a lack of facilities especially in developing countries (Kala, 2023).

In this research, facilitating conditions refers to people's attitude towards available resources and supports, such as smartphones, Wealth Tech platforms, and advisers, during their adoption of Wealth Tech services. Strong IT systems, high-speed internet, and safe digital platforms are required to adopt new technology development (Michael et al., 2023). In the context of digital wealth management, users require consistent access to digital wealth management tools and platforms with no interruptions, delivering a seamless experience. Furthermore, technical assistance and customer assistance such as tutorials, and customer service are critical for assisting users in efficiently navigating these platforms.

2.1.6 Technology Readiness

Parasuraman (2000) proposed the idea of "technology readiness" (TR), which refers to a user's level of acceptance of new technology. The technology readiness measures consumers' positive and negative mental preparedness for technology. The saying that it is hard for individuals to adapt and accept new things or the ability of an individual to embrace and utilise new technologies is the source of technology readiness. Moreover, being technologically ready is a state of mind brought on by optimistic ideas and a barrier that will decide whether or not a person uses technology (Liljander et al, 2006). Technology readiness was subsequently advanced by Parasuraman and Colby (2015), who categorised two elements that can lead to technology readiness: inclusive threat factors (uncertainty and discomfort) and motivating factors (optimism and innovation). In terms of advancement, for optimistic and creative groups, technology is viewed as a technological breakthrough; in contrast, the pragmatic group believes that technology is inferior until the group gains enough confidence. As clarified earlier, technology readiness refers to an individual's capacity to embrace and effectively utilize Wealth Tech services to achieve their goals.

A person's propensity to employ new technologies can be understood as an overall state of mind that arises from a gestalt of mental facilitators and inhibitors referred to as Technology Readiness construct. To gauge people's overall attitudes toward technology, the Technology Readiness Index (TRI) was created at the measurement level. Although TRI gauges consumers' willingness to embrace new technology, positive scores indicate that the demographic being studied is already familiar with technology from their use in other contexts. Therefore, combining the Technology Readiness model with UTAUT can yield more accurate projections of the real-world uptake and application of technology-based services (Tsourela & Roumeliotis, 2015).

The four sub-dimensions that make up the technology readiness construct are insecurity, discomfort, inventiveness, and optimism. A positive attitude toward technology and the conviction that it gives people more efficiency, flexibility, and control are related to optimism. Being innovative is defined as having a propensity to lead thought and pioneer in technology. Research on technology readiness rates innovativeness as an essential determinant which influences people to accept new technologies. The group of innovators takes big risks by adopting technologies at a faster pace than their counterparts the late adopters and laggards (Gupta & Mukherjee, 2024). Innovativeness of individual users stands as a validated concept behind their adoption of wealth tech according to this research. Therefore, innovators are inclined to adopt technology. A sense of being powerless over technology and being overtaken by it are the main causes of discomfort. Technology is viewed with suspicion and its efficacy as a source of insecurity (Lin et al., 2007). The possibility that technology readiness plays a significant role in the association between performance and effort expectancy will be examined. It is hypothesised that respondents with varying technology readiness will exhibit varying degrees indirectly toward Wealth Tech adoption.

2.2 Theoretical Framework

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

The UTAUT model, developed by Venkatesh et al. (2003), is a robust theoretical framework to study technology adoption. The model proposed four key variables of Behavioural Intention (BI) which are Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI) and Facilitating Conditions (FC). PE is the belief that using Wealth Tech will enhance financial decision-making and management. Users are more likely to adopt Wealth Tech if they perceive it as beneficial for increasing efficiency and effectiveness (Nazmi et al., 2024). EE refers to the perceived ease of use of Wealth Tech. If users find it simple and user-friendly, they will be more willing to adopt it (Ma et al., 2025). SI is the extent to which users believe that important people in their social network such as family, friends, and colleagues encourage the use of Wealth Tech. If social pressure is high, adoption likelihood increases. FC refers to the availability of resources, knowledge, and support systems necessary for using Wealth Tech. If users feel they have sufficient guidance, infrastructure, and customer support, they are more likely to adopt it. These four factors directly influence Behavioural Intention (BI), which in turn determines the User Intention to Adopt Wealth Tech.

As highlighted by the UTAUT model proposed, performance expectancy, effort expectancy, social influence, and facilitating conditions are the four main components that UTAUT offers to describe user intents for using information systems and their usage behaviours. Numerous empirical research uses UTAUT as the theoretical foundation. For example, Dwivedi et al. (2019) conducted a meta-analysis of UTAUT studies and found that performance expectancy and facilitating conditions were the most significant predictors of technology adoption. Additionally, research by Riffai et al. (2012) on mobile banking adoption in the Gulf region emphasised the role of social influence and effort expectancy. On the other hand, Im et al. (2011), investigated how Korean and American users adopted Internet banking and MP3 players to see how culture influenced the connections between the elements of the UTAUT model. In an investigation into the effects of mobile banking adoption, Yu (2012) found that social influence, perceived financial cost, performance expectation, and perceived credibility all had an impact on an individual's intention to use mobile banking. The applicability of the UTAUT paradigm for mHealth services for the elderly in developing countries such as Bangladesh was confirmed by Hoque and Sorwar (2017). Regarding the behavioural intention to utilise m-learning from the consumer's perspective, Chao (2019) included perceived enjoyment, mobile self-efficacy, satisfaction, and trust in the classic UTAUT while they also used perceived risk as a moderator.

The UTAUT framework incorporates components from eight other models of technology acceptance to offer a thorough understanding of the factors that influence user intentions and subsequent technology use (Venkatesh et al., 2003). Listed by Venkatesh, the models included are the theory of Planned Behaviour (TPB), Theory of

Reasoned Action (TRA), Technology Acceptance Model (TAM), Motivational Model (MM), a combined model of TAM and TPB (C-TAM-TPB), Model of PC Utilisation (MPCU), Innovation Diffusion Theory (IDT), and Social Cognitive Theory (SCT) (Marikyan & Papagiannidis, 2023). Each of these theories contributes distinct constructs and perspectives that collectively enhance the explanatory power of the UTAUT model which makes it possible to capture the multifaceted factors influencing technology adoption.

Three decades ago, the research community became more interested in the adoption of technology in organisational and private settings (Leonard-Barton & Deschamps, 1988; Davis, 1989). Various research on user behaviour connected to technology adoption had been produced by technology acceptance research by the end of the year 2000 (Hu et al., 1999). This makes the adoption of the technology to be described by an abundance of models and theories, which collectively accounted for approximately 40% of the variation in technology usage intention (Davis, 1989). While each of the models proposed had roots in different manners, this limits the applications of these theories to certain contexts. For example, Ajzen (2011) shows that the Theory of Planned Behaviour and the Theory of Reasoned Action (TRA) look more into psychological perspectives on human behaviour provided by factors like attitude. On the contrary, the diffusion of innovation theory (DOI) is more concerned with the innovation-specific elements that influence users' adoption behaviour of new technologies by reflecting variables from different perspectives such as subjective norms, motivational factors, attitudinal factors related to technology performance, social factors, experience and facilitating conditions (Ajzen, 2011; Moore & Benbasat, 1991; Venkatesh et al., 2003). The choice of either paradigm is said to limit the research findings to specific situations and circumstances. Hence, in order to broaden the theory's applications to many contexts and incorporate variables reflecting various perspectives and disciplines, a unified methodology is required (Venkatesh et al., 2003).

Through comparing all the current theory models proposed to research technological acceptance, Venkatesh (2003) found that the main drawback was that there was no empirical testing or comparison of the prominent technological acceptance models in the literature, which opens up spaces for speculation about the theoretical constructs' capacity for prediction. Research on how people use technology has mostly concentrated on basic systems, for example, personal computers (PCs), and ignored the use of advanced technologies (Venkatesh et al., 2003). The explanatory ability of the existing theories is considered limited when there is only one technology in the focus as different IT systems and technological environments could have different impacts on people's experiences, purchase decisions, and use cases, thereby affecting technological acceptance of each generation (Brown et al., 2015). For instance, people will tend to opt for more recent technology as it is mostly considered more up-to-date and suitable to be employed in required circumstances coupled with its great utilitarian benefit. Prior literature also showed several methodological shortcomings while some constructs, like experience, needed to be studied across time. The majority of studies employed a cross-sectional approach, measuring variables at pre- or post-acceptance stages (Venkatesh et al., 2003). Apart from that, Venkatesh also found that the earlier research is more focused on technology adoption in a voluntary setting, where they assumed that society had no influence over technology usage and acceptance across each generation. Therefore, it is recommended that technological acceptance was to be examined in both required and optional settings to ensure the model is equipped with a broader implication. Through the empirical comparison of the theories, Venkatesh has created a single acceptance model named Unified Theory of Acceptance and Use of Technology (UTAUT) model that includes and reflects all the important acceptance elements (Venkatesh et al., 2003).

To sum up, given the unique socio-economic and cultural setting of Malaysia, the UTAUT model provides a thorough framework for examining Malaysians' adoption of Wealth Tech. Through a comprehensive analysis of the fundamental constructs of performance expectancy, effort expectancy, social influence, and facilitating conditions, scholars can acquire a more profound comprehension of the elements propelling the adoption of Wealth Tech. Compared to other models that look at technological adoption, UTAUT shows that suggested factors account for 70% of the variance in use intention (Venkatesh et al., 2003), providing a higher predictive power. Hence, to fully capture the dynamic character of technology adoption in the fast-paced financial landscape, this theoretical framework is especially pertinent to research on the adoption of Wealth Tech—financial technology solutions that facilitate investment and wealth management among Malaysians.

2.2.2 Theory of Technology Readiness Index (TRI)

The Technology Readiness Index (TRI) developed by Parasuraman (2000) is a psychometric tool that assesses people's willingness to embrace and use new technology. It examines four distinct dimensions: optimism, innovativeness, discomfort, and insecurity. Optimism refers to a favorable attitude toward technology and the perception that it provides more control, adaptability, and productivity in life. Second, innovativeness assesses an individual's proclivity to be a technological innovator and thinking leader. Third, discomfort refers to a perceived loss of control over technology and a sense of being overpowered by it. Finally, insecurity denotes distrust in technology and uncertainty about its ability to function properly. Optimism and innovativeness serve as enablers of technology readiness, fostering a willingness to adopt new technologies. In contrast, discomfort and insecurity operate as deterrents, lowering the likelihood of adoption. The TRI reflects the contradiction that humans can concurrently hold both positive and negative views on technology (Azri & Noviaristanti, 2025).

2.2.3 Integrated TRI and UTAUT

This research is targeted to provide a comprehensive viewpoint on comprehension Malaysia's acceptance of Wealth Tech by analysing the relationship of the TRI model on performance expectancy and effort expectancy, combined with the UTAUT model. Since UTAUT focuses on external factors such as PE, EE, SI and FC, it doesn’t consider the individual psychological traits that influence how people perceive and adopt technology (Marikyan & Papagiannidis, 2023). Hence, the integration of TRI and UTAUT can assess how an individual’s readiness impacts their perceptions of Wealth Tech’s usefulness and ease of use, making it a more personalised adoption model.

Previous Empirical research supports the integration of TRI and UTAUT constructs. For instance, a study by Godoe and Johansen (2012) found that optimism and innovativeness significantly influence perceived usefulness and perceived ease of use, which in turn affect actual usage of technology. This underscores the importance of considering individual differences in technology readiness when assessing technology acceptance (Blut & Wang, 2019). Besides, Amron et al. (2019) also proposed the model for cloud computing adoption in Malaysia's public sector. According to the research (Leong et al., 2020), they integrated TRI and UTAUT on E-wallet adoption in Malaysia. The researchers used UTAUT and TRI factors to identify the likelihood of E-government system adoption by all Malaysian governments and citizens (Safiah & Aiman, 2021). Reyes-Mercado et al. (2022) merged the TRI and UTAUT to study the adoption of digital learning tools during the COVID-19 pandemic. Moreover, Balakrishnan and Eesan (2024) studied the enablers and disablers of contactless payment acceptance among Malaysian adults by using the proposed construct too. Albanna et al. (2022), Neves et al. (2025) and Wu and Lim (2024) support the idea that adding a new construct, such as technology acceptance, into the UTAUT model can increase the predictive ability of the UTAUT model compared to the original model.

2.3 Conceptual Framework

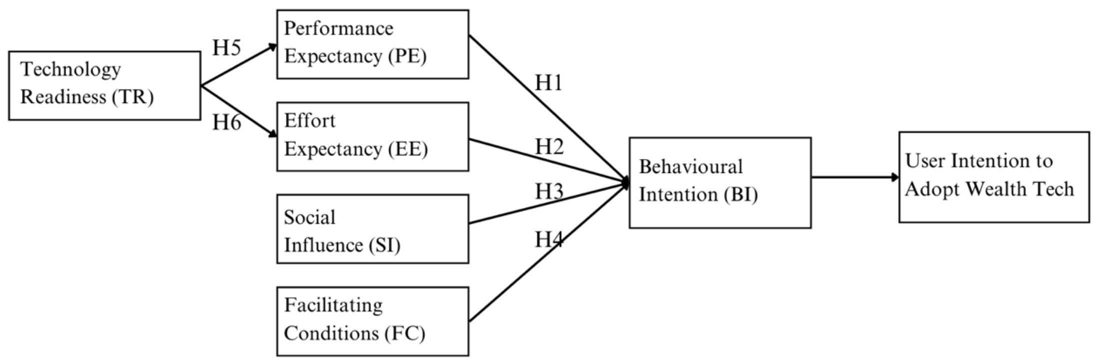


Figure 2.1. Proposed Framework. Note. Developed by the author.

2.4 Hypothesis Development

2.4.1 Performance Expectancy

Referring to Hong et al. (2023), the research indicated that consumers' desire to use robo-advisors is based on their perception of their ability to help with investing and financial management. Its research was conducted for the Covid-19 pandemic period, whereas consumers may have considered using robo-advisors as an alternative to managing their finances and investments because they were unable to meet in person with human advisors through traditional financial advisory processes. In a similar vein, it is anticipated that consumers would keep using wealth tech services, of which robo-advisors are a component of digital wealth management. Previous study has demonstrated that the concept of PE, such as usefulness, has a positive effect on intention to use financial technology (Prabhakaran, 2025).

$H_0$1= Performance Expectancy has no significant effect on the intention of adoption of Wealth Tech in Malaysia.

$H_1$1= Performance Expectancy has significant effect on the intention of adoption of Wealth Tech in Malaysia.

2.4.2 Effort Expectancy

Previous research has consistently demonstrated a strong positive correlation between the intention to use technology and effort anticipation. For example, Kim et al. (2009) discovered that usability-related features, designs, and user interfaces can have a positive impact on innovation uptake. The research found that when potential users perceive robo-advisors as simple to use, their likelihood of Wealth Tech adoption improves (Nguyen et al., 2023). Chiun et al. (2024) study on Malaysian investors' intentions to use robo-advisory services and found no association between effort expectancy and adoption intention. This shows that factors other than perceived ease of use, such as transparency, comparative advantage, and social influence, may have a greater impact on adoption decisions. Similarly, Zheng et al. (2021) explored the intention to use robo-advisory services among Malaysia's income middle class discovered that effort expectancy had no major effect on the intention to act.

$H_0$2= Effort expectancy has no significant effect on the intention of adoption of Wealth Tech in Malaysia.

$H_1$2= Effort expectancy has significant effect on the intention of adoption of Wealth Tech in Malaysia.

2.4.3 Social Influence

Social influence refers to people's opinions of the significance of other's points of view on adopting a new technology (Venkatesh et al., 2003). Social influence is defined as an individual's opinion of important others, such as family and colleagues who trust that the digital wealth management platforms are good to utilise. Multiple research studies also show that people's decisions are positively impacted by society. SI has a positive impact on people's intentions to adopt mobile payments services (De Luna et al., 2019). SI has an enormous effect on individuals' adoption intentions, the research has significant implications for Fintech companies' marketing strategies (Xie et al., 2021). However, Chauhan and Jaiswal (2016) do not consider SI as a research variable when they apply the UTAUT model to their research exploring the adoption of emerging software training.

$H_0 3$ = Social influence has no significant effect on the intention of adoption of Wealth Tech in Malaysia.
$H_1 3$ = Social influence has significant effect on the intention of adoption of Wealth Tech in Malaysia.

2.4.4 Facilitating Conditions

In this research, the terms "facilitating conditions" refer to people's opinions on relevant resources such as gadgets and Fintech-related platforms and support including application vendors' technical assistance and technological advancements when using digital wealth management platforms. Using a digital wealth management platform necessitates some resources and essential skills, such as financial literacy. Individuals are more inclined to use a platform if certain conditions are met.

The impact of limiting variables on the use and adoption of technical advances and systems is lessened by enabling conditions (Venkatesh, 2003). Joshua and Koshy (2011) stated people with simpler access to computers and the Internet are likely to use them more competently, resulting in a greater acceptance of electronic banking among respondents. FC and adoption intention was found to be strongly positively correlated in research looking at Gen Z's behavioural intention to use FinTech services in Malaysia (Amin et al., 2024). According to Venkatesh et al. (2012), they verify that facilitating controls affect people's adoption although this effect fades after the first usage. Some research has shown that FC is positively associated with individuals' adoption intentions (Koh et al., 2024). Previous studies on new technology adoption have validated the concept of a positive association between FC and users' behavioural intentions in mobile banking adoption, mobile commerce, and the Fintech platform (Oliveira et al., 2014; Shaw & Sergueeva, 2019). In addition, previous studies have shown how crucial are the advantageous conditions as a crucial determinant of the intention to adopt different technologies (Bouteraa et al., 2021; Wang et al., 2020). Meanwhile, studies in the field of blockchain technology have shown that facilitating conditions have a major impact on Malaysian banking institutions' behavioural intention to implement such innovations (Yusof et al., 2018).

$H_0 4$ = Facilitating conditions has no significant effect on the intention of adoption of Wealth Tech in Malaysia

$H_1 4$ = Facilitating conditions has significant effect on the intention of adoption of Wealth Tech in Malaysia

2.4.5 Technology Readiness

Adding TR as a consumer attribute to an expanded UTAUT. Davis et al. (1989) assert that perceptions completely mitigate the influence of external variables, including differences in technology use. According to Dabholkar and Bagozzi (2002), the correlations between perceptions and intentions are moderated by individual differences. So, we suggest that TR has an indirect influence on the research.

According to research, performance expectancy and technological readiness are positively correlated (Chiu & Cho, 2020). Among the particular TR dimensions, optimism is a positive driver that is associated with a perception of technology and the conviction that it gives individuals more efficiency, flexibility, and control. Optimists are less concerned with potential drawbacks. Therefore, they view a particular technology as beneficial and helpful to their performance. Yang et al. (2024) also found that people who are optimistic accept situations and are more eager to use new technologies. Additionally, early adopters or people who are more innovative have been discovered by researchers to have more belief and intention to adopt new technologies (Zulkifli & Zainal, 2024).

However, Abdelrahman et al. (2025) stated that user anxiety such as discomfort and uncertainty were the root of certain glaring barriers to technology adoption. There is concern of users about their productivity decline and preconceived negative reactions after wealth technology implementations because the system has rarely been used in wealth management. Lowered expectations for a particular technology's performance are caused by high levels of human fear and unease with technology. Despite that, according to Chong et al. (2021), there are more individual investors actively adopting technology on their wealth management such as mobile trading applications in Malaysia since the usefulness of technology, such as robo-advisor features. We hypothesise that customers with higher TR propensities will be more inclined to anticipate better performance from Wealth Tech, as TR is the outcome of the interaction between positive drivers and negative inhibitors.

$H_0$5 = Technology Readiness has no significant effect on the intention of adoption of Performance Expectancy in Malaysia
$H_1$5 = Technology Readiness has significant effect on the intention of adoption of Performance Expectancy in Malaysia

There remains a positive correlation between the ease of use of a technology-based service and consumers' technology readiness propensities (Chiu & Cho 2020). According to Omrani et al. (2022), consumers who possess higher levels of innovativeness and optimism are inclined to view Wealth Tech platforms as user-friendly. Conversely, those with higher characteristic ratings for uneasiness and insecurity see technology as more complicated, which reduces their belief that it is user-friendly and protective (Bao et al., 2022). Tahar et al. (2020) stated that low expectations of the amount of work required to embrace Wealth Tech could be caused by high levels of general uneasiness such as lack of system integration and personal insecurity. People might be uncomfortable due to risk perception of using technology and reduce the intention to adopt Wealth Tech. We therefore suggest that users will be more likely to believe that Wealth Tech is user-friendly if they have higher TR propensities.

$H_0$6 = Technology Readiness has no significant effect on the intention of adoption of Effort Expectancy in Malaysia
$H_1$6 = Technology Readiness has significant effect on the intention of adoption of Effort Expectancy in Malaysia.

CHAPTER 3 METHODOLOGY

3.0 Introduction

The key components of the method of study will be covered in detail in this chapter. It will start by providing an overview of the research strategy and data gathering methodology. Primary data will be utilized to address the research question and objectives. Additionally, the chapter will explain the sampling design and research instruments to help the reader better understand the methodology employed. Finally, the chapter will cover the construct measurement process to ensure the validity, reliability, and accuracy of the research.

3.1 Research Design

A research design is a methodical strategy that researchers employ to meaningfully address questions. Usually, a research design will outline the specific type of analysis that must be carried out in order to provide the desired outcomes (Khanday & Khanam, 2019).

This research opts for a quantitative method to investigate Malaysians' intention to adopt Wealth Tech between various independent variables such as PE, EE, SI, FC, and TR. The research also investigates the impact of TR on PE and EE. The quantitative approach suits the research mainly to examine the hypothesis development and to analyze the underpinned relationship between dependent variable and independent variables. The data of this research will be collected by using primary data. By applying the methods such as regression analysis and correlation, the data could be adopted for statistical analysis to determine the strengths and significance of relationship between independent variables and intention to adopt Wealth Tech in Malaysia

3.1.1 Quantitative Research

In quantitative design, numerical data is measured and analysed to investigate the link between independent and dependent variables using a mathematical framework (Ghanad, 2023). The questionnaire uses convenience sampling to collect the data from the targeted respondents for each construct to adopt Wealth Tech. It is to ensure that the respondents are easily accessible and reachable via physical and online survey. The research would sufficiently gain initial insights rather than derive perfect distributed sample size over the states of Malaysia.

3.2 Data Collection Method

The quantitative method was employed to collect primary data for this research. The data are collected from respondents in two ways through physical and online. For the offline respondents, the questionnaire will be printed out and distributed physically. Physical data collecting helps to improve the efficiency of the data collecting process due to high response rate and face-to-face interactions with respondents. While completing a physical form, some respondents may provide more thoughtful and detailed answers compared to an online survey. Meanwhile, the online questionnaires are created by using Google Forms, which were shared through social media platforms like WhatsApp, Messenger, and Instagram. All the questions were set as “compulsory” to answer to avoid information incompleteness of questionnaire surveys. The purpose of employing online survey forms ensures responses are not restricted to a particular area by providing access to a geographically distributed population. The respondents were guaranteed that their input would be kept private and utilised just for research, with no information being shared or used for other purposes.

3.2.1 Primary Data

In this research, primary data will be collected through questionnaires consisting of 40 questions designed to gather feedback on respondents' behaviour and information. For this research on the adoption of Wealth Tech, primary data is best suited since it offers firsthand, precise information that is directly relevant to the research topics. Understanding user behaviours and intentions to adopt Wealth Tech by analysing the PE, EE, FC, SI and TR is the main goal of this research. Since these factors are very context-specific, it is necessary to use up-to-date, directly sourced data to accurately represent the target population's views and behaviours.

3.3 Sampling Design

A sampling design involves a combination of sampling techniques that follow specific rules and procedures, along with estimations of the results from the statistical sample (Turner, 2020). The goal of a sampling design is to generate estimates that are precise and accurate enough to fulfill the survey requirements. This research will provide a detailed discussion of the target population, sampling frame and location, sampling elements, sampling techniques, and sample size.

3.3.1 Target Population

A target population is any person or group that meets the research 's criteria (Willie, 2022). In accordance with the objectives of this research, the focus is on both current users and non-users of Wealth Tech to ensure the reliability of the research. The research aims to collect data from those who have an active or potential interest in managing wealth digitally and to explore what factors to arouse their intention to adopt Wealth Tech. According to the data from Department of Statistics Malaysia (2024a), the target population size in this research is 23 million which comprises Malaysians who aged 18 until 79 years old. To analyse the age differences in the adoption behaviour intentions, the research will comprise 4 major groups, which are Gen Z (18 - 27 years old) who adopt Wealth Tech rapidly, driven by digital convenience; Millennials (28 - 43 years old) who likely to take cautious but open approach, favouring hybrid models with human support; Gen X (44 - 59 years old) who might prefer traditional banking institutions; Baby Boomers (60 - 79 years old) who having lower digital literacy and limited exposure to Wealth Tech (Alzahrani & Felimban, 2025). The sampling group includes current users of Wealth Tech applications such as online brokerage, robo-advisors, mobile trading, peer-to-peer lending and blockchain as well as non-current users. In this research, older age groups can be indicated as digital immigrants as they are someone who has learned to use technology later in life, after growing up in a world without computers or the Internet (Hayes, 2022).

3.3.2 Sampling Frame and Location

The sampling frame consists of Malaysian individuals aged 18 to 79 years old, with a focus on those who have engaged with Wealth Tech or have shown interest in Wealth Tech management. Online surveys will be used to gather data, and digital channels such as social media, fintech communities, and professional networking sites will be used to disseminate the results. This approach ensures broader reach and engagement with the targeted respondents. The research will cover respondents from 13 states and East Malaysia to obtain diverse representation of the population. The inclusion of respondents from different geographic locations ensures that the research can analyse the variations in Wealth Tech adoption trends across urban and rural areas.

3.3.3 Sampling Elements

The sampling elements refer to individual respondents to be selected and included in this research. The primary criteria are the Malaysia residents age ranging from 18 years old to 79 years old. Secondly, individuals who are current users of Wealth Tech (online brokerage, robo-advisors, mobile trading, peer-to-peer lending and blockchain). Thirdly, individuals who are potential adopters of Wealth Tech in Malaysia. Besides that, respondents from various demographic backgrounds, different employment statuses, and all income levels will be included to provide a comprehensive understanding of the factors influencing Wealth Tech adoption.

3.3.4 Sampling Techniques

In research, a sampling technique is the procedure used to choose a subset of people, objects, or data points from a larger population in order to make inferences about the full group (Sharma, 2017). This method is critical because studying an entire population can be time-consuming, costly, or impractical. By using a sampling technique, researchers can obtain a manageable and representative sample that reflects the characteristics of the broader population, allowing for more efficient and accurate data collection.

The sampling techniques employed is non-probability, specifically the convenience method, to conduct the survey throughout the targeted respondent in Malaysia. To reach out respondents through an effective and convenient method while meeting certain characteristics, convenience sampling methods are adopted to gather primary data by sharing through online platforms and social media. Adopting convenience sampling is practical to research about the behavioural intention of targeted respondents in Malaysia without regarding the perfect distribution of sample size in each state throughout Malaysia.

3.3.3 Sampling Size

It involves the process of deciding how many observations or replicates to include in a statistical sample (Hossan & Alhasnawi, 2023). The sample size for this research is determined according to the target population. Given by the Department of Statistics Malaysia (2024b) that the population of residents aged 18 to 79 exceeds 250,000, the sample size will be 384. Therefore, the sample size for this research will be 384 with a targeting 5% margin of error.

Table 3.1:

Target Population and Sample Size

Population Size	*Sample Size*		
	Sample Table		*Current article risk-based formula*
	95% Confidence level	*99% Confidence level*	*Risk Probability*

	5% Error	*1% Error*	*5% Error*	*1% Error*	*0.99*	*0.75*
75	63	74	67	75	3	2
300	169	291	207	295	8	6
800	260	739	363	763	20	16
2,500	333	1,984	524	2,173	60	47
25,000	378	6,939	646	9,972	593	462
100,000	383	8,762	662	14,227	2,370	1,848
250,000	384	9,248	662	15,555	6,185	4,618
500,000	384	9,423	663	16,055	12,369	9,235
2,500,000	384	9,423	663	16,478	59,216	46,171

Target population and sample size. Adapted from Orban, H. R. (2021). A Novel Risk-Based Sampling Calculator. https://www.researchgate.net/figure/Sample-Sizes-as-per-a-Sample-Size-Table-and-the-Developed-Risk-Based-Sample-Size Formula_tbl1_351121672

3.4 Research Instruments

3.4.1. Questionnaire Design

Respondent data for this research is gathered using a questionnaire. The questionnaires in this research consist of 2 sections. There are two parts in section A, which first comprises basic questions to evaluate the targeted respondents about the intention of adopting Wealth Tech. In the first part, the questionnaire is dichotomous. The questions provide two options to the respondent, yes or no, which is to divide the respondent in two proportions of Wealth Tech users and non-Wealth Tech users. It is to enhance our research robustness by targeting the respondents who are current or potential to learn about their behavioural characteristic which is consistent with the research. Accordingly, the second part of section A is to collect demographic information about the respondents such as gender, age, educational level, race, occupation and income level. The questions in part B were measured by nominal scale, ordinal scale and ratio. The demographic data serves as the mediator to control the independent variables adopted in our research, ensuring that our findings are more accurate and reliable. After that, the second section of the questionnaire consists of the independent variables that influence the intention of Wealth Tech adoption. It consisted of PE, EE, SI, FC, TR, BI. This part aimed to gain insights about the level of respondents' intention to adopt Wealth Tech. The option is presented for respondents to answer the questions on the scale of a given. A five-point Likert scale ranging from 1, strongly disagree to 5, strongly agree to measure the items that represent each question for the proposed research model.

3.4.2 Pre-test

The validity of the instrument is enhanced by pre-testing, which evaluates how well questions measure the intended constructs (DuBay & Watson, 2019). Prior to the questionnaire distribution, all the questions are promptly reviewed by one of the lecturers of Universiti Tunku Abdul Rahman.

3.4.3 Pilot Test

Pilot test is to verify the validity and practicality of the research tools, research flow and entire research structure. It is crucial to assure smooth research progress by discovering any potential problem and improving survey design and instrument before running full-scale research (Teijlingen & Hundley, 2002). The purpose involves verifying the clarity of questionnaires while ensuring their ability to obtain necessary data. The pilot test allows us to detect any ambiguities or errors in the questions and make necessary adjustments. The preliminary test also reflects whether respondents encounter any difficulties in providing their answers.

It designed to gather data on the determinants of Wealth Tech adoption in Malaysia. A group of 30 respondents was selected to complete the questionnaire, and their feedback was collected and analyzed (Schroder et al., 2010). This process enabled us to refine the wording of questions, ensure logical flow, and confirm that the respondents understood the items as intended. The respondent must be within 18 to 79 years-old and are in Malaysia to fulfil the condition of the research. The dataset collected was imported to the analysis software and captured the output to ensure feasibility of questionnaire for each construct. Modifying questionnaires is needed to ensure optimal results can be obtained after deployment of full-scale research.

Table 3.2:

Pilot Test Cronbach's Alpha Result

Variables	*Coefficient of Cronbach's Alpha*	*Reliability Level*
PE	0.828	Good
EE	0.807	Good

SI	0.850	Good
FC	0.704	Acceptable
TR	0.695	Questionable
BI	0.906	Good

Note. Developed by the author.

Based on the results above, Cronbach's Alpha values for all dependent and independent variables are greater than 0.69, which indicates a strong internal consistency of reliability. Particularly, the dependent variable of BI has the highest value of 0.906. Whereas the TR has the lowest value of 0.695 among all. Given the exploratory nature of this research, a value of 0.695 is still considered sufficient for analysis (Taber, 2018).

3.5 Construct Measurement

3.5.1 Scale of Measurement

It displays the many scales that were employed to collect questionnaire responses. It uses interval, ordinal, and nominal scales to assess the research's constructs.

3.5.1.1 Nominal Scale

The nominal scale is to classify objects into groups and does not involve any number (Frost, 2022). In section A, the scale is attributed to gender. race, employment status, state.

3.5.1.2 Ordinal Scale

The ordinal scale is adopted for collecting categorical data that can be classified and ranked. It is to measure the variables in natural order (Frost, 2022). The scale includes age, education level, net income level in Section A.

3.5.1.3 Interval Scale

The interval scales measure quantitative data between values. The values are in a meaningful order and each value will derive a different degree of the attribute (Frost, 2022). Similarly to the research from Jisham et al. (2024), five Likert scales were suggested. The scale is ranging from 1 - 5, respectively strongly disagree to strongly agree were adopted for measuring each of the constructs in Section B.

3.5.2 Origin of Construct

Table 3.3:
Origin of Construct for Questionnaire Design

Variables	*Items*	*Adapted from*	*Scale*

Independent variable 1: Performance Expectancy	3	Venkatesh et al. (2012)	Strongly Disagree (1) to Strongly Agree (5)
	3	Lu et al. (2019)	
Independent variable 2: Effort Expectancy	4	Venkatesh et al. (2012)	Strongly Disagree (1) to Strongly Agree (5)
Independent variable 3: Social Influence	4	Lu et al. (2019)	Strongly Disagree (1) to Strongly Agree (5)
	1	Venkatesh et al. (2012)	
Independent variable 4: Facilitating Conditions	3	Lu et al. (2019)	Strongly Disagree (1) to Strongly Agree (5)
	3	Venkatesh et al. (2012)	
Independent variable 5: Technology Readiness	6	Parasuraman and Colby (2015), Parasuraman (2000)	Strongly Disagree (1) to Strongly Agree (5)
Dependent variable: Behavioural Intentions to Adopt Wealth Tech	2	Belanche et al. (2019)	Strongly Disagree (1) to Strongly Agree (5)
	2	Venkatesh et al. (2012)	

Note. Developed by the author.

3.6 Data Processing

3.6.1 Data Checking

Firstly, validating questionnaire data and removing invalid entries of obtained information to guarantee accuracy. When there are missing or inconsistent responses, data will be considered invalid if incomplete or illogical. Data from online surveys should be summarised and recorded in an appropriate format for easy organisation.

3.6.2 Data Editing

The primary goal of data editing is to establish both consistency and accuracy as well as complete all necessary data before moving to analytical stages. This phase includes the examination, adjustment, and verification of the data. The data was removed which was excessively incomplete to the total available data. The necessary transformations were implemented on variables to achieve variable standardization.

3.6.3 Data Coding

This phase for computer analysis involves assigning numbers for different variable groups. Therefore, the responses to all questions in Section A are coded as follows:

Table 3.4:
Data Coding for Questionnaire Responses

Part A		
Q1	Have you ever used any Wealth Tech platforms?	"Yes" = 1 "No" = 2
Q2	Which Wealth Tech services are you using?	"Not Applicable" = 0 "Online Brokerages" = 1 "Robo-advisors" = 2 "Mobile Trading App" = 3 "Peer-to-Peer Lending" = 4 "Blockchain" = 5 "Others" = 6
Q3	Are you interested in using Wealth Tech platforms?	"Yes" = 1 "No" = 2
Part B		
Q1	Gender	"Male" = 1 "Female" = 2
Q2	Age	"Generation Z (18-27 years old)" = 1 "Millennials (28-43 years old)" = 2 "Generation X (44-59 years old)" = 3 "Baby Boomers (60-79 years old)" = 4
Q3	Highest educational level	"SPM/O-Level" = 1 "STPM/A-Level" = 2 "Diploma" = 3 "Bachelor's Degree" = 4 "Master's Degree" = 5 "Doctorate's Degree" =6 "Others" = 7

Q4	Race	"Chinese" = 1 "Malay" = 2 "Indian" = 3 "Others" = 4
Q5	Employment status	"Student" = 1 "Government" = 2 "Private" = 3 "Self-employed" = 4 "Unemployed" = 5 "Retired" = 6
Q6	Net income level (Monthly)	"Below RM2,500" = 1 "RM2,501-RM5,000" = 2 "RM5,001-RM7,500" = 3 "RM7,501-RM10,000" = 4 "RM10,001 and above" = 5
Q7	State	"Johor" = 1 "Kedah" = 2 "Kelantan" = 3 "Kuala Lumpur" = 4 "Melaka" = 5 "Negeri Sembilan" = 6 "Perlis" = 7 "Pahang" = 8 "Perak" = 9 "Pulau Pinang" = 10 "Sabah" = 11 "Sarawak" = 12 "Selangor" =13

	"Terengganu" = 14

Note. Developed by the author.

Furthermore, the responses to every question in Section B will be coded using the ranging from 1 to 5, respectively strongly disagree to strongly agree.

3.7 Proposed Data Analysis Tool

Using the data gathered, perform the tests outlined in Part 3.5. Statistical Package for Social Sciences (SPSS) 30.0 was adopted to obtain the results of the following tests: descriptive analysis, internal reliability test, multicollinearity analysis, multiple linear regression and discriminant validity analysis.

3.7.1 Descriptive Analysis

A descriptive analysis of these aspects is presented in this review, with an emphasis on the population's characteristics and how they interact with Wealth Tech solutions. Numerical metrics are used to condense the data. Measures of variability and central tendency such as standard deviation and mean are common descriptive statistics (Manikandan, 2011). These statistics aid in describing the variability within the dataset as well as the overall trends of the data.

3.7.2 Scale Measurement

3.7.2.1 Internal Consistency Reliability (Cronbach Alpha)

Testing for reliability is an essential part of verifying the measurement tools used in research to make sure they reliably yield precise and consistent data. Reliability testing is useful in confirming the validity and consistency of survey instruments or scales used to measure several constructs, including TR, PE, EE, SI, and FC, in the context of researching the factors influencing Wealth Tech adoption in Malaysia.

Cronbach's alpha measures the internal consistency or reliability of a scale or test item. It is commonly used to assess the validity of a survey or questionnaire intended to gauge a particular concept. The values of Cronbach's alpha, which range from 0 to 1. According to Tavakol and Dennick (2011), a good reliability value is generally considered between 0.70 to 1.00, indicating that the items consistently reflect the underlying construct. A value between 0.6 and 0.7 may be deemed acceptable level in the research, while the purpose is to generate hypotheses rather than confirm statements. Values below 0.6 suggest poor internal consistency, showing a low alpha could signify that the items are not well correlated and may need to be revised. The summary of Cronbach’s Alpha is present as follows:

No	*Coefficient of Cronbach's Alpha*	*Reliability Level*
1	More than 0.90	Excellent
2	0.80 – 0.89	Good
3	0.70 – 0.79	Acceptable
4	0.60 – 0.69	Questionable
5	0.50 – 0.59	Poor
6	Less than 0.59	Unacceptable

Figure 3.1. Coefficient Range of Cronbach. Adapted from Arof, K. Z. M., Ismail, S., & Saleh, A. L. (2018). Contractor's performance appraisal system in the malaysian construction industry: Current practice, perception and understanding. *International Journal of Engineering & Technology*, *7*(3.9), 46–51. https://doi.org/10.14419/ijet.v7i3.9.15272

3.7.3 Preliminary Data Screening

Preliminary Data Screening is the process of verifying the data gathered for errors, discrepancies, and value gaps prior to statistical analysis. It guarantees that the data is clean, dependable, and ready for future research (Lawan, 2011).

3.7.3.1 Multicollinearity Analysis

Multicollinearity is a statistical approach for determining the direction and magnitude of a linear relationship between a pair of continuous variables. The Variance Inflation Factor (VIF) is employed to determine the collinearity statistics between the constructs. A VIF value of 1 shows no connections between the independent variables. Moderate correlation of independent variables will indicate VIF value between 1 to 5. However, 5 to 10 VIF value indicates there is a strong correlation between variables, which distort the estimated coefficient and the individual effect of each construct. Subsequently, tolerance value is employed with a value of bigger than 0.2 indicating low multicollinearity between each of the constructs (Poga & Kyriazos, 2023).

3.7.4 Inferential Analysis

Inferential analysis is a quantitative technique used to derive information about a population from a sample to estimate, validate, and find relationships between research variables (GeeksforGeeks, 2024). When examining the factors that influence the adoption of Wealth Tech services in Malaysia, inferential analysis is a useful tool for comprehending the various ways in which users' decisions are influenced. It allows us to conclude how a hypothesis will turn out or to calculate a general parameter about a larger number of samples. It examines the connections between different factors and the uptake of Wealth Tech services and tests particular theories regarding the effects of these factors on Wealth Tech adoption to establish broad generalizations about a larger population (Corbo, 2022).

3.7.4.1 Multiple Linear Regression

Multiple regression analysis is a statistical technique used to examine the relationship between one dependent variable and two or more independent variables. It enables comprehension of the combined impact of several predictors on the result variable such as R-square value to present the reliability of multiple factors. This approach assesses how various factors interact and contribute to the dependent variable, which is especially helpful when the dependent variable is influenced by several factors (Cohen et al., 2013). The purpose is to better understand the key elements influencing Wealth Tech adoption by controlling for the effects of one variable while evaluating the impact of another by using several predictors.

$$BI_i=\beta_0+\beta_1(PE_i)+\beta_2(EE_i)+\beta_3(SI_i)+\beta_4(FC_i)+\varepsilon_i \text{ (Equation 3.1)}$$

$$PE_i=\beta_0+ \beta_1(TR_i)+ \varepsilon_i \text{ (Equation 3.2)}$$

$$EE_i=\beta_0+ \beta_1(TR_i)+ \varepsilon_i \text{ (Equation 3.3)}$$

Where:

BI_i = Behavioural Intention

β_0 = Y-Intercept

PE_i = Performance Expectancy

EE_i = Effort Expectancy

SI_i = Social Influence

FC_i = Facilitating Condition

TRi = Technology Readiness

ε_i = Error term

3.7.4.2 Discriminant Validity Analysis

Discriminant validity measures of dimensions that theoretically shouldn't be significantly related to one another are not shown to be highly associated (Hubley, 2014). By proving discriminant validity, a construct's uniqueness inside a model is highlighted and it is guaranteed to capture occurrences that other measures do not. Fornell-Larcker Criterion is used in the research to compare the Average Variance Extracted (AVE) of each construct to the squared correlations between construct and others. To conduct AVE, the Principal Axis Factor Matrix result is generated by SPSS. Specifically, the square root of a construct's AVE should be greater than its highest correlation with any other construct. This indicates that the construct shares more variance with its own indicators than with those of other constructs (Cheung et al., 2023).

$$AVE = \frac{\sum_{i=1}^{k} \lambda_i^2}{k}$$

Where:

λ_i = standardized factor loading of i

k = number of items in the construct

3.8 Conclusion

Finally, the last section of this research outlines the process of conducting quantitative research. Before the actual examination, preliminary and pilot tests were conducted. During the testing process, 384 respondents will be given a survey to gather initial data.

The data will be analysed using both descriptive and inferential approaches. The proposed methodology will provide fundamentals for analysis. Data analysis and interpretation outcomes are included in the following chapter.

CHAPTER 4 DATA ANALYSIS & FINDINGS

4.0 Introduction

This chapter focuses on data analysis. The analysis and interpretation of the findings are based on responses from 384 participants in Malaysia. The process begins with descriptive analysis, which organizes raw data into meaningful information. This is followed by inferential analysis, where statistical results are generated using the Statistical Package for Social Sciences (SPSS) 30.0 software to better understand the connection between the independent and dependent variables.

4.1 Descriptive Analysis

Descriptive analysis serves as an organised summary of data by outlining the variables' relationship in the sample (Kaur et al., 2018). In this analysis, there are two sections that have been collected. The first section comprises basic questions to evaluate the targeted respondents about the intention of adopting Wealth Tech and the type of services they adopted. Furthermore, it consists of the respondents' demographic data, including genders, age groups, races, states, education levels, net income levels, as well as occupations.

4.1.1 Current / Non-Current User

Table 4.1:

Current / Non-Current User's Descriptive Analysis

Type of Users	Frequency	Cumulative Frequency	Percentage (%)	Cumulative Percentage (%)
Current User	338	338	88.02	88.02
Non-current User	46	384	11.98	100.00

Note. Developed by the author.

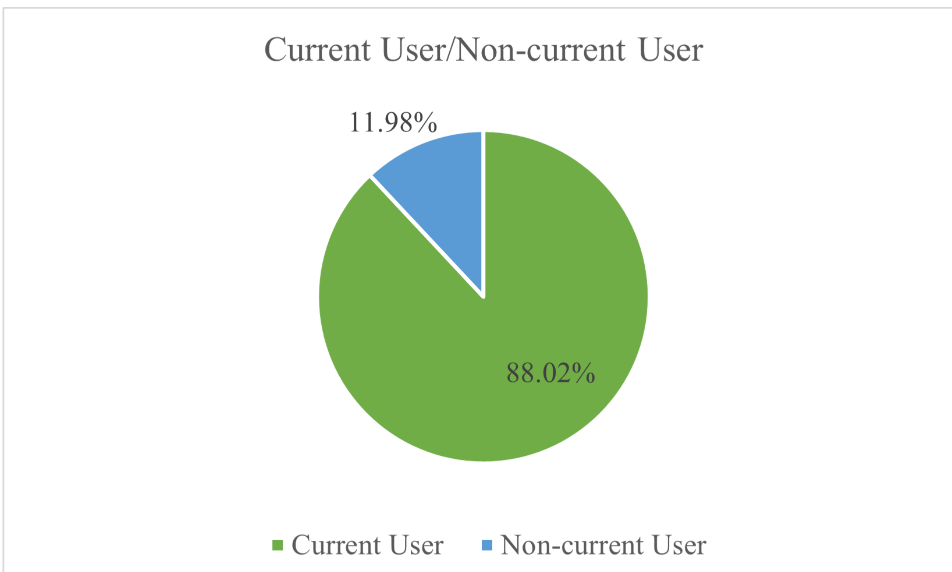


Figure 4.1. Current / Non-Current User's Descriptive Analysis. Note. Developed by the author.

In this survey, 88.02% of the total respondents, which were 338 respondents, responded that they are current users of Wealth Tech. In contrast, only 46 respondents are non-current users, 11.98%. Therefore, current users are more than non-current users in this survey.

4.1.2 Wealth Tech Services

Table 4.2:

Wealth Tech Services' Descriptive Analysis

Services	*Frequency*	*Cumulative Frequency*	*Percentage (%)*	*Cumulative Frequency (%)*
Not Applicable	46	46	11.98	11.98
Online Brokerages	49	95	12.76	24.74
Robo-advisors	52	147	13.54	38.28
Mobile Trading App	155	302	40.36	78.65
Peer-to-Peer Lending	42	344	10.94	89.58
Blockchain	32	376	8.33	97.92
Others	8	384	2.08	100.00

Note. Developed by the author.

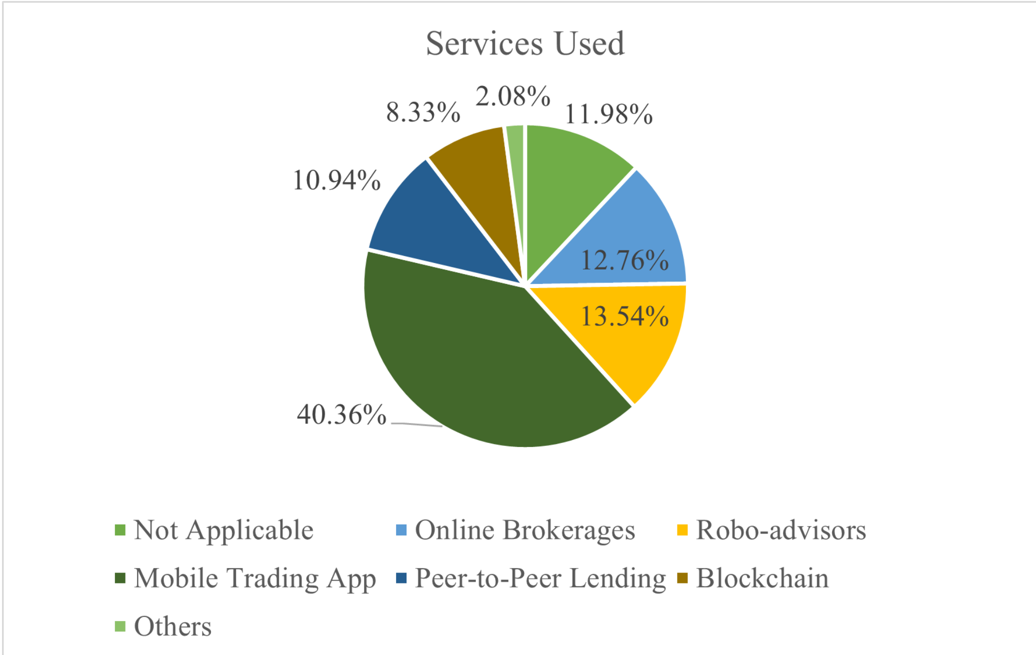


Figure 4.2. Wealth Tech Services' Descriptive Analysis. Note. Developed by the author.

According to the results, robo-advisors are the second most popular service (13.54%), while nearly half of the respondents (40.36%) utilise mobile trading apps. Additionally, 10.94% of respondents use peer-to-peer lending services, whereas 12.76% of all respondents use online broking services. The blockchain service is being used by 32 users.

4.1.3 Interest in Using Wealth Tech

Table 4.3:

Interest of Respondents' Descriptive Analysis

Interest of Respondent	*Frequency*	*Cumulative Frequency*	*Percentage (%)*	*Cumulative Percentage (%)*

toward Wealth Tech				
Yes	384	384	100.00	100.00
No	0	384	0.00	100.00

Note. Developed by the author.

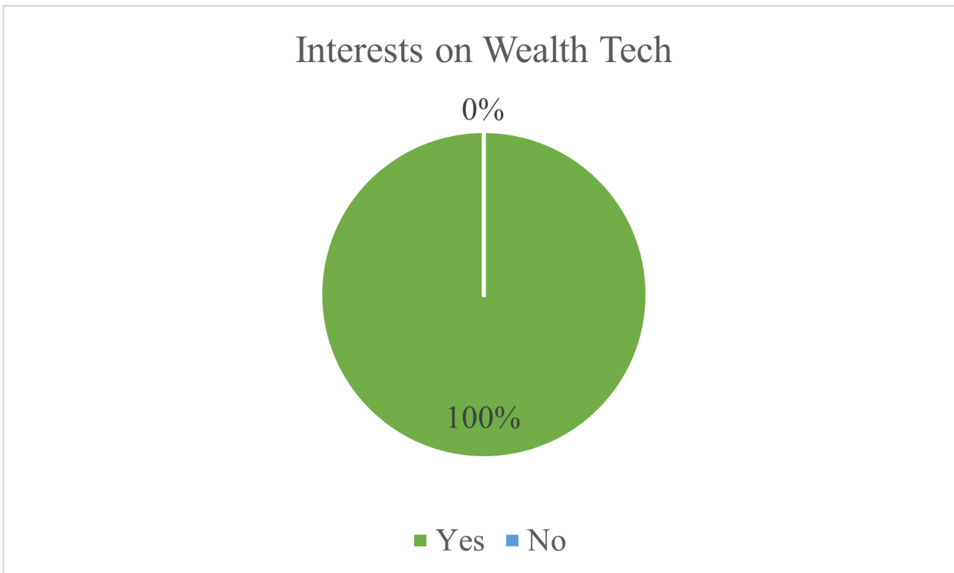


Figure 4.3. Interest of Respondents' Descriptive Analysis. Note. Developed by the author.

Every respondent to this research answered that they would be interested in using Wealth Tech platforms or services. This result suggests that there may be a significant market for online financial services. Additionally, this aids in a better understanding of the variables influencing Wealth Tech adoption.

4.1.4 Gender

Table 4.4:

Gender's Descriptive Analysis

Gender	*Frequency*	*Cumulative Frequency*	*Percentage (%)*	*Cumulative Percentage (%)*
Male	200	200	52.08	52.08
Female	184	384	47.92	100.00

Note. Developed by the author.

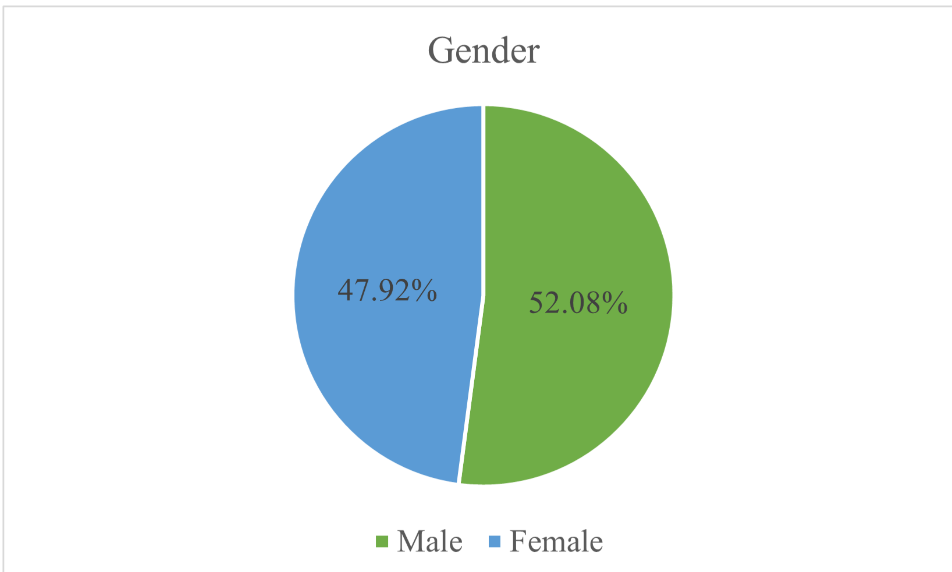


Figure 4.4. Gender's Descriptive Analysis. Note. Developed by the author.

The total number of responders was categorised by gender. Referring to the chart (Figure 4.4), 52.08% of responders were male and 47.92% were female. As a result, there are more male than females who responded to this survey.

4.1.5 Age Group

Table 4.5:

Age's Descriptive Analysis

Age	*Frequency*	*Cumulative frequency*	*Percentage (%)*	*Cumulative percentage (%)*
Generation Z (18-27 years old)	208	208	54.17	54.17
Millennials (28-43 years old)	109	317	28.39	82.56
Generation X (44-59 years old)	15	332	3.91	86.47
Baby Boomers (60-79 years old)	52	384	13.54	100.00

Note. Developed by the author.

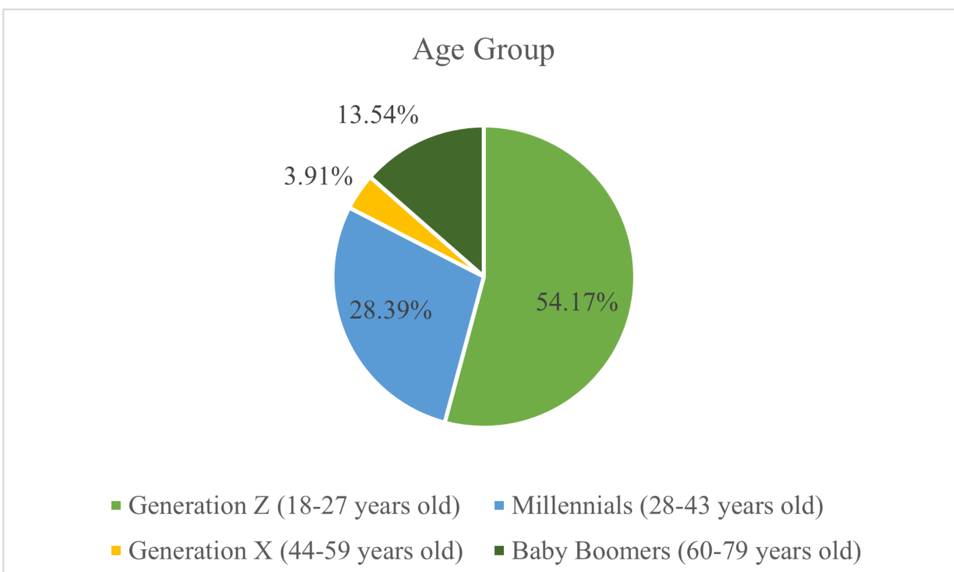


Figure 4.5. Age's Descriptive Analysis. Note. Developed by the author.

The four age groups are Baby Boomers (60 – 79 years old), Millennials (28 – 43 years old), Generation X (44 – 59 years old), and Generation Z (18 – 27 years old). Millennials were the second-largest age group (28.39%), while Generation Z made up the largest proportion of responders (54.17%). Additionally, out of the four age groups, the fewest number of respondents (3.91%) were classified as members of Generation X. Lastly, 52 Baby Boomers responded to the survey.

4.1.6 State

Table 4.6:

State's Descriptive Analysis

Location	*Frequency*	*Cumulative Frequency*	*Percentage (%)*	*Cumulative Percentage (%)*
Johor	24	24	6.25	6.25
Kedah	16	40	4.17	10.42
Kelantan	7	47	1.82	12.24
Kuala Lumpur	109	156	28.39	40.63
Melaka	15	171	3.91	44.54
Negeri Sembilan	11	182	2.86	47.40
Perlis	2	184	0.52	47.92
Pahang	31	215	8.07	55.99
Perak	38	253	9.90	65.89
Pulau Pinang	40	293	10.42	76.31
Sabah	18	311	4.69	81.00

Sarawak	1	312	0.26	81.26
Selangor	64	376	16.67	97.93
Terengganu	8	384	2.08	100.00

Note. Developed by the author.

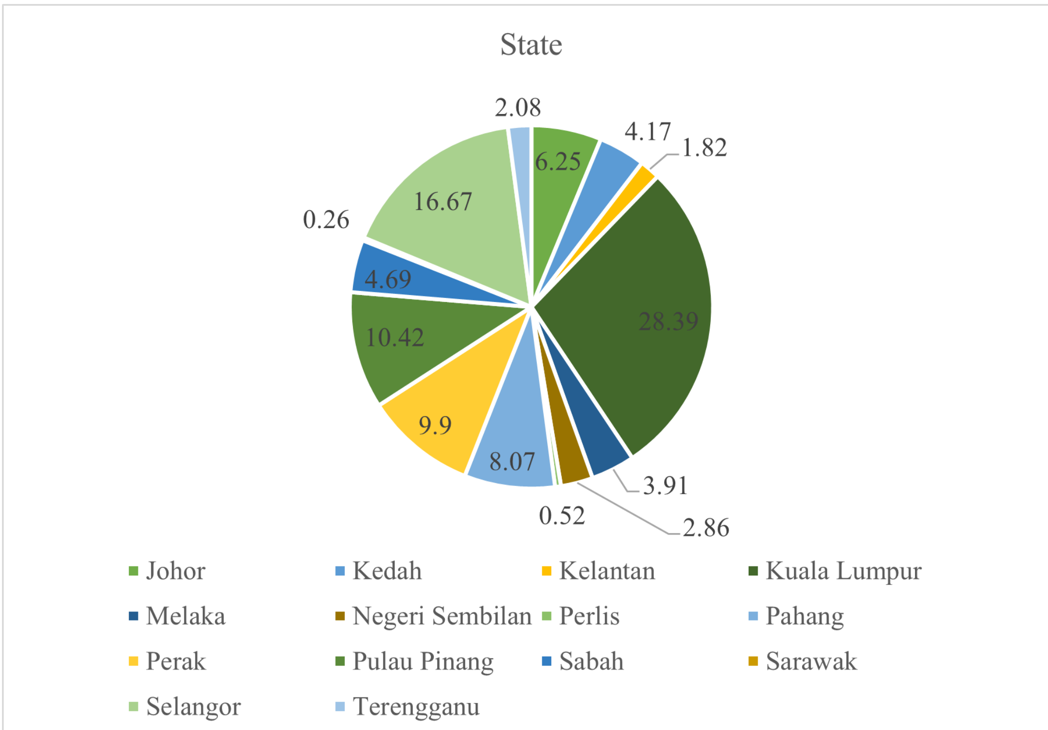


Figure 4.6. State's Descriptive Analysis. Note. Developed by the author.

The survey responses were collected from 13 states across Malaysia and 1 Federal Territory. The highest and second-largest percentages of responses were from Kuala Lumpur (28.39%) and Selangor (16.67%). Additionally, there were nearly similar numbers of respondents from Perak and Pulau Pinang, with 40 and 38 respondents, respectively. 6.25% of respondents were from Johor, and 8.07% of participants were from Pahang. Participants in Kedah and Melaka were 16 and 15, respectively. Furthermore, only 2.86% of those surveyed now reside in Negeri Sembilan. Terengganu (2.08%), Kelantan (1.82%), and Perlis (0.52%) were the three states with fewer than ten answers. Regarding East Malaysia, Sabah and Sarawak accounted for 18 and 1 of the responses, respectively.

4.1.7 Race

Table 4.7:

Race's Descriptive Analysis

Race	*Frequency*	*Cumulative Frequency*	*Percentage (%)*	*Cumulative Percentage (%)*
Chinese	250	250	65.10	65.10
Malay	87	337	22.66	87.76
Indian	43	380	11.20	98.96
Other	4	384	1.04	100.00

Note. Developed by the author.

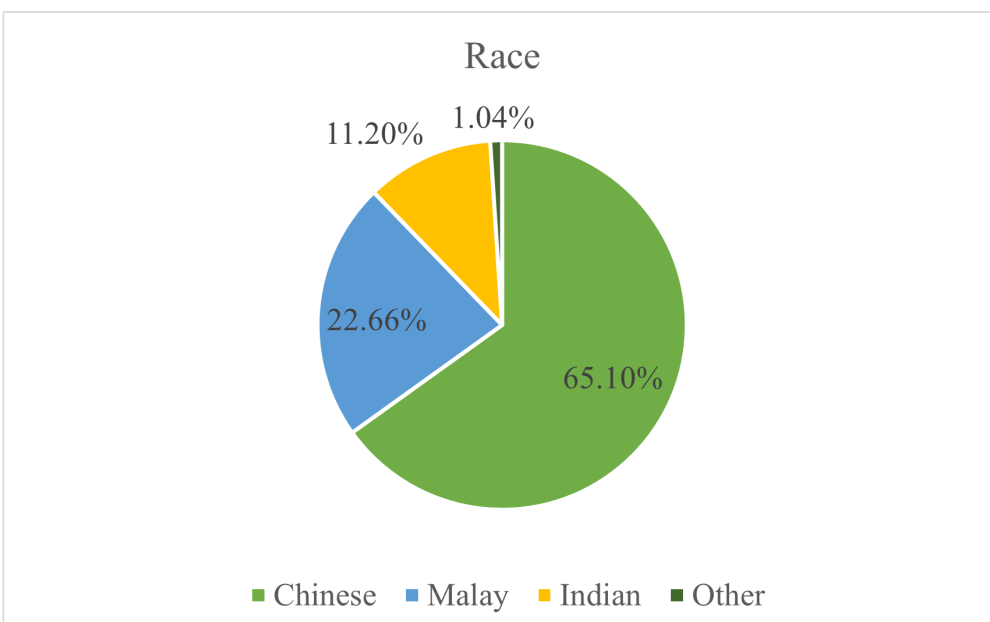


Figure 4.7. Race's Descriptive Analysis. Note. Developed by the author.

Table 4.7 indicated that the respondents were categorised into three primary racial groups: Chinese, Malay, and Indian. Chinese respondents accounted for 65.10% of the total, meaning they comprised over half of the 384 respondents. In addition, 43 Indians and 87 Malay people have answered the survey. Additionally, 4 respondents, or 1.04% of the total, did not fit into any of the three major racial categories.

4.1.8 Highest Educational Level

Table 4.8:

Highest Educational Level's Descriptive Analysis

Level	*Frequency*	*Cumulative Frequency*	*Percentage (%)*	*Cumulative Percentage (%)*
SPM/O-Level	50	50	13.02	13.02
STPM/A-Level	17	67	4.43	17.45
Diploma	29	96	7.55	25.00
Bachelor's Degree	268	364	69.79	94.79
Master's Degree	14	378	3.65	98.44
Doctorate's Degree	6	384	1.56	100.00
Other	0	384	0.00	100.00

Note. Developed by the author.

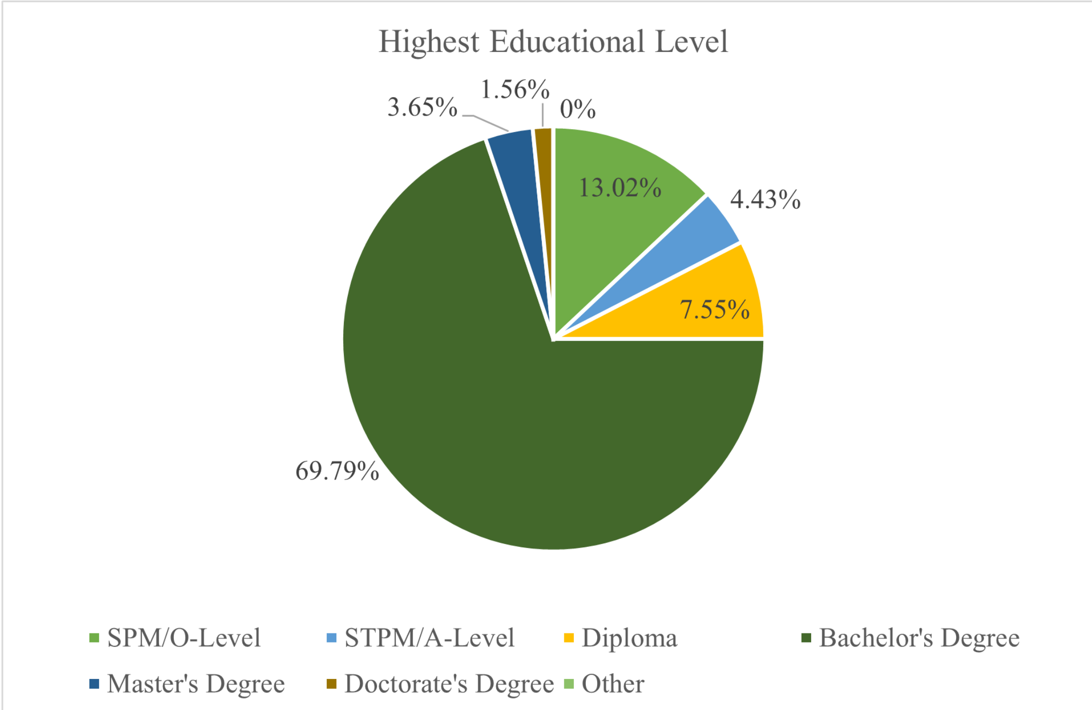


Figure 4.8. Highest Educational Level’s Descriptive Analysis. Note. Developed by the author.

The highest educational level of respondents was displayed in the above table and figure, ranging from SPM or O-Level to a doctorate. 69.79% of the total respondents had a bachelor's degree, making up the majority. Additionally, 29 respondents were from Diploma, and 50 respondents were from SPM or O-Level. The percentages of people who responded with an A-Level or STPM were nearly equal to those with a master's degree, at 14 and 17, respectively. Just 1.56% of respondents said they had a doctorate as their highest level of education.

4.1.9 Net Income Level

Table 4.9:

Net Income Level’s Descriptive Analysis

Level	*Frequency*	*Cumulative Frequency*	*Percentage (%)*	*Cumulative Percentage (%)*
Below RM2,500	127	127	33.07	33.07
RM2,501-RM5,000	110	237	28.65	61.72
RM5,001-RM7,500	77	314	20.05	81.77
RM7,501-RM10,000	52	366	13.54	95.31
RM10,001 and above	18	384	4.69	100.00

Note. Developed by the author.

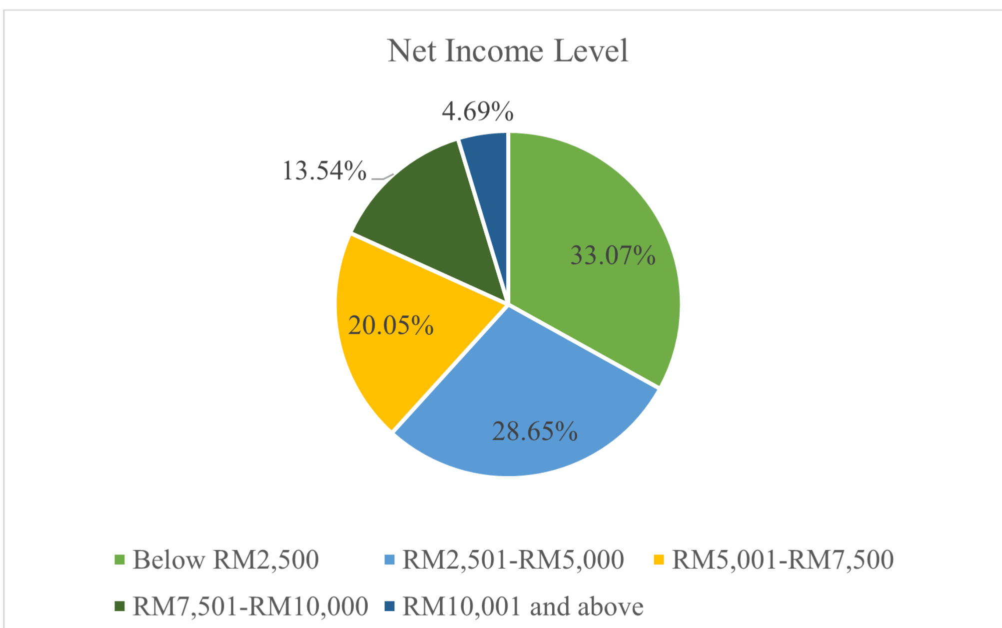


Figure 4.9. Net Income Level's Descriptive Analysis. Note. Developed by the author.

Results show that 33.07% of respondents earn less than RM2,500 per month and these respondents are outnumbered only by those earning between RM2,501 and RM5,000 as 28.65%. The analyzed group consists of two income bands which represent 61.72% of all participants since their total income does not exceed RM5,000 per month. The surveyed group contains 20.05% of respondents who make between RM5,001 and RM7,500 per month as well as 13.54% who currently earn between RM7,501 and RM10,000. A small percentage, 4.69% in the surveyed group earns income beyond RM10,000 per month thus demonstrating that high-income earners are a minority in this population. The analysis confirms these observations since 81.77% of respondents earn below RM7,500 while 95.31% earn below RM10,000. The gathered data reveals that most respondents belong to income groups ranging from lower to middle segments.

4.1.10 Employment Status

Table 4.10:

Employment Status' Descriptive Analysis

Status	*Frequency*	*Cumulative Frequency*	*Percentage (%)*	*Cumulative Percentage (%)*
Student	116	116	30.21	30.21
Government	32	148	8.33	38.54
Private	210	358	54.69	93.23
Self-employed	23	381	5.99	99.22
Unemployed	2	383	0.52	99.74

Retired	1	384	0.26	100.00

Note. Developed by the author.

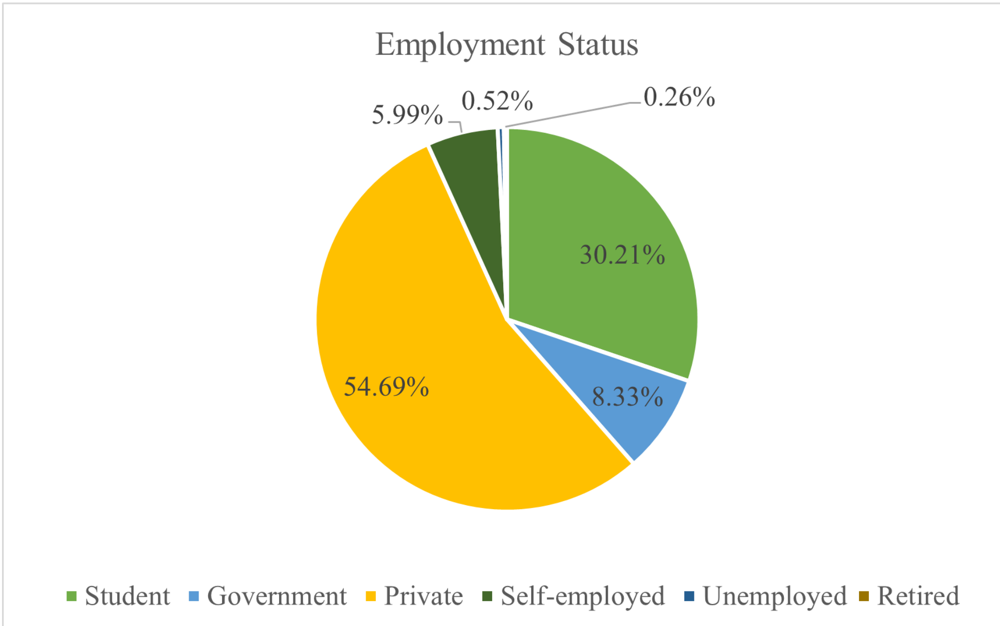


Figure 4.10. Employment Status' Descriptive Analysis. Note. Developed by the author.

Based on survey results, private sector employees comprise the largest labor group with their number totaling 54.69%. A significant number of 30.21% of respondents have identified themselves as students, thus representing the student population entering the workforce. The workers in government positions amount to 8.33% of survey participants. Among the respondents self-employed individuals account for 5.99% showing their presence as a substantial separate group running their own businesses. The survey revealed extremely low numbers of unemployed respondents of 0.52% and retired participants of 0.26% since virtually every participant-maintained employment or academic involvement. As self-employed individuals are added to the analysis the total number of working people or students reaches 99.22% of the sample group. The survey participants mainly work in private enterprises or research at educational institutions while government employment exceeds self-employment plus unemployment and retirement.

4.1.11 Central Tendencies of Independent Variables

The central tendencies evaluation for Wealth Tech adoption constructs allows researchers to examine user's consideration about adoption. The analysis of BI, PE, EE, SI, FC and TR delivers vital understanding regarding how people perceive Wealth Tech. Mean and standard deviation values retrieved from gathered data patterns demonstrate both user response stability and distribution patterns to show where users strongly agree, and which areas need attention.

4.1.11.1 Central Tendencies Measurement of BI

Table 4.11:

Mean and Standard Deviation Measurement of BI

Code	*Question*	*Mean*	*Standard Deviation*	*Mean Ranking*
BI1	I intend to use Wealth Tech for managing investment.	0.686	0.580	4
BI2	I intend to use Wealth Tech rather than any traditional financial advisor.	1.000	0.736	1
BI3	I intend to continue using Wealth Tech for my financial needs in the future.	0.736	1.000	2

BI4	I am motivated to explore and adopt new Wealth Tech.	0.661	0.699	3

Note. Developed by the author.

Participants exhibited moderate to high adoption prospects for Wealth Tech judging by their BI scores between 0.661 and 1.000. The BI2 stands as the most preferred choice among users based on their 1.000 mean score. Recent trends in financial advisory demonstrate that digital services have started replacing traditional advisory roles because they provide users with automatic and convenient solutions (Mohamad et al., 2024). BI1 has the lowest mean of 0.661 and standard deviation of 0.699. This recognizes Wealth Tech advantages exist but individual willingness to use new platforms lacks full motivation. User responses indicate hesitation to fully accept Wealth Tech as a whole. User diversity in trust levels and financial knowledge and perceptive risks would affect differences in motivation when adopting Wealth Tech.

4.1.11.2 Central Tendencies Measurement of PE

Table 4.12:

Mean and Standard Deviation Measurement of PE

Code	*Question*	*Mean*	*Standard Deviation*	*Mean Ranking*
PE1	I expect that Wealth Tech will make my financial tasks easier and more efficient.	4.04	0.880	3

PE2	I expect that Wealth Tech will help me save time and effort when managing my finances.	4.09	1.048	2
PE3	I expect that Wealth Tech will offer a higher level of convenience compared to traditional financial methods.	4.18	0.907	1
PE4	I expect Wealth Tech is more accurate in financial analysis and information.	4.01	1.101	5
PE5	I expect Wealth Tech writes and follows the investment strategy and provides more consistent service in wealth management.	3.96	1.034	6
PE6	I expect information provided by Wealth Tech is more consistent.	4.02	0.883	4

Note. Developed by the author.

PE3 about expecting Wealth Tech to provide better convenience than standard financial systems present the highest mean at 4.18 with minimal standard deviation of 0.907. Users see Wealth Tech as a tool which provides efficient and convenient financial solutions, so they strongly associate it with these benefits (Mohamad et al., 2024). Consumer evaluation of PE5 stands at 3.96 while its standard deviation reaches 1.034. Users demonstrate cautiousness toward automated investment strategies because they lack assurance about their constant performance and reliable results. Research has shown digital wealth management tools are efficient, yet customers have doubts about automated investment possibilities (Senteio & Hughes, 2024).

4.1.11.3 Central Tendencies Measurement of EE

Table 4.13:

Mean and Standard Deviation Measurement of EE

Code	*Question*	*Mean*	*Standard Deviation*	*Mean Ranking*
EE1	I expect that I can quickly learn how to use Wealth Tech.	3.98	0.959	2
EE2	I believe that Wealth Tech platforms are user-friendly.	4.05	1.073	1
EE3	I believe that using Wealth Tech will not require a significant amount of time to get things done.	3.89	1.078	4
EE4	I expect that I will not need extensive training or assistance to use Wealth Tech effectively.	3.95	1.000	3

Note. Developed by the author.

Participants achieved the most agreement with the statement of EE2 as indicated by the mean of 4.05. The standard deviation of 1.073 indicates that while most users find the platforms “easy to use” there is some variability. The lowest mean score of 3.89 along with highest standard deviation of 1.078 was detected in EE3. Users acknowledge the benefits of Wealth Tech although some individuals still experience challenges when using digital platforms according to this research. The research literature supports digital technology adoption measurements through quality education efforts and users' familiarity with digital platforms (Horowitz et al., 2023). The successful adoption of

Wealth Tech solutions depends on financial literacy suggesting comprehensive user guidance as well as onboarding help to assist digital wealth management adoption.

4.1.11.4 Central Tendencies Measurement of SI

Table 4.14:
Mean and Standard Deviation Measurement of SI

Code	*Question*	*Mean*	*Standard Deviation*	*Mean Ranking*
SI1	People who influence my behaviour would want me to utilise Wealth Tech.	3.72	0.987	3
SI2	People in my social networks who would utilise Wealth Tech will have a high profile.	3.68	1.144	4
SI3	Significant proportion of my coworkers would want me to utilise Wealth Tech.	3.66	0.981	5
SI4	People whose opinions I value prefer that I use Wealth Tech.	3.76	1.146	2
SI5	People who provide positive feedback and reviews motivate me to use Wealth Tech.	3.97	0.973	1

Note. Developed by the author.

Overall, mean scores range from 3.66 to 3.97, indicating that the respondents are either neutral or agree with this independent variable SI. The highest mean is 3.97 for SI5. This finding suggests that respondents would most like to be encouraged to utilise Wealth Tech by those who offer favourable comments and evaluations. An individual internalises a referent's belief when they incorporate it into their own cognitive belief framework through value matching (Graf-Vlachy et al., 2018). Furthermore, SI5 has a standard deviation of 0.973. This result indicates that there is moderate variability or dispersion around the mean, even though the mean rating is relatively high. Conversely, SI3 has the lowest mean of 3.66. As a result, even if respondents recognised the value of SI, they could be less inclined to use Wealth Tech due to the impact of their colleagues.

4.1.11.5 Central Tendencies Measurement of FC

Table 4.15:

Mean and Standard Deviation Measurement of FC

Code	*Question*	*Mean*	*Standard Deviation*	*Mean Ranking*
FC1	It will be time consuming to learn how to adopt Wealth Tech.	3.22	1.374	6
FC2	Wealth Tech will be so difficult to understand and use.	3.30	1.439	5
FC3	Wealth Tech will be intimidating to me.	3.32	1.455	4

FC4	I have access to the required technology (e.g., internet, smartphone) for using Wealth Tech.	3.95	0.934	1
FC5	I have the knowledge necessary to use Wealth Tech.	3.89	1.114	2
FC6	There is sufficient customer support and assistance available when I encounter issues with Wealth Tech services.	3.86	0.918	3

Note. Developed by the author.

FC4 has the greatest mean of 3.95 among the questions in the facilitating condition, whereas FC1 has the lowest mean of 3.22. It shows that respondents agree more that they are able to access the necessary technologies to use Wealth Tech. The fact that 34.9 million people in Malaysia were internet users at the beginning of 2025, when online penetration was 97.7%, gives validity to this conclusion (Simon, 2025). On the contrary, people generally believe that adopting Wealth Tech does not require a substantial amount of time spent. Additionally, FC4 has the second lowest standard deviation, at 0.934. It indicates that there was a large consensus among participants because the responses were tightly grouped around the high mean.

4.1.11.6 Central Tendencies Measurement of TR

Table 4.16:

Mean and Standard Deviation Measurement of TR

Code	*Question*	*Mean*	*Standard Deviation*	*Mean Ranking*
TR1	I believe new technologies contribute to a better quality of life.	4.03	0.874	1
TR2	I am among the first in my circle of friends to acquire new technology when it appears.	3.72	1.248	4
TR3	I can usually figure out new high-tech products and services without help from others.	3.75	1.166	3
TR4	I prefer to use the most advanced technology available.	3.87	1.111	2
TR5	I do not feel confident doing any transaction through an online exclusive platform.	3.11	1.344	5
TR6	I do have safety concerns about providing my personal information over the Internet.	2.77	1.465	6

Note. Developed by the author.

Results show that the mean values of all TR range from 2.77 to 4.03. With a mean of 2.77 and standard deviation of 1.465, TR6 has the lowest mean and biggest standard deviation. With the lowest mean, it indicates that respondents disagree that giving personal information online raises safety issues. Since the internet has matured in recent years, sharing personal information is now safe and traceable. Nonetheless, the biggest standard deviation indicates that respondents are widely dispersed, which means some may feel unprepared, while others feel highly prepared. Additionally, TR1 has the lowest standard deviation which is 0.874 and the highest mean which is 4.03. Thus, most respondents strongly agreed that modern technologies improve people's quality of life. The lowest standard deviation score indicates that participants' opinions were strongly in agreement with one another. The idea of customisation has quickly progressed from being a preference to a need, particularly in the field of wealth management. The growing need for specialised financial strategies has accelerated this shift, highlighting the need of personalised portfolios for investors globally (Oi, 2023).

4.2 Scale Measurement

4.2.1 Internal Consistency Reliability

Table 4.17:

Analysis of Cronbach's Alpha Reliability

No.	*Variable Type*	*Construct*	*Number of Items*	*Cronbach's Alpha*	*Reliability Test*
1	DV	BI	4	0.888	Good
2	IV	PE	6	0.923	Excellent
3	IV	EE	4	0.880	Good
4	IV	SI	5	0.909	Excellent
5	IV	FC	6	0.797	Acceptable
6	IV	TR	6	0.756	Acceptable

Note. Developed by the author.

Cronbach's Alpha is adopted to assess internal consistency and dependability of constructs which appear in Table 4.17. Research findings show that measurement item consistency is ensured because all constructs demonstrate acceptable through excellent reliability levels. BI along with EE achieve good reliability according to Cronbach's Alpha values of 0.888 and 0.880. PE and SI demonstrate outstanding reliability based on their alpha scores which reach 0.923 and 0.909 thus indicating robust internal consistency between the variables.

Meanwhile, the alpha values of 0.797 and 0.756 for FC and TR respectively show acceptable dependability. The reliability values meet the accepted minimum threshold even though they are slightly below the values observed in other constructs. The research results demonstrate that the utilized measurement scales exhibit reliable properties sufficient for statistical analysis because every construct exceeds the 0.70 Cronbach's Alpha criterion.

4.3 Preliminary Data Screening

4.3.1 Multicollinearity Analysis (Variance Inflation Factor)

Table 4.18:

Analysis of Multicollinearity

Independent Variables	*Collinearity Statistics*	
	VIF	*Tolerance*

PE	3.659	0.273
EE	3.459	0.289
SI	2.789	0.359
FC	1.630	0.614
TR	1.000	1.000

Note. Developed by the author.

This research employed multicollinearity analysis to determine any high correlations between independent variables within the regression model. A standard analysis for detecting multicollinearity used Variance Inflation Factor (VIF) and Tolerance Value as indicators for this assessment. The analysis revealed that all VIF values rest beneath the usual threshold of 5 thereby establishing the independent variables show minimal multicollinearity problems. The analytics show PE with VIF value at 3.659 while EE showed 3.459 and SI had 2.789. The observed variable relationships are moderately connected but the values stay within the acceptable zone thereby sustaining the regression model's authenticity. The investigation revealed that FC generates minimal VIF values of 1.630 and TR of 1.000 since it is separated from the model.

The tolerance measures indicate no significant multicollinearity effects because they show the part of predictor variables that remains unexplained by other independent variables. The tolerance values (0.273) for PE along with (0.289) for EE and (0.359) for SI display moderate correlations yet all remain above the critical limit of 0.20 therefore no predictor variable depends significantly on the others. FC demonstrate an independent relationship since their tolerance values measure 0.614 and TR variable of 1.000 indicating no multicollinearity. This research demonstrates that multicollinearity does not impact the analysis therefore all independent variables should stay included in the regression model. The analysis maintains its statistical validity even though PE, EE, and SI show correlation because this correlation remains below levels that would affect the analysis's validity. The model does not require any additional modifications such as variable removal or complex statistical methodologies to handle multicollinearity.

4.4 Inferential Analysis

4.4.1 Multiple Linear Regression Analysis

Table 4.19:

Result of Multiple Linear Regression Analysis

	Unstandardised Coefficient Beta	*Coefficient Std. Error*	*Standardized Coefficient Beta*	*t-statistics*	*P-value*
(Constant)	0.334	0.120	-	2.772	0.006 ***
PE	0.432	0.052	0.422	8.209	<0.001 ***
EE	0.125	0.048	0.129	2.588	0.010 **
SI	0.250	0.042	0.264	5.880	<0.001 ***

FC	0.139	0.034	0.141	4.110	<0.001 ***
R-squared					0.726
Adjusted R-squared					0.723
F-test					251.097
P-value					<0.001
Durbin Watson					1.903

Note. Developed by the author.

Table 4.20:

Statistical Significance Level

*P<0.1	**P<0.05	***P<0.01

Note. Developed by the author.

The table presents multiple linear regression analysis examining the relationship between four independent variables (PE, EE, SI, FC) and the dependent variable (BI). The unstandardised coefficient (β) shows the extent to which each independent variable influences BI while holding other factors are constant. Firstly, PE ($\beta = 0.432$, $p < 0.001$) has the most significant effect on BI, suggesting that Malaysians are more likely to adopt Wealth Tech if they perceive it to enhance their performance. Secondly, SI ($\beta= 0.250$, $p < 0.001$) also has a significant effect on BI, implying that the recommendations from peers or social activities play an important role in Wealth Tech adoption as well. Lastly, FC ($\beta=0.139$, $p <0.001$) and EE ($\beta = 0.135$, $p < 0.01$) are both significant on BI, but their impact is lower compared to PE and SI.

R-squared (Coefficient of Determination) = 0.726, which means 72.60% of the variance in BI is explained by PE, EE, SI and FC. Meanwhile, the Adjusted R-squared is 0.723, providing a more reliable measure in the variability on BI. The ANOVA Test (F=251.097, p<0.001) suggested that the model constructed is significant, which means at least one of the independent variables significantly explained BI. Lastly, the Durbin-Watson value = 1.903, which is close to 2.0, indicating no serious autocorrelation in the residuals.

In conclusion, the PE, SI, and FC in the model significantly influence the dependent variable, supported at different significant levels which are 90%, 95%, 99%, while EE is supported at significant levels of 90% and 95% Performance Expectancy is the strongest factor, followed by Social Influence, Facilitating Conditions and Effort Expectancy. The model suggests that Malaysians are more likely to adopt Wealth Tech if they perceive Wealth Tech is useful to their lives and are influenced by social norms. have necessary support and are easy to use.

Table 4.21:

Result of Independent Variable (TR) to PE

	Unstandardised Coefficient Beta	*Coefficient Std. Error*	*Standardized Coefficient Beta*	*t-statistics*	*P-value*
(Constant)	1.348	0.127		10.665	<0.001 ***
TR	0.763	0.035	0.746	21.922	<0.001 ***
R-squared					0.557
Adjusted R-squared					0.556

F-test	480.588
P-value	<0.001
Durbin Watson	1.386

Note. Developed by the author.

For every one unit increase in TR, PE will be increased by 0.763. The P-value (<0.001) is smaller than 0.01, showing TR has a significant effect on PE. High t-statistics (21.922) also reinforces strong significance. R-squared = 0.557, means 55.7% of the variance in PE is explained by TR. The ANOVA Test (450.588, p<0.001) indicates that the model is significant. The Durbin-Watson value (1.386) indicates no serious autocorrelation issues, ensuring reliability of the results.

Table 4.22:

Result of Independent Variable (TR) to EE

	Unstandardised Coefficient Beta	Coefficient Std. Error	Standardized Coefficient Beta	t-statistics	P-value
(Constant)	1.275	0.143		8.897	<0.001 ***
TR	0.760	0.030	0.702	19.280	<0.001 ***
R-squared					0.493
Adjusted R-squared					0.492
F-test					371.725

P-value	<0.001
Durbin Watson	1.535

Note. Developed by the author.

For every one unit increase in TR, EE will be increased by 0.76. The p-value (<0.001) is smaller than 0.01, showing TR has a significant effect on EE. Meanwhile, high t-statistics (19.280) indicate strong significance. R-squared = 0.493, means 49.30% of the variance in EE is explained by TR. The ANOVA Test (371.725, p <0.001) indicates that the model is significant. The Durbin-Watson value (1.535) indicates no serious autocorrelation issues, confirming that residuals are independent.

In short, TR plays a significant and positive impact on PE and EE, supported at different significant levels (90%, 95%, 99%), meaning Malaysians with higher TR perceive digital wealth management tools are more useful. Both models fit well. However, we can see that impacts on PE are slightly higher than EE because of higher beta, R-squared and F-test value.

4.4.2 Discriminant Validity

Table 4.23:

Fornell-Larcker Criterion Table for PE, EE, SI, FC to BI

Construct	*PE*	*EE*	*SI*	*FC*	*BI*
PE	**0.896**				
EE	0.811	**0.863**			

SI	0.774	0.753	**0.835**		
FC	0.601	0.601	0.532	**0.710**	
BI	0.812	0.753	0.762	0.600	**0.878**

Note. Developed by the author.

Table 4.24:

Fornell-Larcker Criterion Table for TR to PE, EE

Construct	*PE*	*EE*	*TR*
PE	**0.896**		
EE	0.811	**0.863**	
TR	0.746	0.702	**0.868**

Note. Developed by the author.

The tables above are evaluating Fornell-Larcker Criterion Table to identify the discriminant validity of constructs within the model. The diagonal values (bolded) represent the square root of Average Variance Extracted (AVE) (Kavuta et al., 2023). The square root of the AVE of each construct should be higher than the off-diagonal values (correlations with other constructs). For example, the square root of AVE for PE (0.896) is higher than the highest correlations between PE and BI (r = 0.812), verifying that discriminant validity is established for PE. Moreover, the AVE for EE (0.863) is higher than the correlation value between TR and EE, verifying that the discriminant validity is sound for TR. Besides that, all the AVE are above 0.50 or higher, suggesting that the construct explains at least half of the variance of the indicators (Cheung et al., 2023).

From the result, we can determine that diagonal values of all the constructs are greater than the correlations with other constructs, and discriminant validity is established for all independent and dependent variables.

4.5 Conclusion

The data is analyzed using IBM SPSS 30.0.0, which is effective in analysing and organizing the information gathered from responders. Furthermore, the survey questions were proven to be credible. Aside from that, no non-normality, multicollinearity and autocorrelation issues were discovered during the research. The multiple regression analysis shows that, in general, all the independent variables (PE, EE, SI, FC) significantly explained the behavioural intention to adopt Wealth Tech in Malaysia, while TR is positively impact PE and EE.

CHAPTER 5 CONCLUSION

5.0 Introduction

This chapter synthesises the findings from the research on the adoption of Wealth Tech in Malaysia, focusing on the influence of PE, EE, SI, FC and TR.

5.1 Summary of Statistical Analysis

Table 5.1:
Statistical Analysis Summary

Hypothesis	t-statistics	P-value	Findings
H1	8.209	<0.001 ***	Supported
H2	2.588	0.010 **	Supported
H3	5.880	<0.001 ***	Supported
H4	4.110	<0.001 ***	Supported
H5	21.922	<0.001 ***	Supported
H6	19.280	<0.001 ***	Supported

Note. Developed by the author.

The variables of PE, EE, SI, and FC have significant relationships with the behavioural intention to adopt Wealth Tech. Meanwhile, the TR on the relationship between PE and EE on BI is significant.

5.2 Discussion on Major Findings

This part offers a detailed examination of primary findings presented in Section 5.1. These findings are explored individually and relate to the initiatives undertaken by the financial and banking institutions.

5.2.1 Key determinants of Behavioural Intention to Adopt Wealth Tech among Malaysians

5.2.1.1 Performance Expectancy and Behavioural Intentions to Adopt Wealth Tech

The analysis indicates that PE significantly impacts BI to adopt Wealth Tech services. This result is consistent with UTAUT, which holds that people are more likely to embrace technology if they believe it will improve their productivity at work or in their personal lives. In the Malaysian context, the burgeoning interest in digital wealth management tools, such as robo-advisors and online investment platforms, underscores the perceived benefits of these technologies in optimising financial decision-making processes. This trend is consistent with the broader Asia Pacific region, where Wealth Tech is emerging as a significant force in financial innovation (McKinsey, 2023).

The Malaysian government has made some efforts to introduce policies to foster a digital economy, recognizing fintech as a crucial component of financial sector growth

(International Monetary Fund, 2022). These initiatives aim to create a conducive environment for Wealth Tech innovations. Besides that, the adoption of advanced technologies such as Artificial Intelligence (AI) and blockchain is transforming Wealth Tech services in Malaysia. These technologies enhance the efficiency and transparency of financial services, contributing to the sector's growth. Moreover, the launch of digital banks in Malaysia such as GxBank, KAF Digital Bank is expected to revolutionize the Wealth Tech landscape (Fintech News Malaysia, 2024). These banks offer innovative financial products and services, increasing competition and encouraging traditional institutions to adopt digital solutions.

5.2.1.2 Effort Expectancy and Behavioural Intentions to Adopt Wealth Tech

The research findings establish a strong positive relationship because users develop higher adoption intentions when they experience easy access and comfortable use of Wealth Tech technology platforms. The research findings support previous research outcomes conducted in the financial technology field. The previous findings from Roh (2023), Bajunaied et al. (2023), Darmansyah et al. (2020) have demonstrated that EE produces a strong effect on BI toward FinTech services, especially when users perceive the technology to be easy to use.

The basis for this connection comes from recognizing that simple-to-use technologies decrease mental effort in people leading to increased adoption behaviour (Scherer et al., 2019). People tend to adopt new technologies that require minimal effort for navigation and usage thus integrating such tools into their routines. Wealth Tech systems that provide step-by-step guidance and real-time support bring convenience to financial consumers. Such friendly features both improve tool usability and decrease user concerns about automated financial management systems. Therefore, ease of use is their core fundamental factor because it consistently proves significant in shaping adoption decisions. Wealth Tech platforms' user experience affects adoption rates because if a system requires too much work to operate, consumers will give up the adoption process.

5.2.1.3 Social Influence and Behavioural Intentions to Adopt Wealth Tech

According to the findings of the SI research, individuals are impacted by their social networks, friends, financial experts, and digital communities when deciding whether to use Wealth Tech services. This result is in line with earlier studies that have repeatedly demonstrated the importance of peer recommendations, expert endorsements, and social validation in the adoption of technology (Kartini et al., 2025; Jisham et al., 2024; Nair et al., 2022) but contrast with the other studies (Senyo & Osabutey, 2020; Jha & Dangwal, 2025). The research findings contradicted previous studies by Srivastava (2023) and Arun (2023). The paradox may result from the fact that social influence on technology adoption is becoming less important over time as the market is crowded with early adopters who influence later consumers who make decisions based on personal interactions rather than peer pressure (Wedlock et al., 2019).

Wealth Tech solutions often feel unfamiliar and risky to users, but potential adopters turn to advice and assurance from their friends along with their colleagues and financial influencers before trying digital financial services which their peers successfully demonstrate. The research found that advice from reliable financial professionals acted as an effective method to comfort users about trustworthiness (Moin et al., 2017). The Wealth Tech adoption process emerges as a collective social phenomenon that operates through community opinions and acknowledgment from outside sources. Wealth Tech services become more attractive to users because they can access reviews and view discussions about them on social networks.

5.2.1.4 Facilitating Condition and Behavioural Intentions to Adopt Wealth Tech

The research results verify that FC significantly exhibits behavioural intention which leads users to adopt Wealth Tech services better when they access technological infrastructure with financial literacy resources. Research findings affirm current academic literature showing that proper technical support systems boost the adoption of emerging technologies (Nandru et al.,2023; Jena, 2022; Alkhwaldi et al., 2022; Khatun & Tamanna, 2020).

The components of FC consist of obtaining essential tools such as smartphones and laptops together with secure internet connections and trustworthy support systems. Research findings reveal that enabling factors act as direct determinants of users who adopt digital financial solutions. Research findings demonstrate that customers heavily depend on both customer support services for sustaining their use of Wealth Tech solutions. Digital financial service users stay loyal to their platforms when supportive customer help systems integrate with AI-based chatbots, and human staff are quickly available to assist users. Digital wealth management platforms become more appealing and accessible to users when they make various resources available which ensures better overall experience and reduces user frustration.

5.2.2 Effect of Technology Readiness

The research demonstrates that TR significantly impacts the relationship toward PE and EE in digital finance adoption systems. Users who demonstrate higher technological readiness view Wealth Tech solutions more positively in terms of usefulness and ease of use until they form intentions to adopt digital wealth management tools (Flavián et al., 2021). Research findings contribute to the comprehension of the effect of technological readiness on digital finance adoption behaviours. These findings deepen understanding of how personal technological inclination influences expectation on performance and usefulness of Wealth Tech applications.

5.2.2.1 Technology Readiness to Performance Expectancy

A positive impact exists TR to PE. People who demonstrate strong TR tend to see positive value in Wealth Tech since they trust in the superior efficiency of digital financial services tools. Studies have proven that users with high TR experience better viewpoints toward digital financial services because advanced technology solutions are commonplace in their daily routines (Flavián et al., 2021; Tahar et al., 2020).

Higher TR levels among individuals help them become more active in using digital financial platforms. Such users proactively search for information and examine features and try out platform functions to directly experience automated financial solutions. People who are technologically comfortable tend to put more trust in digital tools. Higher beliefs regarding Wealth Tech usefulness led users to consolidate PE impact (Lim et al., 2024). The users display confidence in the digital wealth management tools because they believe these digital solutions maximize efficiency levels while offering improved returns and simpler portfolio management.

5.2.2.2 Technology Readiness to Effort Expectancy

TR also significantly impacts on EE. The results indicate that users with higher TR find Wealth Tech platforms less complicated and more intuitive, positively impacting EE. The findings highlight that technologically prepared users have a higher ability to navigate digital tools, reducing their perception of complexity. Baba et al. (2023) and Senali et al. (2022) support this finding.

Users tend to adapt quickly to new interfaces, features, and system updates as they view emerging technology as easy to use. This leads to a stronger influence of EE on their decision to adopt the platform. Additionally, users with high TR tend to have greater perceived control over digital systems, believing they can learn and use Wealth Tech effectively (Lim et al., 2024). This belief increases their likelihood of technology in wealth management. According to research findings, technologically experienced users actively participate with digital tools to simplify the perception of complexity when using new systems (Baba et al., 2023). The learning behaviour supports that Wealth Tech demands minimal effort to use.

5.3 Implications of the Research

This part will highlight the implications that are familiar to a variety of organisations, including government agencies, policymakers, academic organisations, and wealth management firms. The multiple regression analysis's findings show that both independent factors significantly influence Malaysians' behavioural intention to use Wealth Tech.

This research may help government agencies or legislators implement adequate laws or regulations to improve the safety and stability of the financial industry. The adoption of Wealth Tech requires digital literacy or mental readiness for technology in financial applications (Shakeel et al., 2024). Therefore, through the implementation of educational programs or seminars, relevant government entities should enhance Malaysians' digital literacy to increase their technological readiness. It is advised that government organisations should host events that inform the public about digital technology, the benefits of Wealth Tech services, and their features to reduce concerns and boost confidence. For example, the government ought to undertake additional projects like the 2022 MyDIGITAL initiative, a nationwide program designed to empower Malaysians by expanding their access to digital financial services and digital knowledge (Carissa, 2022).

Additionally, it is recommended that the Malaysian government work with industry players to invest in extending internet infrastructure to boost Internet accessibility. By taking this step, reliable and safe access to online financial services can be guaranteed. For instance, encouraging mobile wallets and digital banking can increase individuals' financial stability and inclusion, which will facilitate their adoption of Wealth Tech. Unquestionably, regions with more robust digital infrastructure will experience far lower levels of financial anxiety or anxieties (Shakeel et al., 2024).

The government, as the authorised party, should periodically review regulatory frameworks to keep up with the rapid advancements in technology. Its purpose is to shield users from potential dangers related to Wealth Tech and make sure that people feel safe using these services. Financial laws are necessary to keep an eye on Wealth Tech, which may be vulnerable to cybersecurity attacks and data breaches. Federal securities laws, which include guidelines for the use of AI and data analytics, must be followed by Wealth Tech enterprises. Policymakers can also learn the value of consumer protection laws from this research. The purpose of this regulation is to specify precisely how personal information must be gathered, kept, and handled. To guarantee that customer data is safe from any threats, the government should also mandate that Wealth Tech companies follow specific guidelines.

Additionally, the development of Wealth Tech is equally crucial. This research may assist Wealth Tech service providers in expanding the scope of the variables under this research to boost Malaysians' tendency to embrace Wealth Tech. The digital transformation path of wealth management organisations has been prompted by the user experience. Wealth Tech service providers might concentrate on making the platform's features more aesthetically pleasing as well as simple to use and rapidly understand. For instance, to promote a feeling of community and mutual learning, businesses should set up feedback channels and community forums where people can express their thoughts and experiences. With that, performance expectations are raised and perceived effort is reduced with an intuitive user interface. In result, users of Wealth Tech can benefit from interactive tutorials and consistent, pertinent investment knowledge.

The majority of customers anticipate that Wealth Tech will offer more precise financial analysis. As a result, this research points out to service providers that sophisticated advisory models will have the ability to grow the market. By concentrating on intricate client wants and situations, it may set itself apart. Therefore, it is crucial to invest in AI-powered automation models to improve user experiences, increase efficiency, and streamline procedures. To improve their services and minimise product gaps, Wealth Tech companies should collaborate with banks, fintechs, and other financial organisations beforehand. Consequently, these strategic alliances have the potential to establish all-encompassing wealth management ecosystems (Deloitte, 2024).

5.4 Limitations of the Research

Although this research offers insightful information about the factors impacting Wealth Tech adoption among Malaysians, a number of limitations should be carefully considered to provide opportunity for further research and to assist interpret the findings in context. The cross-sectional design of the data collection is one of the study's major limitations. The research employed a survey-based approach, capturing a snapshot of behavioural intention at a single point in time. As a result, it does not account for how these intentions may evolve or how users' attitudes and behaviours might change as they interact with Wealth Tech platforms. Adoption behaviour, especially in the case of financial technologies, is often a dynamic process, influenced by factors such as trust development, experience, and market changes.

Besides that, another limitation is the sampling technique of the research. While the survey targeted Malaysians, the sample might not demonstrate the entire range of demographic features found in Malaysian society. Convenience sampling, while easy to implement, often results in a sample that is not representative of the broader population. For instance, the sample may be skewed towards urban, tech-savvy individuals who are more likely to adopt Wealth Tech, potentially overlooking the perspectives of rural or less technologically inclined investors. As an example, this research encompasses 109 respondents from Kuala Lumpur but only successfully gathered 1 responsdent from Sarawak. Similarly, convenience sampling is said to be prone to selection bias, as it often attracts participants who are more willing or able to participate, such as tech-savvy individuals or those with a strong interest in financial technologies. As a result, this bias could distort the findings and restrict the generalizability of the research’s conclusions.

Lastly, one significant limitation of the research is its limited scope of independent variables, particularly in relation to regulatory policies and government intervention.

While the research examines key constructs such as PE, EE, SI, FC, and TR, it does not account for the role of regulatory frameworks and government initiatives in shaping the adoption of Wealth Tech. Since government intervention and regulatory policies are important drivers of technological adoption in the financial industry, this exclusion limits the research's capacity to offer a comprehensive knowledge of the factors driving Wealth Tech adoption in Malaysia. Although, understandably, regulatory policies and government interventions are not static as they would have evolved in response to technological advancements, economic conditions, and societal needs, it remains a pivotal role in fostering trust and confidence among investors, which are essential for the adoption of Wealth Tech. For instance, robust data protection laws, cybersecurity regulations, and consumer protection measures can alleviate concerns about privacy and security, which are often significant barriers to adoption. The absence of these variables in the research limits its ability to explain how regulatory frameworks influence investors' perceptions of risk and trust, which are critical determinants of behavioural intention.

5.5 Future Research Recommendations

Building on the findings from the current research, future research could explore several avenues to further understand the adoption of Wealth Tech among Malaysians. To address the cross-sectional design issue of the research, longitudinal studies could be another useful approach for future researchers to explore how the factors influencing Wealth Tech adoption would have evolved. Provided that the current research is cross-sectional in nature, it only captures a snapshot of investors' BI at a specific point of time. As technological advancements continue to shape the financial services industry, it would be valuable to track the shifting perceptions of PE, EE, and other independent variables. This would help determine whether early adopters maintain their interest in

Wealth Tech or if the long-term usage patterns of these platforms evolve differently as technology becomes more integrated into everyday life. This would help in a better understanding of the long-term sustainability of adoption and whether initial perceptions of PE, EE, and SI change as users become more familiar with the technology. Consecutively, this could provide insights into the reasons behind the discontinuation or continued use of Wealth Tech platforms, which could help financial institutions to develop strategies to improve user retention and satisfaction.

This research possesses an alternative sampling technique for future research which is stratified sampling as it can ensure that the sample is representative by dividing the population into distinct subgroups or strata based on key characteristics like age, income, education, and geographic location. By proportionally including participants from each stratum, stratified sampling can provide a more accurate reflection of the diverse Malaysian investor population, thereby addressing the issue of sample representation more effectively. Similarly, it can minimise selection bias issue by ensuring that each subgroup within the population is adequately represented. For example, if rural investors are a significant segment of the population, stratified sampling would ensure their inclusion in the sample. It is highly anticipated that this decrease in bias would further improve the validity and dependability of the research findings. However, stratified sampling is considered a more complex and resource-intensive option though it offers a more robust solution to the issue of sample representation. The process of identifying and dividing the population into strata and then selecting participants from each stratum often requires careful planning and execution. Additionally, recruiting participants from each stratum can be more time-consuming and costly compared to convenience sampling. Hence, despite its complexity and resource requirements, future researchers can aim for a stratified sampling technique to enhance the validity, reliability, and generalizability of the findings, thereby providing a more accurate and comprehensive understanding of the factors influencing the adoption of Wealth Tech among Malaysians.

On the other hand, another important area for future research is the impact of regulatory policies and government intervention on Wealth Tech adoption in Malaysia. As the financial technology sector continues to grow, government regulations and policies will be likely to play an increasingly important role in shaping consumer perceptions and trust in these platforms. Future research could examine how regulations related to data privacy, consumer protection, and fintech licensing would influence investors' willingness to adopt Wealth Tech. Additionally, researchers could also investigate whether government initiatives to promote financial inclusion and digital literacy are effective in encouraging adoption, particularly among the underserved populations. This is said to be important as understanding the regulatory environment's influence on adoption can guide policymakers and industry stakeholders in creating an ecosystem which is conducive to Wealth Tech's growth. For instance, variables such as data protection laws, cybersecurity regulations, and consumer protection policies can be integrated into the research model. Researchers could also measure how stringent regulatory frameworks enhance or hinder adoption by assessing investors' perceptions of safety and reliability when using Wealth Tech platforms as this would ultimately enhance the academic rigor of the research.

5.6 Conclusion

The purpose of this study is to investigate the variables influencing Malaysians' behavioural intention to use wealth technology in wealth management. Physical and online survey questionnaires were distributed in order to collect data for the entire study. Additionally, data analysis was conducted using Run Statistical Package for Social Sciences (SPSS) 30.0. According to the study's findings, there is a significant relationship between the intention to embrace Wealth Tech and both independent variables—performance expectancy, effort expectancy, social influence, facilitating condition, and technology readiness. Additionally, the study's weaknesses were evaluated, and suggestions were discussed. As a result, this study might offer some recommendations to future researchers and related parties.

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Appendices

Appendix 1 Ethical Approval for Research Project

UNIVERSITI TUNKU ABDUL RAHMAN

Re: U/SERC/78-378/2024

7 October 2024

Mr Chong Tun Pin
Head, Department of Banking and Risk Management
Faculty of Business and Finance
Universiti Tunku Abdul Rahman
Jalan Universiti, Bandar Baru Barat
31900 Kampar, Perak.

Dear Mr Chong,

Ethical Approval For Research Project/Protocol

We refer to your application for ethical approval for your students' research project from Bachelor of Business Administration (Honours) Banking and Finance programme enrolled in course UBFZ3026. We are pleased to inform you that the application has been approved under Expedited Review.

The details of the research projects are as follows:

No.	Research Title	Student's Name	Supervisor's Name	Approval Validity
1.	Tech Savvy Investors: Adoption of Wealth Tech for Wealth Management in Malaysia	1. Lai An Xuan 2. Lim Wei Hong 3. Siow Pei Yee 4. Tan Joey	Mr Chong Tun Pin	7 October 2024 - 6 October 2025

The conduct of this research is subject to the following:

(1) The participants' informed consent be obtained prior to the commencement of the research; (2) Confidentiality of participants' personal data must be maintained; and

(3) Compliance with procedures set out in related policies of UTAR such as the UTAR Research Ethics and Code of Conduct, Code of Practice for Research Involving Humans and other related policies/guidelines.

(4) Written consent be obtained from the institution(s)/company(ies) in which the physical or/and online survey will be carried out, prior to the commencement of the research.

Should the students collect personal data of participants in their studies, please have the participants sign the attached Personal Data Protection Statement for records.

Thank you.

Yours sincerely,

Professor Ts Dr Faidz bin Abd Rahman
Chairman
UTAR Scientific and Ethical Review Committee

c.c Dean, Faculty of Business and Finance

Director, Institute of Postgraduate Studies and Research

Appendix 2 Survey Questionnaire

Universiti Tunku Abdul Rahman

Faculty of Business and Finance

Bachelor of Business Administration (Honours) Banking and Finance

Survey Questionnaire

"Tech Savvy Investors: Adoption of Wealth Tech for Wealth Management in Malaysia"

Dear Respondents,

We are final-year undergraduate students studying in a Bachelor of Business Administration (Honours) in Banking and Finance from Universiti Tunku Abdul Rahman (UTAR). We are currently undergoing our Final Year Project titled " Tech Savvy Investors: Adoption of Wealth Tech for Wealth Management in Malaysia".

Your participation in completing this questionnaire is greatly valued as it will significantly aid us in our study's progress and in meeting its goals. Please read each question carefully and select the most appropriate response. Your answers will remain confidential and will be used for research purposes only.

This questionnaire includes 2 sections which are demographic information and studied variables. This questionnaire will take 5 to 10 minutes to complete. Your answers will remain confidential and will be used for research purposes only. Thank you for your participation.

If have any questions regarding this questionnaire, you may contact us:

Lai An Xuan 0167144034

Lim Wei Hong 01110571388

Siow Pei Yee 0176860049

Tan Joey 0173265285

Yours sincerely.

PERSONAL DATA PROTECTION STATEMENT

Please be informed that in accordance with Personal Data Protection Act 2010 ("PDPA") which came into force on 15 November 2013, Universiti Tunku Abdul Rahman ("UTAR") is hereby bound to make notice and require consent in relation to collection, recording, storage, usage and retention of personal information.

Notice:

1. The purposes for which your personal data may be used are inclusive but not limited to:-
    - For assessment of any application to UTAR
    - For processing any benefits and services
    - For communication purposes
    - For advertorial and news
    - For general administration and record purposes
    - For enhancing the value of education
    - For educational and related purposes consequential to UTAR
    - For the purpose of our corporate governance
    - For consideration as a guarantor for UTAR staff/ student applying for his/her scholarship/ study loan

2. Your personal data may be transferred and/or disclosed to third party and/or UTAR collaborative partners including but not limited to the respective and appointed outsourcing agents for purpose of fulfilling our obligations to you in respect of the purposes and all such other purposes that are related to the purposes and also in providing integrated services, maintaining and storing records. Your data may be shared when required by laws and when disclosure is necessary to comply with applicable laws.
3. Any personal information retained by UTAR shall be destroyed and/or deleted in accordance with our retention policy applicable for us in the event such information is no longer required.
4. UTAR is committed in ensuring the confidentiality, protection, security and accuracy of your personal information made available to us and it has been our ongoing strict policy to ensure that your personal information is accurate, complete, not misleading and updated. UTAR would also ensure that your personal data shall not be used for political and commercial purposes.

Consent:

1. By submitting this form you hereby authorise and consent to us processing (including disclosing) your personal data and any updates of your information, for the purposes and/or for any other purposes related to the purpose.

2. If you do not consent or subsequently withdraw your consent to the processing and disclosure of your personal data, UTAR will not be able to fulfill our obligations or to contact you or to assist you in respect of the purposes and/or for any other purposes related to the purpose.

3. You may access and update your personal data by writing to us at Lai An Xuan - 0167144034. Lim Wei Hong- 01110571388, Siow Pei Yee - 0176860049 , Tan Joey – 0173265285.

Acknowledgment of Notice

[ ] I have been notified by you and that I hereby understood, consented and agreed per UTAR above notice.

[ ] I disagree, my personal data will not be processed.

…………………………

Name:

Date:

Section A

The following question aims to collect respondents' demographic information. Please provide the appropriate information to help us understand the respondent's background.

Part A

Q1. Have you ever used any Wealth Tech platforms (eg. Versa, Kenanga Digital Investing, Touch n Go, Moomoo, Rakuten Trade, M+ Online)?

- Yes
- No (Proceed to Question 3)

Q2. Which Wealth Tech services are you using? (You may choose more than 1)

[Proceed to Part B]

- Online Brokerages
- Robo-Advisors
- Mobile Trading App
- Peer-to-Peer Lending
- Blockchain
- Others: ___________

Q3. Are you interested in using Wealth Tech platforms?

- Yes
- No

Part B

Q1. Gender

- Male
- Female

Q2. Age

- Generation Z (18 years old -27 years old)
- Millennials (28 years old -43 years old)
- Generation X (44 years old -59 years old)
- Baby Boomers (60 years old – 79 years old)

Q3. Highest Educational Level

- SPM/ O-Level
- STPM/ A-Level
- Diploma
- Bachelor’s Degree
- Master’s Degree
- Doctorate’s Degree
- Other:_____

Q4. Race

- Chinese
- Malay
- Indian
- Other: _______

Q5. Employment Status

- Student
- Government
- Private
- Self-Employed
- Unemployed
- Retired

Q6. Net Income Level (Monthly)

- Below RM2,500
- RM2,501 - RM5,000
- RM5,001 - RM7,500
- RM7,501 - RM10,000
- RM10,001 and above

Q7. State (Currently staying)

- Johor
- Kedah
- Kelantan
- Kuala Lumpur
- Melaka
- Negeri Sembilan
- Perlis
- Pahang
- Perak

- Pulau Pinang
- Sabah
- Sarawak
- Selangor
- Terengganu

Section B

Based on your experience, kindly indicate the level to which you agree or disagree.

Strongly Disagree (SD) = 1, Disagree (D) = 2, Neutral (N) = 3, Agree (A) = 4, Strongly agree (SA) = 5

Independent variable 1: Performance Expectancy		**SD**	**D**	**N**	**A**	**SA**
PE1	I expect that Wealth Tech will make my financial tasks easier and more efficient.	1	2	3	4	5
PE2	I expect that Wealth Tech will help me save time and effort when managing my finances.	1	2	3	4	5
PE3	I expect that Wealth Tech will offer a higher level of convenience compared to traditional financial methods.	1	2	3	4	5
PE4	I expect Wealth Tech is more accurate in financial analysis and information.	1	2	3	4	5
PE5	I expect Wealth Tech writes and follows the investment strategy and provides more consistent service in wealth management.	1	2	3	4	5
PE6	I expect information provided by Wealth Tech is more consistent.	1	2	3	4	5

Independent variable 2: Effort Expectancy		**SD**	**D**	**N**	**A**	**SA**
EE1	I expect that I can quickly learn how to use Wealth Tech.	1	2	3	4	5
EE2	I believe that Wealth Tech platforms are user-friendly.	1	2	3	4	5
EE3	I believe that using Wealth Tech will not require a significant amount of time to get things done.	1	2	3	4	5

EE4	I expect that I will not need extensive training or assistance to use Wealth Tech effectively.	1	2	3	4	5

Independent variable 3: Social Influence		**SD**	**D**	**N**	**A**	**SA**
SI1	People who influence my behaviour would want me to utilise Wealth Tech.	1	2	3	4	5
SI2	People in my social networks who would utilise Wealth Tech will have a high profile. | (Note: High profile means attract a lot of attraction)	1	2	3	4	5
SI3	Significant proportion of my coworkers would want me to utilise Wealth Tech.	1	2	3	4	5
SI4	People whose opinions I value prefer that I use Wealth Tech.	1	2	3	4	5
SI5	People who provide positive feedback and reviews motivate me to use Wealth Tech.	1	2	3	4	5

Independent variable 4: Facilitating Conditions		**SD**	**D**	**N**	**A**	**SA**
FC1*	It will be time consuming to learn how to adopt Wealth Tech.	1	2	3	4	5
FC2*	Wealth Tech will be so difficult to understand and use.	1	2	3	4	5
FC3*	Wealth Tech will be intimidating to me.	1	2	3	4	5
FC4	I have access to the required technology (e.g., internet, smartphone) for using Wealth Tech.	1	2	3	4	5
FC5	I have the knowledge necessary to use Wealth Tech.	1	2	3	4	5
FC6	There is sufficient customer support and assistance available when I encounter issues with Wealth Tech services.	1	2	3	4	5

Independent variable 5: Technology readiness		**SD**	**D**	**N**	**A**	**SA**
TR1	I believe new technologies contribute to a better quality of life.	1	2	3	4	5

TR2	I am among the first in my circle of friends to acquire new technology when it appears.	1	2	3	4	5
TR3	I can usually figure out new high-tech products and services without help from others.	1	2	3	4	5
TR4	I prefer to use the most advanced technology available.	1	2	3	4	5
TR5*	I do not feel confident doing any transaction through an online exclusive platform.	1	2	3	4	5
TR6*	I do have safety concerns about providing my personal information over the Internet.	1	2	3	4	5

Dependent variable: Behavioural Intentions to Adopt Wealth Tech		**SD**	**D**	**N**	**A**	**SA**
BI1	I intend to use Wealth Tech for managing investment.	1	2	3	4	5
BI2	I intend to use Wealth Tech rather than any traditional financial advisor.	1	2	3	4	5
BI3	I intend to continue using Wealth Tech for my financial needs in the future.	1	2	3	4	5
BI4	I am motivated to explore and adopt new Wealth Tech.	1	2	3	4	5

- Thank You :) -

Appendix 3 SPSS Results

Appendix 3.1 Descriptive Statistic (Central Tendencies & Standard Deviation)

Performance Expectancy

Item Statistics

	Mean	Std. Deviation	N
Performance Expectancy 1	4.04	.880	384
Performance Expectancy 2	4.09	1.048	384
Performance Expectancy 3	4.18	.907	384
Performance Expectancy 4	4.01	1.101	384
Performance Expectancy 5	3.96	1.034	384
Performance Expectancy 6	4.02	.883	384

Effort Expectancy

Item Statistics

	Mean	Std. Deviation	N
Effort Expectancy 1	3.98	.959	384
Effort Expectancy 2	4.05	1.073	384
Effort Expectancy 3	3.89	1.078	384
Effort Expectancy 4	3.95	1.000	384

Social Influence

Item Statistics

	Mean	Std. Deviation	N
Social Influence 1	3.72	.987	384
Social Influence 2	3.68	1.144	384
Social Influence 3	3.66	.981	384
Social Influence 4	3.76	1.146	384
Social Influence 5	3.97	.973	384

Facilitating Condition

Item Statistics

	Mean	Std. Deviation	N
Facilitating Condition 1*	3.22	1.374	384
Facilitating Condition 2*	3.30	1.439	384
Facilitating Condition 3*	3.32	1.455	384
Facilitating Condition 4	3.95	.934	384
Facilitating Condition 5	3.89	1.114	384
Facilitating Condition 6	3.86	.918	384

Technology Readiness

Item Statistics

	Mean	Std. Deviation	N
Technology Readiness 1	4.03	.874	384
Technology Readiness 2	3.72	1.248	384
Technology Readiness 3	3.75	1.166	384
Technology Readiness 4	3.87	1.111	384
Technology Readiness 5*	3.11	1.344	384
Technology Readiness 6*	2.77	1.465	384

Appendix 3.2 Reliability Statistic (Cronbach Alpha)

Behavioral Intention to adopt Wealth Tech

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.888	.890	4

Performance Expectancy

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.923	.923	6

Effort Expectancy

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.880	.880	4

Social Influence

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.909	.909	5

Facilitating Condition

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.797	.788	6

Technology Readiness

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.756	.772	6

Appendix 3.3 Multicollinearity Analysis (Variance Inflation Factor & Tolerance)

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	.334	.120		2.772	.006	.097	.570					
	Performance Expectancy	.431	.052	.422	8.209	<.001	.327	.534	.812	.389	.221	.273	3.659
	Effort Expectancy	.125	.048	.129	2.588	.010	.030	.219	.753	.132	.070	.289	3.459
	Social Influence	.250	.042	.264	5.880	<.001	.166	.333	.762	.289	.158	.359	2.789
	Facilitating Condition	.139	.034	.141	4.110	<.001	.072	.205	.600	.207	.110	.614	1.630

a. Dependent Variable: Behavioural Intention

Appendix 3.4 Multiple Regression

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	.334	.120		2.772	.006	.097	.570					
	Performance Expectancy	.431	.052	.422	8.209	<.001	.327	.534	.812	.389	.221	.273	3.659
	Effort Expectancy	.125	.048	.129	2.588	.010	.030	.219	.753	.132	.070	.289	3.459
	Social Influence	.250	.042	.264	5.880	<.001	.166	.333	.762	.289	.158	.359	2.789
	Facilitating Condition	.139	.034	.141	4.110	<.001	.072	.205	.600	.207	.110	.614	1.630

a. Dependent Variable: Behavioural Intention

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.852[a]	.726	.723	.44715	.726	251.097	4	379	<.001	1.903

a. Predictors: (Constant), Facilitating Condition, Social Influence, Effort Expectancy, Performance Expectancy

b. Dependent Variable: Behavioural Intention

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	200.816	4	50.204	251.097	<.001[b]
	Residual	75.777	379	.200		
	Total	276.593	383			

a. Dependent Variable: Behavioural Intention

b. Predictors: (Constant), Facilitating Condition, Social Influence, Effort Expectancy, Performance Expectancy

Appendix 3.5 Direct Effect of TR to PE/EE

Technology Readiness -> Performance Expectancy

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.746[a]	.557	.556	.55519	.557	480.588	1	382	<.001	1.386

a. Predictors: (Constant), Technology Readiness

b. Dependent Variable: Performance Expectancy

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	148.136	1	148.136	480.588	<.001[b]
	Residual	117.747	382	.308		
	Total	265.883	383			

a. Dependent Variable: Performance Expectancy

b. Predictors: (Constant), Technology Readiness

Technology Readiness -> Effort Expectancy

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.702[a]	.493	.492	.62888	.493	371.725	1	382	<.001	1.535

a. Predictors: (Constant), Technology Readiness

b. Dependent Variable: Effort Expectancy

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	147.015	1	147.015	371.725	<.001[b]
	Residual	151.078	382	.395		
	Total	298.093	383			

a. Dependent Variable: Effort Expectancy

b. Predictors: (Constant), Technology Readiness

Appendix 3.6: Discriminant Validity

Correlations between the constructs (BI, PE, EE, SI, FC)

Correlations

		Behavioural Intention	Performance Expectancy	Effort Expectancy	Social Influence	Facilitating Condition
Pearson Correlation	Behavioural Intention	1.000	.812	.753	.762	.600
	Performance Expectancy	.812	1.000	.811	.774	.570
	Effort Expectancy	.753	.811	1.000	.744	.601
	Social Influence	.762	.774	.744	1.000	.532
	Facilitating Condition	.600	.570	.601	.532	1.000

Correlations between construct (TR, PE)

Correlations

		Performance Expectancy	Technology Readiness
Pearson Correlation	Performance Expectancy	1.000	.746
	Technology Readiness	.746	1.000

Correlations between construct (TR, EE)

Correlations

		Effort Expectancy	Technology Readiness
Pearson Correlation	Effort Expectancy	1.000	.702
	Technology Readiness	.702	1.000

Factors Loading to calculate AVE

Factor Matrix[a]

	Factor 1
Performance Expectancy	.896
Effort Expectancy	.863
Social Influence	.835
Facilitating Condition	.710
Technology Readiness	.868
Behavioural Intention	.878

Extraction Method: Principal Axis Factoring.

a. 1 factors extracted. 5 iterations required.