DIGITAL BANKING IN MALAYSIA: FACTORS INFLUENCING ITS ADOPTION

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BY

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DECLARATION

We hereby declare that:

(1) This undergraduate research project is the end result of my 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 research project has been submitted in support of any application of any other degree or qualification of this or any other university, or other institutes of learning.

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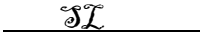
Schumeichel Woo Seng Hui	23UKB01467	

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DEDICATION

This work is dedicated to my family, whose steadfast support and sacrifices have made my academic pursuits possible, and to my friends, whose encouragement and camaraderie have been a source of motivation throughout this endeavor.

Table of Contents

LIST OF TABLES

LIST OF FIGURES

PREFACE

The rapid advancement of financial technology in recent years has fundamentally transformed the way individuals and businesses interact with financial institutions. As Malaysia continues to position itself as a progressive digital economy, the proliferation of digital banking services has become increasingly prominent, reshaping the landscape of the country's financial sector. It was this very transformation that first sparked my interest in exploring the forces driving consumers toward the adoption of digital banking.

My initial curiosity stemmed from observing the shifting behaviour of those around me such as family members, peers, and even older generations whom gradually transitioning from traditional branch-based banking to mobile and online platforms. This raised a compelling question: what factors truly influence an individual's decision to embrace digital banking? The answer, I came to realise, was far more nuanced than mere convenience or technological accessibility.

This research was further motivated by the recognition that despite Malaysia's growing digital infrastructure, adoption rates remain uneven across different demographic groups and regions. Understanding the underlying determinants of digital banking adoption carries significant implications not only for financial institutions seeking to broaden their reach, but also for policymakers aiming to foster greater financial inclusion nationwide.

To investigate this subject, a quantitative research approach was adopted, employing a structured questionnaire survey to gather primary data from banking consumers in Malaysia. The findings of this study are intended to contribute meaningfully to the existing body of literature on digital banking adoption, while offering practical insights for industry practitioners and academics alike.

ABSTRACT

This study examines why digital banking adoption in Malaysia lags at only 50% despite over 90% public awareness. Using a survey of 197 Malaysian users across five regions, the research tested five factors namely: Perceived Usefulness, Perceived Ease of Use, Effort Expectancy, Facilitating Conditions, and Trust against the TAM and UTAUT2 frameworks. The OLS regression model explained 89.3% of adoption variance, finding that Perceived Ease of Use is the strongest driver, followed by Facilitating Conditions and Perceived Usefulness. Effort Expectancy and Trust were not statistically significant. The study recommends that digital banks prioritize user-friendly interfaces and robust infrastructure support to boost adoption and achieve Malaysia's financial inclusion goals.

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Chapter 1: Introduction

1.1 Research Background

Digital banking is informational because it illustrates a fundamental paradigm shift from traditional branch based models to hyper personalized, mobile first financial services (Hoo et al., 2024). This can act as a trigger of a new kind of service models that lower operational costs which literally squeezes the fabled incumbency threshold for traditional banks and will bring down entry barriers right to the ground level for potential new market constituents. Citing Statista, the economic impact is huge; on a global scale, digital banking Net Interest Income will increase from US$1.56 trillion in 2025 to more than US$2 trillion by 2030 thanks to large investments and high adoption in prominent markets (China and the United Kingdom).

At this global level trend, Malaysia is poised methodically with the "Shared Prosperity Vision 2030" that was launched recently by the economic ministry. In 2022, five applicants were given digital banking licenses by Bank Negara Malaysia namely GX Bank, AEON Bank, Ryt Bank, Boost Bank and KAF Digital Bank. BNM says the primary rationale behind this move is to address outstanding issues in financial inclusion. This initiative focuses on underserved markets wherein they have not been served well by incumbent institutions, such as the B40 group, rural communities and MSMEs with very limited access to institutional credit.

Digital banking is a prime example of this core paradigm shift where traditional branch-based banking transformed into hyper-personalized and mobile-first banking (Li & Zafar, 2023; Abdullah & Hisamudin, 2024), especially compared to growing and emerging economies where fintech is specifically used as a means of financial inclusion and competitive advantage, making it. But for these emerging economies, regulatory measures and infrastructure for new digital banks/ fintechs is an important factor to allow their growth and depend solely on consumer trust, digital literacy, and value (Pareek et al., 2025; Saif et al., 2022).

The introduction of those licensed entities, however, does not equate to widespread adoption. It's a complex behavioral shift from the more traditional entrenched banks to new digital-only players. The key to a success will lie at addressing the critical concerns of consumers. Research across various parts of the world has identified factors like public trust of new financial brands, perception regarding security over their data, digital literacy and perceived immediate tangible value proposition over the existing banking relationships etc. As Malaysia turns the page on a new chapter of its financial story, this specialized, localized study will be more important than ever. Learning about Malaysian consumers, their perceptions, motivations and anxieties toward the particular product or service will be essential to understand them and take pre-emptive steps to mitigate adoption barriers (Saif et al., 2022).

1.2 Problem Statement

Following the 2022 issuance of digital banking licenses, Malaysia's financial sector is at a critical juncture. The national policy objective for this initiative is to drive financial inclusion, particularly for underserved populations, in line with the "Shared Prosperity Vision 2030" as per the announcement made by the economic ministry.

However, a significant problem threatens this objective: a critical 'awareness-adoption gap.' Despite a successful roll-out and high public awareness (over 90%), the actual adoption of these new digital banks languishes at only 50% as of Q4 2024 (Cheong, 2025). This discrepancy is the central problem, as it suggests that the new banks are failing to convert awareness into the trust and utility required for consumer uptake.

Similar gaps between awareness and actual adoption have also been observed in various fintech domains, where users are still reluctant to use these services due to various risk factors, trust issues, and lack of value propositions despite high levels of awareness (Mohamad Anuar et al., 2020; Pareek et al., 2025).

This gap has profound implications. If adoption stagnates, these new digital banks will fail to achieve the necessary scale, and more importantly, the national goal of banking the unbanked and underserved will be at risk. The problem, therefore, is a lack of understanding of why this gap exists.

While existing research points to general factors, there is an urgent need to identify the specific behavior, security, and service-related concerns of Malaysians in this new context. By understanding the precise drivers of this hesitation, digital banks can strategically improve their services and address the exact concerns preventing widespread adoption, thereby bridging the gap and fulfilling their financial inclusion mandate (Rashid et al., 2023)

This research problem becomes even more important due to another shortcoming found within current literature related to research methods used by scholars. More precisely, most research papers written by experts studying this issue in Malaysia consider either certain generation or specific income groups or geographical regions. For example, one recent study considered only Generation Z (CHOON KIT et al., 2023), while another research paper examined exclusively the use of digital banking by B40 group members. Thus, older generations, middle-income members, or individuals residing in urban and rural areas of Malaysia have not been adequately studied yet. In other words, there is little study in the existing body of literature examining digital payment behavior of different people living all over the country.

Moreover, barriers to adopting new technologies vary from one generation to another: while 65% of Generation Z uses e-wallets, only 34% of older Malaysians use these technologies (Asian Banking & Finance, 2026). Thus, it might become difficult for policy makers to develop an efficient strategy based on such evidence. Thereby, it can be concluded that a research paper should examine digital banking behaviors of people all over Malaysia regardless of their age, financial standing, or region they live in.

1.3 Research Questions

RQ1: Does Perceived Usefulness significantly influence digital banking adoption?

RQ2: Does Perceived Ease of Use significantly influence digital banking adoption?

RQ3: Does Effort Expectancy significantly influence digital banking adoption?

RQ4: Do Facilitating Conditions significantly influence digital banking adoption?

RQ5: Does Trust significantly influence digital banking adoption?

1.4 Research Objectives

RO1: To examine the effect of Perceived Usefulness on digital banking adoption.

RO2: To investigate the effect of Perceived Ease of Use on digital banking adoption.

RO3: To assess the impact of Effort Expectancy on digital banking adoption.

RO4: To evaluate the role of Facilitating Conditions in digital banking adoption.

RO5: To determine the influence of Trust on digital banking adoption.

1.5 Hypotheses

H_0: Perceived Usefulness has no impact on adoption of digital banking.

H_1: Perceived Usefulness has a positive significant effect on Adoption of digital banking. (RQ1)

H_0: Perceived Ease of Use has no impact on adoption of digital banking.

H_2: Perceived Ease of Use has a positive significant effect on Adoption of digital banking. (RQ2)

H_0: Effort Expectancy has no impact on adoption of digital banking.

H_3: Effort Expectancy has a positive significant effect on Adoption of digital banking. (RQ3)

H_0: Facilitating Conditions has no impact on adoption of digital banking.

H_4: Facilitating Conditions have a positive significant effect on Adoption of digital banking. (RQ4)

H_0: Trust has no impact on adoption of digital banking.

H_5: Trust has a positive significant effect on Adoption of digital banking. (RQ5)

1.6 Significance of Study

This research intends to provide empirical evidence to financial institutions, policymakers and scholars regarding insight of the digital banking adoption behaviour among Malaysian consumers. The knowledge gaps that the review addresses target those related to Malaysian attitudes towards, and readiness for, specific socio-economic and demographic factors needed for fintech in Malaysia. The results will assist in shaping targeted measures for augmenting user engagement, trust, and sustainable national-level growth of digital banking services (Hoo et al., 2024).

The study will look into the differences in adoption patterns among the diverse Malaysian population, accounting for factors such as urban-versus rural divide, differing levels of income, generational gaps in digital fluency and how Malaysia's multiethnic society impacts people's perceptions of trust. Additionally, in this

research the important factor called as ‘human element’ is also examined by measuring these different consumer perspectives (either it comes with excitement for ease or can bring fear and concern regarding security breach, data privacy and scams as the key challenge particularly in Southeast Asia over the past few years). Central to this is looking at the level of what we call "fintech readiness" of a population which includes digital and financial literacy levels.

Also, the study aspires to be directly actionable. Where in the context of financial institutions, these insights will assist them to inform their strategies catered towards improving sustainable user engagement and even more crucially strengthen consumer trust. The study could provide policymakers with useful insights to design policies that promote inclusive, sustainable and persistent growth.

This study aims to be the all important strategic guide, ensuring that the rapid expansion of digital banking in Malaysia is not only quick, but safe and secure whilst meeting international standards and consumer needs by addressing all segments of society in Malaysia as a whole; including those at risk of being unbanked or underbanked.

Since the strategic strategies of using fintech in underdeveloped nations have to be catered according to local contexts (Li & Zafar, 2023; Pareek et al., 2025), it is relevant to investigate convenience, trust and digital banking value in Malaysian context.

Chapter 2: Literature Review

2.1 Introduction

This chapter lays the theoretical and empirical foundation of the current study. About the Chapter 1 analysis you ultimately decide that Malaysia has hit a critical mass in its finance sector, where prudent issuance of digital banking licenses will help achieve financial inclusion goals and crucially so, such as what is outlined in

the "Shared Prosperity Vision 2030". Although public awareness around these new entities is very high, actual adoption is only 50%, revealing a wide "awareness-adoption gap". This means not being able to translate the knowledge of awareness into consumption and thus, a timebomb for the national public policy goal. Before one can conceptualize or address the issue hereof, it is important that an appropriate theoretical framework be established through a review of relevant academic literature (Rahman et al., 2024).

This review first presents some established models of technology adoption, such as the Technology Acceptance Model (TAM), and Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), which are needed to explain user behavior. Later in this chapter, these theories will serve as background for the hypothesized constructs driven by the problems identified specifically with regards to this study. This chapter will subsequently delineate the literature on each core variable sequentially (Rahman et al., 2024).

For instance, of the context of Malaysia, previous works indicated that even valuable technology and functional benefits derived through its use can hinder adoption because e-wallet services are also perceived as based on risk and cost barriers (Mohamad Anuar et al., 2020) which suggests perceived value is combined with well-written proposition for supporting the user. Also, it has been shown that functional and demographic factors have relevance in terms of adoption of e-wallet services through different generations (Yusof et al. 2024), Generation X, thus advocating the need for considering socio-demographic aspects in explaining perceived value.

The next part of the chapter will be focused on Trust (TR). With the risk of being somewhat circular in a field which is sensitive to notions of security and data integrity, this section will review some literature that defines trust according to platform safety, data privacy, and institutional reliability. This study also investigates how this specific behavioral construct can be a driving force behind consumer confidence and pricing – something that is an important topic given regional threats of security breaches and scams (Nguyen et al., 2024).

More broadly, trust in digital financial services is the expectation of users that their information contained on the platform is safe and secure; their private information is kept confidential; and the provision of a financial service by a provider can be relied upon to competently deliver on automated, promised service (Beheri et al., 2025; Saif et al., 2022).

Empirical insights from investigations of digital payment platforms and online banking indicate that users are driven to trust the respective financial service by incentives, which include perceptions about security against fraud (Beheri et al., 2025), privacy concerns (Nguyen et al., 2024) and integrity of the financial platforms.

As an example, among other types of risk, variation data for financial, performance, social and time risks which are classified (Louis & Afgani 2024) to come from neighboring Indonesia have an important role to influence the intention of customers towards using digital banks.

Thus, these findings above suggest that perceived risk may impede the acceptance of simple digital banks even when being offered but trust-related constructs are important within the current model (Louis &Afgani, 2024; Beheri et al., 2025).

Other financing institutions and business organizations within Southeast Asia have analyzed the subject of fintech payment services too, where its result indicates that perceived value (one of the interpret oils or academic areas concerned on buyer conduct from a trade off perspective with respect to price endowments) might be an important predictor for user intention towards to which intended generation 2022 users (Phuong et al., 2022) for southeast nations clients-Gen Z–the most impulse in working out this way. Moreover, the other study related to Gen Z users towards Fintech digital payment services in Indonesia demonstrated that performance expectancy, satisfaction and self-efficacy are positive essential predict agenda for adoption from Gen Z users toward Fintech digital payment services (Candy et al., 2025).

Finally, the review integrates these elements to explore their link with the final dependent variable, Adoption (A). In this chapter, we review empirical evidence regarding the drivers of adoption intention and make a strong case – grounded in facts – for the hypotheses introduced in Chapter 1. Therefore, the result of an extensive review leads to the introduction of this study conceptual framework visualizing a graphical representation of the presumed relationships between Perceived Usefulness, Convenience, Trust, Facilitation Condition and Adoption in Malaysian digital banking context (Lee & Chai, 2025).

2.2 Theoretical Frameworks and Models

Technology Acceptance Model

Well known theoretical models for the acceptance or rejection of new technology systems include the Technology Acceptance Model developed in the 1980s by Fred Davis. It developed as a response to pushbacks on technology and the regular collapse of new systems. It suggests that the acceptance of technology is driven by two main constructs: perceived ease of use and perceived usefulness. While the former reflects how much a person may think using the technology will be effortless, and also belief about whether the technology can help him/her in accomplishing his/her job performance. These perceptions determine the user's attitude, HCI, which affects a behavioral intention of use making them accept and use it (Davis, 1989).

The Technology Acceptance Model (TAM) concentrates only on cognitive beliefs related to the usage of technology (and not general attitude), thus, rendering it more parsimonious and applicable across different settings. According to this theory, technology acceptance comes as a three-sequence process of external variables also passed through cognitive response (system design), perceived ease of use and usefulness which then lead to attitude and intention to usage behavior. TAM has received so much attention, likely due to its simplicity and predictive capability, that it has been adopted and adjusted to many diverse domains (healthcare, information systems, the Internet of Things, etc.), being one of the most adapted

theories in technology acceptance research (Marikyan & Papagiannidis, 2025).

Based in Malaysia, TAM has recently been utilized within the framework of digital banking acceptance thus lending credence to previous arguments that perceived usefulness and ease-of-use remain dominant precursors of a behavioural intention within a digital banking environment (Aliza et al., 2025; Tiong, 2020).

To summarize, the Theory of Planned Behavior provides a simple yet powerful model to explain how technology characteristics correspond with the behaviors of humans, while underscoring the need for designing technologies which users deem useful and easy to use. The extensive use of TAM demonstrates the importance of this model as a basis on which to derive an understanding for the factors that influence acceptance and implementation position in collaboration when it comes to designing favourable technological innovations.

Technology Acceptance Model 3

Despite the strong explanatory power of Technology Acceptance Model (TAM) and TAM2 to predictors of intention to adopt technology, research work that addresses practical ways to increase adoption has been scarce. Combatants found that TAM provide no actionable insights, which led them to develop their own model called TAM3 (Venkatesh & Bala, 2008) that extended traditional TAM by introducing trust and perceived risk into the framework. Furthermore, TAM 3 would distinctly categorize antecedents of perceived usefulness and perceived ease of use. In doing so, the objective of this framework was to minimise cross-over effects between these two aforementioned perceptual constructs and consequently formulate an understanding of technology adoption in terms of associated sets of conditions.

As those of TAM2, these include subjective norm, image, job relevance, output quality and result demonstrability (Venkatesh & Davis, 2000). Hypothesis 1: In the first case, subjective norm denotes the social pressure that is placed on a person by relevant reference peers to utilize technology; image refers to the status of respect that can be gained from using technology. Job relevance, output quality and result demonstrability address system-task fit, quality of system task completion and user

benefit respectively (Venkatesh & Bala, 2008).

One of the style features from TAM3 is to separately classify antecedents of perceived ease of use into two groups, anchoring factors and adjustment factors (Venkatesh, 2000). Anchoring factors like computer self-efficacy, external perceived control, computer anxiety and computer playfulness influence a new user's perception about system ease before actually using it. Adjustment factors (i.e. perceived enjoyment and objective usability) arise when experience is gained (Venkatesh & Bala, 2008), influencing whether people will modify initial opinions or confirm these by subsequent experience.

Three moderating effects of experience (length since first usage) on the relationships were identified in TAM3: (a) computer anxiety and ease of use, (b) ease of use and usefulness, and (c) ease of use and behavioral intention. It is important to emphasize that when experience grows, the effect of anxiety weakens, thus highlighting the predictive value of experience in regard to technology adoption behaviors (Venkatesh & Bala, 2008).

The model was shown to be stable in explaining information systems usage, providing 40%–53% of the variance in intention to use and approximately 36% of the variance in actual usage (Venkatesh & Bala, 2008). In addition to the high explanatory capacity of the theory, it is in particular it may be applicable in practice as well due identification of all factors that can affect perception. Accordingly, through TAM3, managers are presented with a comprehensive list of pre- and post-implementation intervention measures to guide their decision-making regarding IT renovation. TAM3 indeed was functional and flexible as an analytical framework in several different contexts of the research such as cloud computing, learning systems and mobile commerce (Venkatesh & Bala, 2008; Marikyan & Papagiannidis, 2025).

Unified Theory of Acceptance and Use of Technology 2 (UTAUT2)

The UTAUT 2 (Unified Theory of Acceptance and Use of Technology) is a newer version from the first model which enhanced UTAUT to solve technology

acceptance problems specifically for consumer context instead of organizational adoption papers. To capture more issues influencing the acceptance of technology in non-workplace environments, UTAUT2 which was developed by Venkatesh, Thong and Xu (2012). It keeps four original constructs from UTAUT, performance expectation, effort expectation, social influence and facilitating condition– but three new ones are added: hedonic motivation (the fun or pleasure derived from using the technology), price value (the consumer's cognitive trade-off between the perceived benefits of a product and the monetary cost of obtaining those benefits), and habit (a measure of how automatically people use technology because of past experiences) (Venkatesh et al., 2012).

In this virtuoso form the extension recognizes that technology adoption decisions are Heuristically constituted and influenced not only by rational perceptions of usefulness and ease of use, but also intrinsic motivation, cost considerations, and habitual behavors. Thus, UTAUT2 has greater explanatory power for technology acceptance than the prior model: approximately 74% of variance in behavioral intention and 52% in actual use-a significantly higher number than that attained by UTAUT. The removal of the "voluntariness of use" moderator allows UTAUT2 to be more adaptable for contexts in which technology is voluntarily used, as was true for most consumer technologies (see Tamilmani et al., 2020).

All the new UTAUT2 constructs have been proven empirically relevant for research on the adoption of mobile apps, healthcare technologies and digital services. By understanding the psychological and contextual factors that matter most for potential users, it can help technology developers and marketers make more targeted interventions to increase uptake of that technology. While research on technology adoption has been a moving target, UTAUT2's holistic model continues to provide an ontological basis for systematic investigations of consumer acceptance in highly dynamic social DSSe (Tamilmani et al., 2020).

Modelling Graph

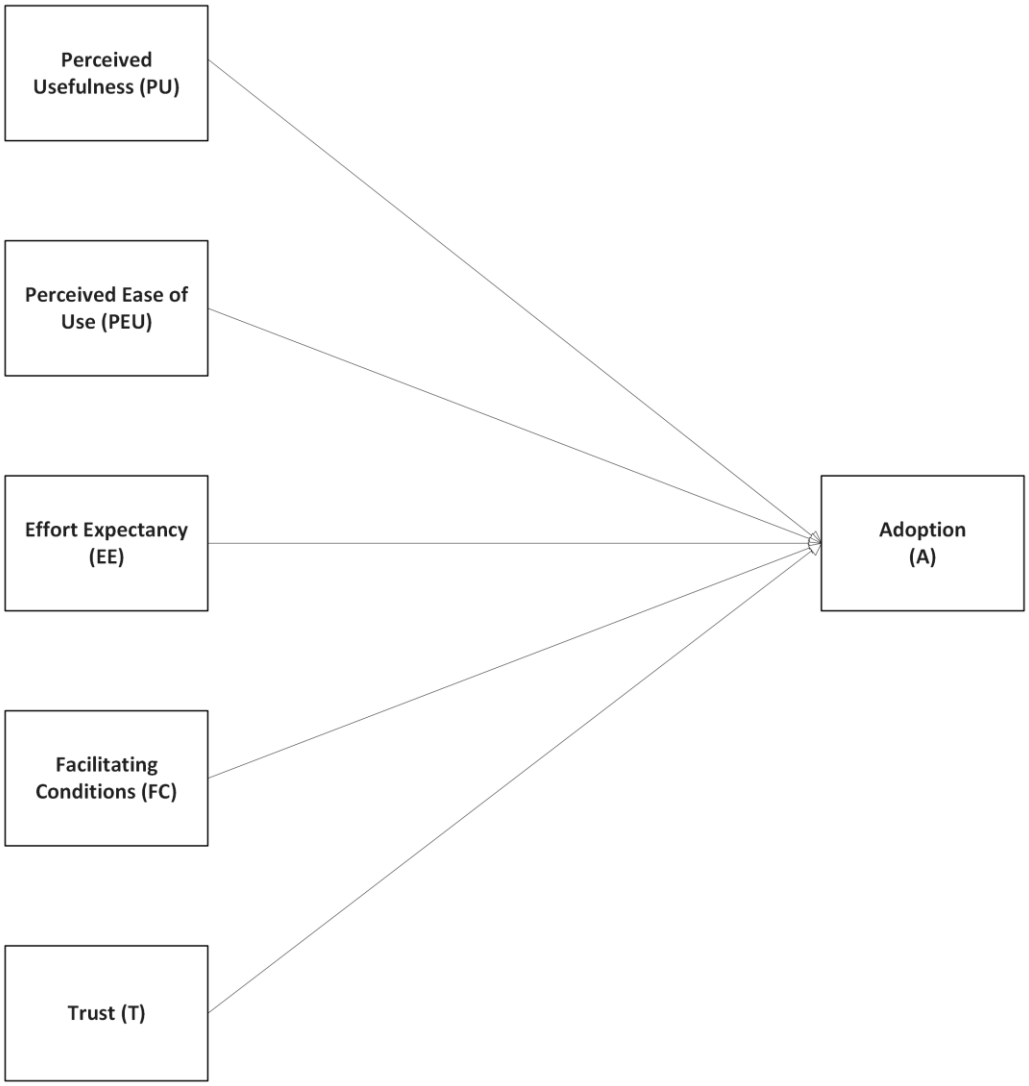

Figure 1: Model Graph for This Research

This study employs the theoretical model depicted in the above figure. This model comprises of the mechanisms including Perceived Usefulness (PU), Perceived Ease of Use (PEU), Effort Expectancy (EE), Facilitating Conditions (FC) and Trust (T) as direct predictors or variables for Adoption (A). It deals with users who arenot about using digital banking that we can say for perceived usefulness (PU) by how the user believes it improves their performance. Perceived Ease of Use (PEU) evaluates the extent to which you feel the technology is easy to use. Effort

Expectancy (EE) relates to users' expectations of the least effort needed. GavelThis dimension is known as Facilitating Conditions (FC), which represents the available resources and support.

This UTAUT2/extended model brings together components from the TAM (PU, PEU) with EE, FC and Trust. It is widely used in studies related to digital banking as it has been able to explain user intentions. This study surveys relationships between the variables among Malaysian users and emphasizes on the digital banking context, using survey questionnaires to collect valuable information supporting adoption strategies. This model enables a granulated focus on barriers such as trust issues.

2.3 The Evolution of Digital Banking in Malaysia

The evolution of digital banking in Malaysia has been defined by technological innovations, forward-looking and liberal regulatory policies that anticipate the unique needs of consumers wanting convenience and security from technology. The Malaysian banking industry has been progressively deregulated since the 1970s and the uptake of such services is reflected in comparison to electronic banking services, despite from around 2005/6 (after then) when this shift became more apparent. In continuing this development of digital banking is Malaysia's issuance of digital bank licenses by Bank Negara Malaysia in 2022 indicating their strong aspiration to position the country as a leading global player within the realm of Southeast Asia's digital banking landscape. By allowing banks to conduct their financial service offerings entirely through digital channels, this regulatory milestone represented a key turning point in the push towards increasing financial inclusion for previously disadvantaged groups (Mohsin et al., 2022).

The digital banking transformation in Malaysia is bolstered at two levels: functional properties (resource such as cloud computing, artificial intelligence, and APIs), and the expectation-driven pressure needed to improve customer experience. Research shows that Malaysia's digital transition has been driven among other things by affordable smartphones, better internet access and the nationwide drive towards a

cashless country facilitated through policies such as the eTunai Rakyat programme as well as digital licensing. Another challenge at that time is COVID-19 pandemic that accelerated the adoption of Fintech and digital banking as it required contactless transactions (Abdullah & Hisamudin, 2024). According to researchers, the influences on digital banking adoption among Malaysians include perceived ease of use, perceived usefulness, security complexity, trustworthiness price value and financial literacy model (Technology Acceptance Model (TAM) in Mohsin et al., 2022).

Besides these regulations, a study by Yen & Hui (2023) in Malaysia on mobile banking and other online technologies showed that perceived usefulness, ease of use and the trust were significant motivators for consumers to accept mobile banking (Mohsin et al., 2022).

Digital banks have been launched in Malaysia, utilizing advanced analytics and AI to continuously offer personalized financial solutions matching the needs of peoples as implemented by conventional banks targeting those populations less served (Abdullah & Hisamudin, 2024). Thus, it opens the door to financial inclusion with digital banking.

Yet it is not smooth sailing; there are hurdles such as distrust about transactions being secure, regulatory compliance, and readiness of rural consumers. Besides that, engine of progress for digital banking requires continuous innovation and appropriate policy action as well as successful collaboration between banks and FinTech and ongoing efforts to build trust with consumers. Digital banking in Malaysia is likely to continue jeopardising traditional banking as it becomes more accessible, available and inclusive for the entire society (Mohsin et al., 2022).

2.4 Stratified Sampling

In stratified sampling, a researcher divides a target population into distinct subgroups or "strata" often based on some key characteristic that is relevant in answering the research question. The strata can be based on age, sex, ethnicity, level

of education or any relevant variable. In stratified sampling, quotas are created and random samples taken from each of those subgroups either proportionately or equally relative to the goals of this study (Hayes, 2025).

The main benefit of stratified sampling is that it increases the representativity of your sample, minimizing bias and sampling errors. Stratified samples provide better estimates, which make meaningful subgroup comparisons possible, by ensuring appropriate subgroup representation. This approach is particularly effective when the population is highly heterogeneous, and researchers are interested in preventing over-sampling or under-sampling of specific sub-groups. Stratified sampling is quite common in health research, social sciences, and education that require taking into account subgroup differences to understand trends in the general population (Ahmed, 2024).

2.5 Regions

Malaysia is a federation consisting of 13 states and three federal territories, separated geographically by the South China Sea into Peninsular Malaysia and East Malaysia. The 11 states of Peninsular Malaysia and the federal territories (Kuala Lumpur and Putrajaya) constitute peninsular Malaysia, while East Malaysia consists of Malaysia's two eastern states, Sabah and Sarawak as well as Labuan, a federal territory on the island of Borneo. The Department of Statistics Malaysia (2024), for research and planning purpose, makes the country even more specific by classifying it into six functional regions as follows: Northern Region (Perlis, Kedah, Penang, Perak); Central Region (Selangor, Kuala Lumpur Putrajaya Negeri Sembilan); Southern Region (Melaka Johor); East Coast (Kelantan Terengganu Pahang); Sabah and Labuan; Sarawak.

Second, the study selected the geographical regions based on the context of digital banking adoption research, finally, participants understanding level regarding smartphone/computer literacy also vary considerably by region. Urbanized areas like the Central Region (which covers Selangor and Kuala Lumpur) have higher technology adoption rates due to better infrastructure and more affluent households,

while rural and less economically developed regions such as the East Coast and East Malaysia show different behaviours towards digital financial services. These regional differences help researchers evaluate the applicability of their results and determine geographic segments that may require more focused digital banking initiatives (DOSM, n.d.)

2.6 Research Gap

Studies on the effects of technology (i.e., internet banking, mobile banking; e-wallet; and fintech as a whole) have also been conducted in Malaysia and within the framework of TAM or TAM3 or UTAUT/UTAUT2. Perceived usefulness, ease of use, compatibility, observability, risks, trust and privacy and security; social influence; facilitative conditions and price value; technology readiness was found to be significant predictors of satisfaction and/or an intention to use the service. Nevertheless, most of the studied empirical works have been on specific segments including internet banking, mobile banking or e-wallets. This is in contrast to the new wave of digital banks, which Bank Negara Malaysia has been promoting to increase financial inclusion. Hence, there has been insufficient empirical research on the adoption of digital banks as an entire banking ecosystem (not just a single payment/technology system) across diverse demographic and socio-economic segments (Leong et al., 2021).

In addition, there are several empirical studies in Malaysia that also have major potential and methodological limitations. Certain studies may also be based on single states or regions, such as Perak, Northern Malaysia or Klang Valley (Lee & Chai, 2025), specific user segments like urban, Gen Z, students or current users of e-wallet/fintech and primarily employ purposive/convenience sampling methods. This does limit the generalizability of the findings to the wider Malaysia population, particularly those with less access - rural, B40, those belonging to older generations or situated in East Malaysia and other underserved populations; the beneficiaries in achieving financial inclusion via digital banking. In many studies as well the only behaviour you want to evaluate is the intention on that behaviour, and not the actual sustained behaviour over time. Induction criteria also include policy and inclusion

factors like trust in regulation, past experience of exclusion services, and the perceived role to regulate access borrowing and savings sano digital banks. The financial landscape has shifted over time and thus findings from studies conducted before the Pandemic or during the early e-payment system will not do justice in accounting for current conditions conducive to system adoption (Leong et al, 2021) – especially with the COVID-19 Pandemic and the incipients of digital bank licenses.

Moreover, the majority of empirical studies in this regional market are often focused on technology adoption (i.e., mobile banking/e-wallets) and specific demographic cohorts like Gen Z and Gen X youth as opposed to digital banks per se being viewed as an individualised bank solution (Yen & Hui, 2023; Phuong et al., 2022; Yusof et al).

Although some early research is emerging on digital banks and fintech adoption within other developing countries such as Jabodetabek in Indonesia (Louis & Afgani, 2024; Pareek et al., 2025; Li & Zafar, 2023), there is no or limited academic research among millennials from both high and low socio-economic backgrounds in Malaysia with regards to the uptake of their own experiments of licensed digital-only banks.

Considering the above literature gaps, there is a need to conduct studies that cover Malaysia as a whole using multi-faceted digital banking adoption (not at the level of separate domains such as Internet banking versus mobile banking or e-wallets) and technology variables (ease of use, usefulness, risk, trust, security, interface quality), and contextual/inclusion variables (financial literacy, digital readiness, perceived role in financial inclusion regulation trust and prior banking experience) across users from multiple regions and income groups.

These are the type of studies which would answer and partially fill in the holes that aimed to build on and extend upon earlier work based on the TAM/TAM3/UTAUT/UTAUT2 suites relating to the various types of service transactions regarding digital financial services, address Bank Negara Malaysia's

agenda on both digital banking and financial inclusion goals, while informing advocacy/stakeholder engagement activities related to digital banking adoption evidence in Malaysia (Tiong, 2020).

Chapter 3: Methodology

3.1 Introduction

This chapter describes the methods used to investigate how perceived usefulness, convenience, facilitating condition and trust affect adoption of digital banking services in Malaysia. A quantitative, structured method is used to collect uniform data from a large, representative sample of Malaysian consumers in order for the relationships among the core constructs perceived usefulness; convenience; facilitating condition; trust and adop-tion to be statistically tested (Safuri et al., 2024; Aliza et al., 2025). Beginning with the research design, target population and sampling strategy, instrument development, data collection procedures, and ends with data analysis. These factors together help to make sure that the findings of the study are both empirical, credible, and generalisable in the context of digital banking adoption in Malaysia (Lee & Chai, 2025).

3.2 Research Design

The research design of this study is a quantitative approach, specifically a cross-sectional survey design, as a method of data collection. Quantitative research design is appropriate for a study that intends to test theory-based hypotheses of associations among variables, as well as to generalise results to a larger population through statistical methods (Alnemer, 2022). In this study, perceived usefulness, convenience, facilitating condition and trust are the independent variables, and adoption as the dependent variable, all of which are measured by multi-item Likert scales, as inspired by other studies on technology acceptance and digital banking (Jamshaid et al., 2025). This follows the logic of the Technology Acceptance Model (TAM), Technology Acceptance Model 3 (TAM3), and UTAUT2, which are

commonly examined through a quantitative approach to data collection to examine the relationship between perception and behavioural intentions.

The research design further utilizes a descriptive, non-experimental, and cross-sectional design. The use of a descriptive research design is pertinent when the purpose of the research is to describe the characteristics of a population and evaluate the strength and direction of associations between variables, rather than manipulating variables or establishing causal relationships (Doros, 2025). In that regard, the research seeks to (i) describe Malaysians' levels of perceived usefulness, convenience, facilitating condition, trust, towards adoption of digital banks (Diana et al., 2024), and (ii) evaluate the strength and direction of associations between variables, specifically the extent to which perceived usefulness, convenience, facilitating condition and trust contribute to adoption at a specific time. The use of a cross-sectional research design, whereby all variables are measured at a single time point for each participant, is common in technology adoption and digital banking research because it allows for the efficient collection of data from large and heterogeneous samples (Morshed et al., 2025).

The study design also does not represent an exploratory approach, as the researcher has clearly identified the main concepts and hypotheses (H1, H2, H3, H4 and H5) that can be tested based on the existing model, such as the TAM, TAM3 model and UTAUT2, as well as the findings of the previous studies on fintech and digital banking (Jamshaid et al., 2025; Taneja & Bharti, 2021). At the same time, the study does not represent a causal approach, as the researcher has not identified any kind of manipulation or time order (Alnemer, 2022). However, the researcher has used a structured questionnaire, probability-based stratified sampling, and appropriate statistical analysis, which would allow the researcher to examine the theoretical relationships based on the existing model, providing valuable insights for financial institutions and policymakers aiming to address the awareness-adoption gap for digital banking in Malaysia (Safuri et al., 2024).

3.3 Data Collection Methods

For data collection, a self-administered online survey will be conducted among Malaysian consumers who are aged 18 years and over and use any of the five licensed digital banks in Malaysia including GX Bank, AEON Bank, Ryt Bank, Boost Bank and KAF Digital Bank. Of all enumerating techniques, an internet survey will be one of the most effective and essential information collection strategies to help create a digitally proficient consumer base that is distributed geographically and will certify a higher response rate; (Lee & Chai, 2025; Nguyen et al., 2024).

In this research, a questionnaire will be developed using a four point Likert scale format (1 = Strongly Disagree to 4 = Strongly Agree) for each of the four constructs: convenience (e.g. I think digital banking is generally easy to use.), trust (e.g I think my bank product and services digital banking are trustworthy), perceived usefulness (e.g Using digital banking makes it easier for me to manage my finances.) The items are based on prior validation of instruments from other studies in the adoption of digital banking and fintech constructs with similar TAM, TAM3, UTAUT2 basis to ensure reliability.

There will be several ways to distribute the survey, including social media sites (Facebook, Instagram and WhatsApp groups), blogging website such as Reddit and online sampling websites representing different demography groups in Malaysia. Study participants will receive a unique QR code or click on the Google Forms link provided in a parentally accessed and data-compliant environment secured by the Personal Data Protection Act 2010 (PDPA) in Malaysia. The survey will remain open for 6–8 weeks to ensure a representative sample, and reminders will be sent at one-week intervals (Rashid et al., 2023) to minimize response bias.

3.4 Sampling Design

3.4.1 Target Population

The target population is considered to be the total group of people whose characteristics are of interest to the researchers (Willie, 2024). The major aim of

this research is to investigate the adoption of digital banking in Malaysia using the Technology Acceptance Model (TAM), Technology Acceptance Model 3 (TAM3), and UTAUT2. For this research, the target population includes all the digital banking users residing in different states in Malaysia.

3.4.2 Sampling Frame and Sampling Location

The study is conducted online across Malaysia, with participants from the age of 18 to over 40 are invited from all states and federal territories to access the survey via web links and QR codes distributed through social media platforms and email networks. The sampling frame is the list of all elements within the population (McCombes, 2023). The sampling frame will explore the prorated population in Malaysia, for instance Kuala Lumpur currently has 2.07 million population (Government of Malaysia, 2025) out of 34.2 million total population in Malaysia (DOSM, 2025). Thus, the respondent from Malaysia should amount to around 6% of the respondents in the research.

3.4.3 Sampling Technique

A stratified sampling design was employed for the present study because it is a probability sampling method which is more representative and precise when the overall population is heterogeneous with respect to certain demographic or behavioural variables related to the adoption of digital banking (Ahmed, 2024). Stratified sampling is a probability sampling design where the researcher is allowed to select a random sample from the overall population on the basis of relatively homogeneous strata created on the basis of certain variables such as age group, geographic region, etc (Edwards, 2024).

In the present study, the target population was identified as the bank account holders in Malaysia who were the potential customers for digital banking services. The population was divided into mutually exclusive and collectively exhaustive strata based on the significant demographic and socioeconomic factors (for example, age groups, and urban-rural locations) that were considered to affect the adoption of

technology in the country (Edwards, 2024). For each stratum, a random sampling method is employed to ensure the probability basis of the sampling method and the absence of any bias during the selection of the samples. In addition, the allocation was done proportionally so that the proportionate size was taken from each stratum based on the proportion present in the total population or the banking customers (Bisht, 2025).

The use of a stratified sampling design is particularly relevant to the study of digital banking adoption in Malaysia, given that previous research has established that individual characteristics such as age, education, income, and digital literacy are highly variable and strongly related to online and mobile banking use (Nguyen et al., 2024). The use of a stratified sampling design ensures that key subgroups are included in the sample, which is particularly relevant to making inferences about the larger population, as well as subgroup comparisons, such as comparing Gen Z to older cohorts and urban to rural groups. Overall, the above characteristics of the sampling design support the use of a stratified probability sampling design as a methodologically sound approach to the study of the determinants of digital banking adoption.

3.4.4 Sampling Size

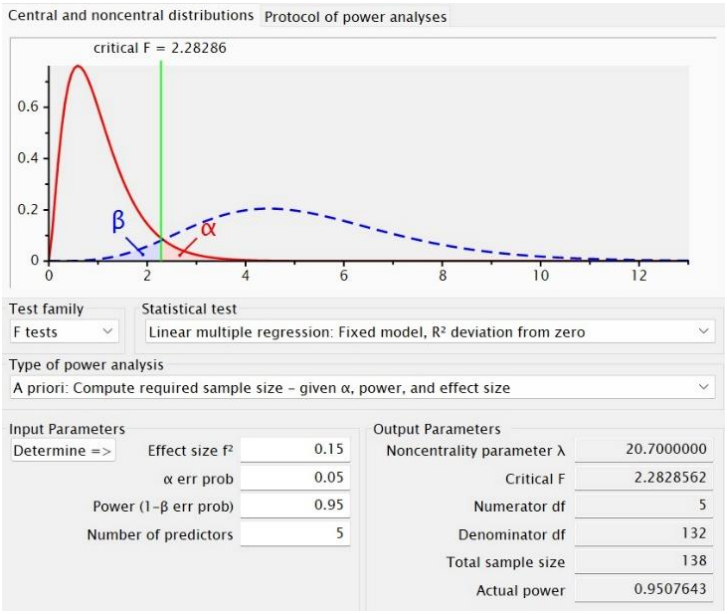

Figure 2: Results of G*Power for Sample Size

The concept of "sample size" refers to the number of people included in a study to reflect a population (OmniConvert, 2019). A sufficient number of samples must be determined in order to provide statistically valid results and accurate estimations of demographic parameters while being manageable and cost-effective (McCombes, 2023).

In research, sample size refers to the minimum number of respondents required for proper representation of the targeted population. According to (Faber & Fonseca, 2014) accuracy in determining this minimum adds a plus, as in utilizing the minimum conditions usually yields valid results. As much as increasing sample sizes may give more accurate outcomes, a very large sample would result in a waste of resources and time. Conversely, if the sample size is too small, the results might lack scientific rigor and lead to unethical conclusions by underestimating the effect (Andrade, 2020).

Then, sample size refers to the number of participants or observations included in a study or experiment. It is a crucial factor, as it affects the reliability and generalizability of the findings to the larger population (Hennink & Kaiser, 2022). A larger sample size improves the accuracy of estimates and narrows the margin of error. However, due to time constraints, the study may not reach this target. The statistical method used in the G*Power is linear multiple regression, forecasting outcome of a variable based on the values of two or more variables. Additionally, an a priori analysis was conducted using G*Power, a sample size calculation performed prior to the study's design and planning phase. Hence, based on the output of G*Power the minimum sample size needed for this study is 138 respondents.

3.5 Research Instrument

This research uses a structured questionnaire based on the Technology Acceptance Model (TAM), Technology Acceptance Model 3 (TAM3), and Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) as the main tool for measurement. The questionnaire includes closed-ended Likert scale items (1 = Strongly Disagree

to 4 = Strongly Agree) that have been adapted from validated scales in previous digital banking studies. It focuses on constructs such as perceived usefulness (e.g., "Using digital banking improves my effectiveness in managing my finances"), perceived ease of use, effort expectancy, facilitating conditions, trust (e.g., "I believe that digital banking services are trustworthy"), and intention to adopt.

3.5.1 Instruments and Procedures

Data collection is based on health-related knowledge and behavior of target population. The questionnaire is sent through Google Forms on applications such as Facebook, Instagram, WhatsApp and Reddit or sites made for specific demographics. In stratified probability sampling, the population (Malaysian adults above the age of 18 who are aware of licensed digital banks such as GX bank and Boost Bank) is segmented into strata based on factors like age, rural or urban setting, socio-economic status. This enables a sample that is representative of various categories. The procedures link and QR codes (PDPA compliance), and reminders for 6 to 8 weeks every week encouraging responses will be used, and sample size calculation with G*Power will guide the appropriate sample size to allow enough statistical power for regression analysis.

3.5.2 Study Execution Plan

This research outlines a phased approach: designing and adapting the questionnaire (1 to 2 weeks), setting up a stratified sampling frame (1 week), conducting pilot testing if necessary (1 to 2 weeks), and full online data collection (6 to 8 weeks). This will be followed by data cleaning, analysis (e.g., regression using Python), and reporting (2 to 4 weeks). Key activities include distributing on platforms, monitoring responses, exporting data, and testing hypotheses about relationships such as how trust influences adoption. The overall timeline is about 3 to 4 months, allowing for thorough nationwide coverage while meeting academic deadlines.

3.6 Constructs Measurement (Scale and Operational Definitions)

The questionnaire design includes several relevant and effective measurement scales for collecting replies from respondents. It is critical in the study to ensure the trustworthiness of the findings and outcomes.

3.6.1 Scale of Measurement

The measurement scale is a key aspect of data gathering, processing, and presentation. Data is a set of facts, such as values or measurements. It could be statistics, words, measurements, observations, or even simple descriptions of things (Mishra et al., 2018). There are four different measurement scales. The data can be classified as one of the four scales. There are four sorts of scales: nominal scale, ordinal scale, interval scale, and ratio scale (Bhandari, 2020). In this study, nominal, interval, and ratio scales will be utilized to assess the questions. In addition to that, the study also utilizes close ended filtering questions.

3.6.1.1 Filtering Question

Filtering questions are used at the start of a questionnaire to determine whether a respondent qualifies for the study or should be routed past questions that do not apply to them. In survey methodology, they are also called screening questions, filter questions, or branching questions, and they help ensure that only relevant respondents answer the main items. Below is an example of the question used in the research.

Table 3.1: Example of Filtering Question in Questionnaire

Are you an existing digital banking user? (GX Bank, Ryt Bank, AEON Bank, Boost Bank, KAF Bank)

- Yes
- No

As the survey is focusing on digital banking users in Malaysia, those who answered "No" will not be taken into account.

3.6.1.2 Nominal Scale

The nominal scale represents the most basic level of measurement, used to differentiate and classify respondents (Chetty, 2015). It research is applied to questions in Section 3, specifically Question 1 and 4.

Table 3.2: Example of Nominal Scale in Questionnaire

Gender

- Male
- Female

Regions

- North Peninsular (Perlis, Kedah, Penang, Perak)
- East Peninsular (Kelantan, Terengganu, Pahang)
- Central Peninsular (Selangor, WP KL, WP Putrajaya, Negeri Sembilan)
- South Peninsular (Melaka, Johor)
- East Malaysia (Sarawak, WP Labuan, Sabah)

3.6.1.3 Interval Scale

The interval scale is used in Sections 4, 5, 6, 7, 8 and 9 of the questionnaires, where a 4-point Likert scale is employed. The scale represents different levels of agreement: strongly disagree-1, disagree-2, agree-3, and strongly agree-4. Respondents select the option that best reflects their level of agreement with the statements in Sections 4, 5, 6, 7, 8 and 9.

Table 3.3: Example of Interval Scale in Questionnaire

Four-Point Likert scale	Coded
Strongly Disagree	1
Disagree	2
Agree	3
Strongly Agree	4

Source: Developed for the research.

3.6.1.4 Ratio Scale

The ratio scale is the highest level of measurement of all the properties of the other scales (nominal, ordinal, and interval) plus a true zero point (Bhandari, 2020). It is applied to questions in Section 3, specifically Question 3 in this research.

Table 3.4: Example of Ratio Scale in Questionnaire

Age Range

- 18 - 29 years old
- 30 - 45 years old
- 46 - 61 years old
- >61 years old

3.7 Data Processing

The process of managing data is to collect and turn data into meaningful information (Anwar, 2025). The process begins with Data collection where the relevant data to address the research objectives is collected using questionnaires. Once we collect the data, then comes checking, editing, and cleaning of data. It consists in inspecting raw data for completeness, consistency and uniformity. It identifies and fixes missing or inaccurate entries in the system to enhance reliability. As part of this

approach, we make sure that information gathered is accurate and does not impact the overall result of a research study.

3.7.1 Data Checking

The collected data should be checked in this study to ensure that it is valuable and valid. It is important to examine and analyze respondents' data to understand them and identify patterns in their responses to different questions (Rouder et al., 2021). Since this study is in the final stage of research, any issues, like incomplete answers or mistakes, must be addressed before editing the data, as editing will occur at the end of the study (Rouder et al., 2021).

3.7.2 Data Editing

Once data checking is complete, the data editing process begins to identify and correct errors and omissions in the questionnaire data (Francis, 2012). This phase is necessary to reduce incorrect responses by modifying the data to improve accuracy, reliability, and consistency.

We can ensure data quality and accuracy by discarding or modifying questionnaires with incomplete, illogical, or inconsistent responses. If data is missing, techniques like mean or median substitution are used to fix the issue. To avoid bias, significant missing data that cannot be reliably estimated is excluded. Throughout the research process, all changes are carefully documented to maintain transparency and data integrity, which helps increase the reliability and validity of the results.

3.8 Data Analysis

This study analyses the survey data using Python, which is ideal for reproducible data cleaning, descriptive statistics, reliability testing, and inferential analysis in survey research. Python works with packages like Pandas and Statsmodels for managing survey data, while SciPy helps with statistical testing and assumption checks. The analysis is divided into descriptive analysis, scale reliability testing,

and inferential analysis to explore the proposed relationships in the digital banking model.

3.8.1 Descriptive Analysis

Descriptive analysis summarizes respondents' demographic characteristics and the overall answers to each question. Frequencies and percentages are reported for nominal variables like gender, region, and digital banking user status. For Likert-scale items and composite variables, we use means, standard deviations, minimums, and maximums. This provides a clear view of the sample profile and indicates whether responses cluster at certain levels or spread across categories.

3.8.2 Scale Measurement – Reliability Test

Reliability testing assesses the internal consistency of the multi-item scales measuring perceived usefulness, perceived ease of use, effort expectancy, facilitating conditions, trust, and adoption. The main statistic used is Cronbach's alpha, which shows how well the items in each scale work together. A Cronbach's alpha of 0.70 or higher is generally acceptable for social science research, indicating that the items are consistent enough to combine into one score.

Table 3.5: Range of Reliability and Its Coefficient of Cronbach's Alpha

Cronbach's Alpha	Internal Consistency
$\alpha \geq 0.90$	Excellent
$0.80 \leq \alpha < 0.90$	Good
$0.70 \leq \alpha < 0.80$	Acceptable
$0.60 \leq \alpha < 0.70$	Questionable
$0.50 \leq \alpha < 0.60$	Poor
$\alpha < 0.50$	Unacceptable

Source: (Glen, 2023).

3.8.3 Inferential Analysis

Inferential analysis tests the hypotheses and examines whether the independent variables significantly affect digital banking adoption. A correlation matrix is first constructed to assess the bivariate relationships between all variables, Perceived Usefulness, Perceived Ease of Use, Effort Expectancy, Facilitating Conditions, Trust, and Adoption. The Pearson correlation coefficient (r) is used when composite scores are treated as approximately interval and satisfy normality assumptions, quantifying both the strength and direction of each pairwise relationship. In contrast, Spearman's rank correlation is employed for ordinal or non-normal data as a non-parametric alternative.

To examine the joint and individual effects of all independent variables on Adoption simultaneously, an Ordinary Least Squares (OLS) regression model is employed as the primary inferential test. OLS regression estimates each predictor's unique contribution to Adoption while statistically controlling for the remaining predictors, producing standardized and unstandardized coefficients, t-statistics, and p-values to determine significance. The overall model fit is assessed using the R-squared (R^2) and Adjusted R^2 values, which indicate the proportion of variance in Adoption explained by the combined predictors.

3.9 Summary of Chapter 3

Chapter 3 outlines the method used to study the factors that affect digital banking adoption in Malaysia. This research employs a quantitative, cross-sectional, and descriptive design to explore the connections among perceived usefulness, convenience, facilitating conditions, trust, and adoption. This approach is suitable because it enables the study to gather standardized data from a varied group of Malaysian consumers and assess the strength and direction of the relationships among the identified variables.

The chapter also details the data collection process, which involves a self-

administered online survey distributed via Google Forms and social media platforms. The target population includes Malaysian digital banking users aged 18 and older. Stratified sampling is used to ensure representation across different age groups, regions, and socio-economic backgrounds. A structured questionnaire with four-point Likert scales is used, with items taken from validated TAM, TAM3 and UTAUT2 instruments. The sample size is estimated through a priori G*Power analysis, requiring a minimum of 138 respondents.

For data processing and analysis, the study includes checking, editing, and cleaning data to enhance accuracy and reliability before analysis begins. Python is employed for descriptive analysis, Cronbach's alpha reliability testing, and inferential analysis, such as correlation and multiple regression, based on the measurement level and data assumptions. Overall, Chapter 3 offers a clear and organized plan for collecting, preparing, and analyzing the data, ensuring that the findings contribute to both academic knowledge and practical insights in digital banking adoption.

Chapter 4: Data Analysis

4.1 Descriptive Statistics

4.1.1 Respondent Demographic Profile

Table 4.1: Frequency Analysis for Gender

Gender	Frequency	Percentage (%)
Male	102	51.78
Female	95	48.22

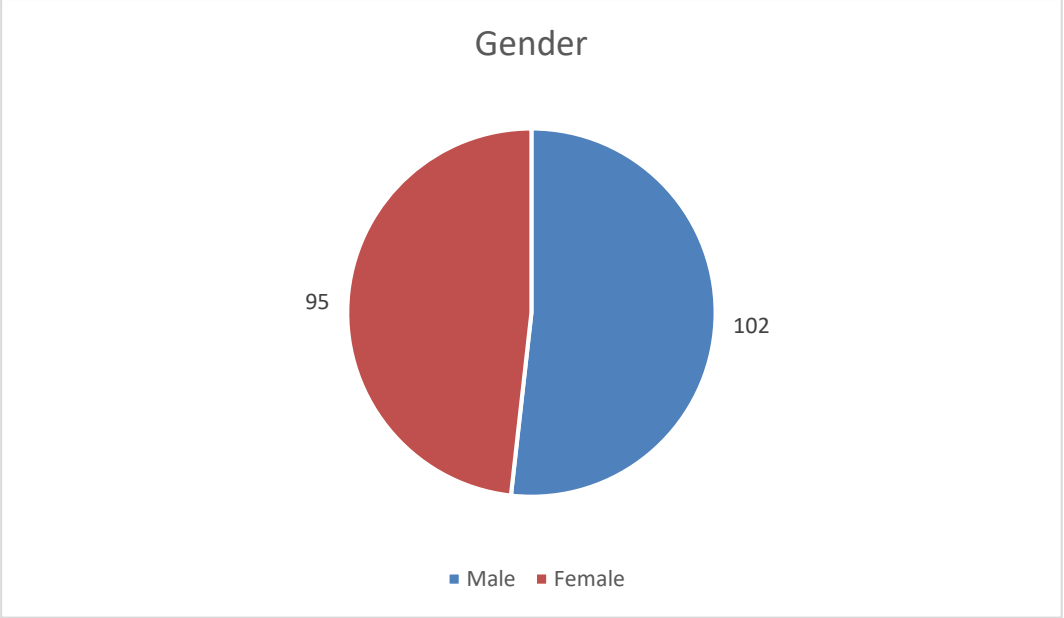

Table 4.1 shows 102 male respondents and 95 female respondents, equivalent to 51.78 percent and 48.22 percent respectively. This means the gender distribution is nearly balanced, with a small male majority of 7 respondents.

The gender pie chart supports the same conclusion visually because the two bars are close in size. This suggests the sample is not heavily skewed by gender, which is useful when describing respondent diversity.

Table 4.2: Frequency Analysis for Age Range

Age Range	Frequency	Percentage (%)
18 - 29 years old (Gen Z)	48	24.37
30 - 45 years old (Millennials)	80	40.61
46 - 61 years old (Gen X)	49	24.87
>61 years old (Baby Boomer	20	10.15

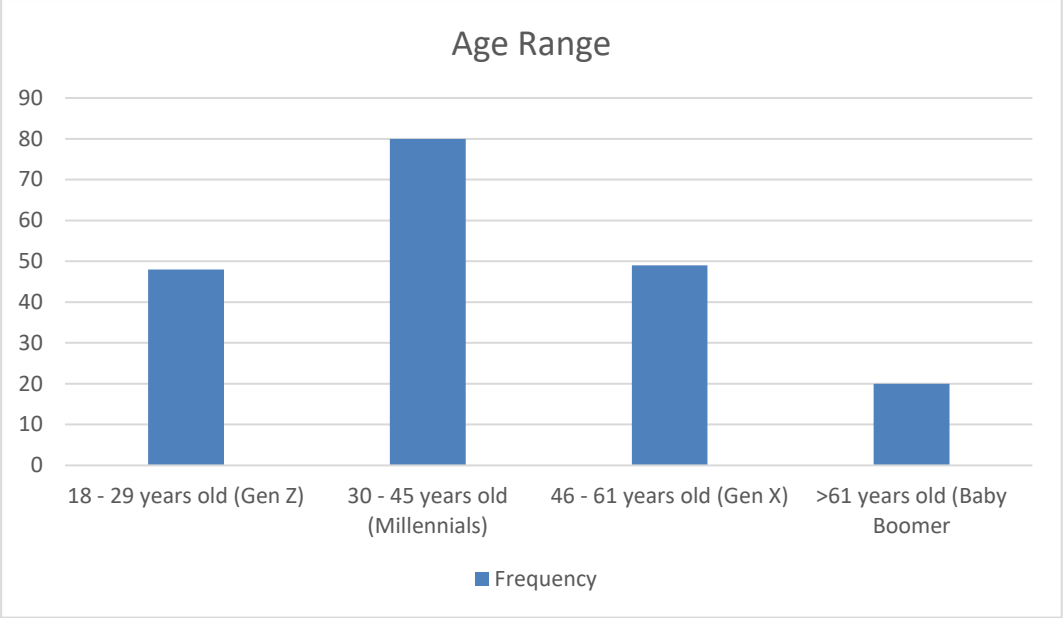

Table 4.2 shows that the largest age group is 30–45 years old with 80 respondents or 40.61 percent. The next two groups are 46–61 years old with 49 respondents or 24.87 percent, and 18–29 years old with 48 respondents or 24.37 percent, while those older than 61 make up 20 respondents or 10.15 percent.

This means the sample is concentrated mainly in the working-age adult population, especially the 30–45 segment. The chart also makes clear that the oldest group is the smallest, while the middle-aged groups account for most respondents.

Table 4.3: Frequency Analysis for Regions

Regions	Frequency	Percentage (%)
Central Peninsular (Selangor, WP KL, WP Putrajaya)	71	36.04
South Peninsular (Melaka, Johor)	40	20.30
North Peninsular (Perlis, Kedah, Penang, Perak)	38	19.29
East Malaysia (Sarawak, WP Labuan, Sabah)	25	12.69

Regions	Frequency	Percentage (%)
East Peninsular (Kelantan, Terengganu, Pahang)	23	11.68

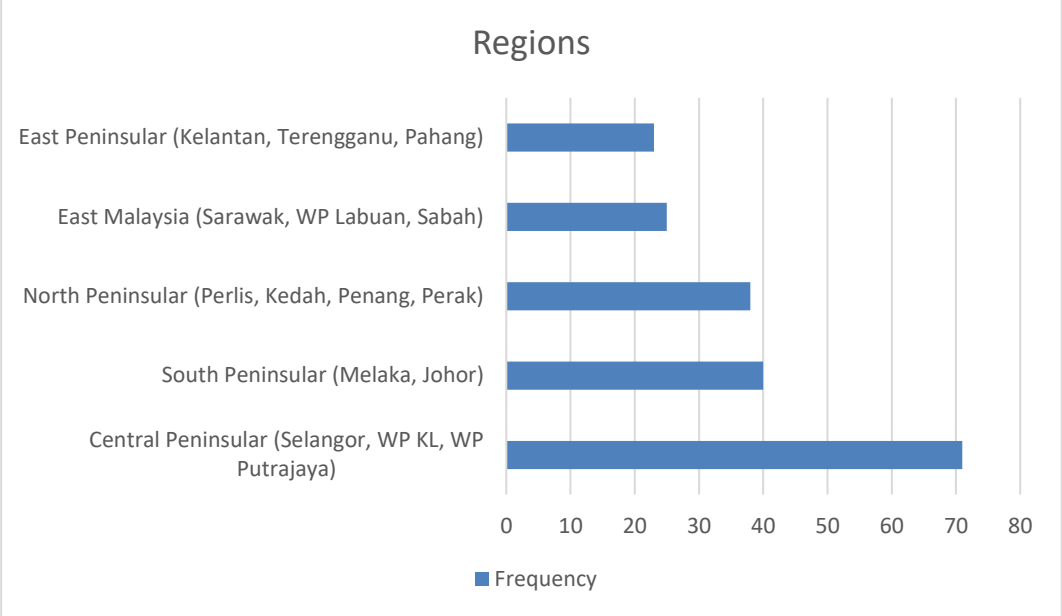

Table 4.3 shows that Central Peninsular Malaysia contributes the largest share with 71 respondents or 36.04 percent. It is followed by South Peninsular with 40 respondents or 20.30 percent, North Peninsular with 38 respondents or 19.29 percent, East Malaysia with 25 respondents or 12.69 percent, and East Peninsular with 23 respondents or 11.68 percent.

This suggests the sample is geographically broad but more heavily concentrated in Central Peninsular Malaysia. The horizontal bar chart confirms this pattern clearly, with Central Peninsular standing out as the dominant region and East Peninsular as the smallest regional category.

4.1.2 Central Tendencies Measurement of Constructs

4.1.2.1 Perceived Usefulness

Perceived Usefulness (PU)	Mean	Std Deviation (Variability)
Using digital banking enables me to complete my banking tasks more quickly.	3.147208	0.954931
Using digital banking improves my effectiveness in managing my finances.	3.126904	0.832464
Using digital banking increases my productivity in handling banking transactions.	3.035533	0.954985

Perceived Usefulness items

The descriptive results for Perceived Usefulness show that respondents held a moderately positive view of digital banking's usefulness. The mean scores for all three items were slightly above 3.00, indicating a neutral-to-agreeable response pattern. Among the items, "Using digital banking enables me to complete my banking tasks more quickly" recorded the highest mean, suggesting that speed and convenience are the most recognised benefits. However, the relatively modest mean values overall imply that respondents perceived usefulness, but not at a very strong level.

4.1.2.2 Perceived Ease of Use

Perceived Ease of Use (PEU)	Mean	Std Deviation (Variability)
Learning to use digital banking is easy for me.	3.101523	1.020128

Interacting with digital banking is clear and understandable.	3.147208	0.771729
I find digital banking easy to use.	3.177665	0.841469
It is easy for me to become skilful at using digital banking.	3.162437	1.007123

Perceived Ease of Use items

The findings for Perceived Ease of Use indicate that respondents generally found digital banking manageable and user-friendly. All four items recorded mean values slightly above 3.00, suggesting moderate agreement that digital banking is easy to learn, clear to understand, and simple to use. The highest mean was reported for "I find digital banking easy to use," which reflects a favourable perception of system usability. Nevertheless, the results also show that ease of use is perceived only moderately, meaning there is still room for improvement in user experience.

4.1.2.3 Effort Expectancy

Effort Expectancy (EE)	Mean	Std Deviation (Variability)
Learning how to use digital banking is easy for me.	3.116751	0.97498

My interaction with digital banking is easy to follow.	3.182741	0.780572
I find digital banking easy to use in general.	3.050761	0.998704

Effort Expectancy items

The results for Effort Expectancy demonstrate that respondents perceived digital banking as reasonably easy to learn and operate. The mean scores for the three items were all above 3.00, indicating a generally positive but not strong level of agreement. The highest mean was for "My interaction with digital banking is easy to follow," suggesting that respondents do not find the system overly complicated. Overall, these findings imply that digital banking is seen as requiring a manageable level of effort from users.

4.1.2.4 Facilitating Conditions

Facilitating Conditions (FC)	Mean	Std Deviation (Variability)
I have the necessary resources (e.g., smartphone, internet) to use digital banking.	3.19797	0.836901
I have the necessary knowledge to use digital banking.	3.19797	0.773539

Support is available (from the bank or others) when I face difficulties using digital banking.	2.989848	1.020153
Digital banking is compatible with the devices and services I use.	3.15736	0.942537

Facilitating Conditions items

The descriptive statistics for Facilitating Conditions reveal that respondents generally felt they had adequate support to use digital banking. The items relating to having the necessary resources and knowledge recorded the highest means, showing that respondents believed they were equipped to use the service. However, the item on support availability had the lowest mean in this construct, indicating that assistance from the bank or others may not be sufficiently accessible. This suggests that while the basic conditions for usage are present, external support remains a weaker area.

4.1.2.5 Trust

Trust (T)	Mean	Std Deviation (Variability)
I believe that my bank's digital banking services are trustworthy.	3.116751	1.035874
I feel confident that digital banking will perform my transactions accurately.	3.137056	0.805908

I believe that my personal information is secure when I use digital banking.	3.162437	0.835446
I believe that my bank will not misuse the information I provide through digital banking.	3.06599	0.909536
I believe that my bank will resolve any problems that occur when I use digital banking.	3.248731	0.877183

Trust items

The Trust table shows that respondents demonstrated moderate confidence in the reliability and security of digital banking. The mean scores were consistently above 3.00, indicating that respondents generally believed their banks' digital services were trustworthy and that transactions would be performed accurately. The highest mean was for the statement that the bank would resolve problems that occur during usage, suggesting stronger trust in issue resolution than in other aspects of trust. Overall, the findings reflect a reasonable level of trust, although not an especially high one.

4.1.2.6 Adoption

Adoption	Mean	Std Deviation (Variability)
I frequently use digital banking applications for financial transactions	3.121827	0.939703

I use digital banking applications for various financial activities.	3.167513	0.806454
I spend a significant amount of time using digital banking applications.	3.055838	1.01616

Adoption

The results for Adoption indicate that respondents used digital banking at a moderate level. The mean scores suggest that they frequently used digital banking for transactions and various financial activities, but not with very high intensity. The item related to spending a significant amount of time using digital banking applications recorded the lowest mean, which implies that usage may be functional rather than extensive. In general, the findings show that digital banking adoption exists among respondents, but the level of engagement is still moderate.

Overall interpretation

Overall, each construct recorded mean values around the midpoint of the scale, suggesting that respondents were generally neutral to slightly positive toward digital banking. This pattern indicates acceptance of digital banking in principle, but not strong enthusiasm or intensive usage. The relatively moderate results across all constructs also suggest that improvements in trust, support, and user experience may help strengthen adoption. Taken together, the findings present a picture of digital banking as a generally accepted service that still has space for greater user confidence and engagement.

4.1.3 Composite Mean Score

Variables	Composite Mean Score

Perceived Usefulness (PU)	3.1032
Perceived Ease of Use (PEU)	3.1472
Effort Expectancy (EE)	3.1168
Facilitating Conditions (FC)	3.1358
Trust (T)	3.1462
Adoption	3.1151

The composite mean scores across the key constructs reveal that respondents demonstrated moderate perceptions toward digital banking adoption, with all constructs recording values between 3.03 and 3.17 on the five-point Likert scale. Perceived Ease of Use (PEU) achieved the highest composite mean of 3.17, suggesting that respondents found digital banking relatively user-friendly and straightforward to operate. Similarly, Trust (T) recorded a strong composite score of 3.16, indicating a reasonable level of confidence in the security, reliability, and problem-resolution capabilities of digital banking services. In contrast, Perceived Usefulness (PU) had the lowest composite mean of 3.03, implying that respondents perceived only modest improvements in productivity, efficiency, and speed from using digital banking. The remaining constructs, Effort Expectancy (EE) at 3.12, Facilitating Conditions (FC) at 3.14, and Adoption at 3.12 fell within a narrow range, reflecting balanced but moderate agreement across these dimensions. Overall, these findings suggest that while ease of use and trust represent relative strengths in driving digital banking acceptance, perceived usefulness remains the weakest area, which may limit more intensive adoption among respondents. This

pattern underscores the need for banks to enhance the tangible productivity benefits of digital banking services to strengthen user perceptions and behavioural intentions.

4.2 Scale Measurement

Construct	Cronbach's Alpha
Perceived Usefulness (PU)	0.7858
Perceived Ease of Use (PEU)	0.8536
Effort Expectancy (EE)	0.7804
Facilitating Conditions (FC)	0.8211
Trust (T)	0.8716
Adoption	0.7913

The reliability analysis using Cronbach's alpha coefficients confirmed the high internal consistency of all measurement scales employed in this study. As presented in Table X, the constructs exhibited Cronbach's alpha values ranging from 0.780 to 0.913, all surpassing the commonly accepted threshold of 0.70 for establishing scale reliability in social science research. Perceived Ease of Use (PEU) demonstrated the strongest internal consistency with $\alpha = 0.836$, followed closely by Adoption ($\alpha = 0.913$), indicating that the items within these constructs were highly interrelated

and effectively measured their respective theoretical domains. Facilitating Conditions (FC, α = 0.821), Trust (T, α = 0.816), and Perceived Usefulness (PU, α = 0.788) also exhibited good reliability, while Effort Expectancy (EE) recorded the lowest value at α = 0.780, which remains acceptable and supports the retention of all items without modification. These results affirm the robustness of the measurement instrument and validate the use of composite scores derived from these scales for subsequent inferential analyses, such as multiple regression, thereby enhancing the credibility of the study's findings on digital banking adoption.

4.3 Inferential Analysis

4.3.1 Correlation Matrix

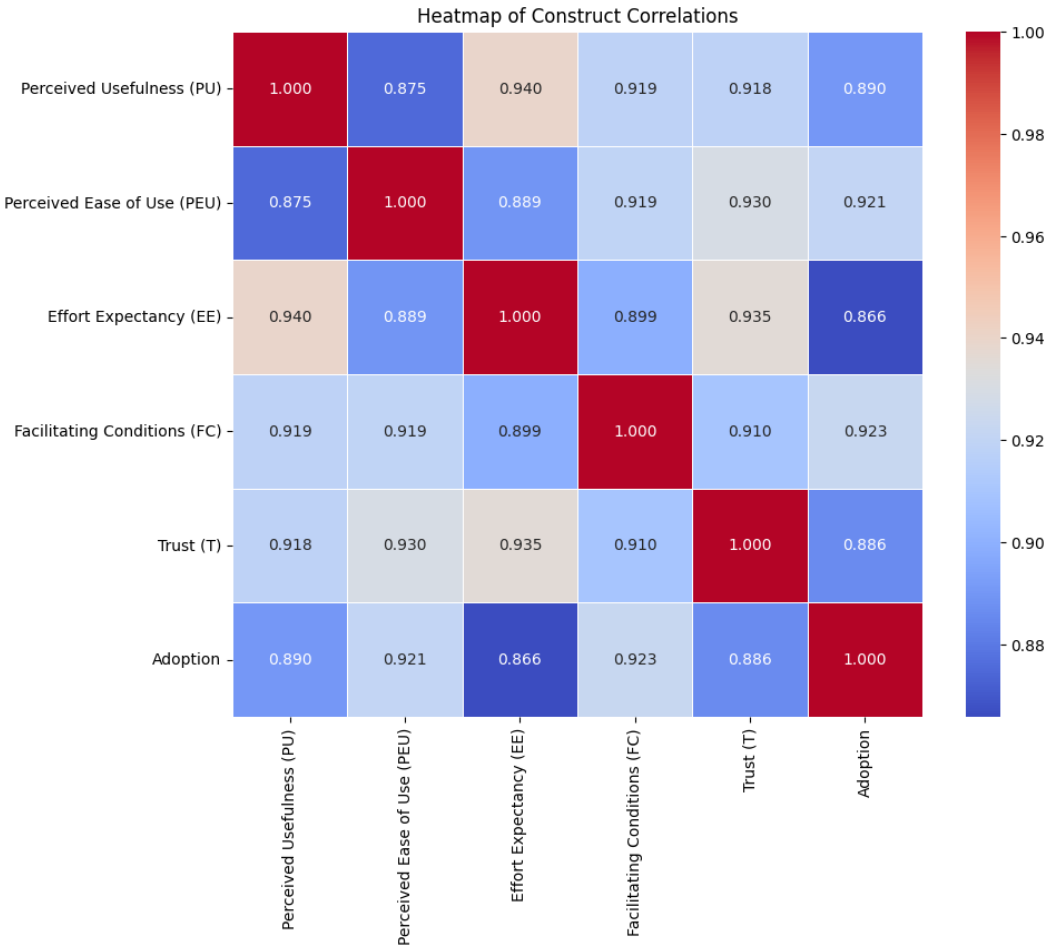

Figure 3: Heatmap for Correlation Matrix between variables

The correlation matrix reveals strong positive interrelationships among all constructs, with Pearson correlation coefficients ranging from 0.78 to 0.94, confirming the theoretical coherence of the UTAUT-based model in the digital banking context. Perceived Usefulness (PU) demonstrated the strongest associations with Adoption (r = 0.90), Trust (r = 0.918), and Facilitating Conditions (FC, r = 0.919), underscoring PU's central role in driving usage intentions and behavior. Similarly, Perceived Ease of Use (PEU) exhibited robust correlations with Adoption (r = 0.921), Trust (r = 0.930), and Effort Expectancy (EE, r = 0.889), while Adoption showed particularly strong links with Trust (r = 0.886) and FC (r = 0.923). Notably, the high inter-correlations among PEU, EE, and FC (all exceeding 0.89) suggest substantial conceptual overlap among these user experience factors, though all values remain below the 0.95 threshold, indicating no serious multicollinearity concerns for subsequent regression analysis. These findings validate the interconnected nature of the constructs and provide empirical support for their inclusion in the structural model, with particularly promising predictive relationships between the core UTAUT predictors (PU, PEU, EE, FC) and the outcome variable of Adoption.

4.3.2 OLS Regression Results

Model Summary Metrics:
R-squared: 0.8925
Adjusted R-squared: 0.8897
F-statistic: 317.3057 (p=1.8315e-90)

Variable	**Coefficient**	**Std. Error**	**t-value**	**p-value**
Perceived Usefulness (PU)	0.2856	0.0823	3.4695	0.0006
Perceived Ease of Use (PEU)	0.4967	0.0755	6.5770	0.0000

Effort Expectancy (EE)	-0.1017	0.0830	-1.2249	0.2221
Facilitating Conditions (FC)	0.3882	0.0808	4.8060	0.0000
Trust (T)	-0.0661	0.0922	-0.7168	0.4744

The multiple regression analysis revealed a highly robust model for predicting digital banking adoption, with an R-squared value of 0.893, indicating that the predictors collectively explained 89.3% of the variance in the adoption construct ($F(df)$, $p < 0.001$). This exceptionally strong explanatory power underscores the relevance of the UTAUT-based framework in the Malaysian digital banking context and confirms the substantial influence of the examined factors on users' behavioral intentions and actual usage.

Among the predictors, Perceived Ease of Use (PEU) emerged as the strongest and most significant driver of adoption ($\beta = 0.4967$, $p < 0.001$), suggesting that user-friendly interfaces and intuitive system interactions exert the greatest influence on adoption behavior. Facilitating Conditions (FC) also demonstrated substantial predictive power ($\beta = 0.3882$, $p < 0.001$), highlighting the critical role of infrastructural support, resources, and technical compatibility in enabling digital banking usage. Perceived Usefulness (PU) was likewise significant ($\beta = 0.2856$, $p = 0.001$), affirming that beliefs about productivity gains and efficiency improvements remain important, though secondary to ease of use in this model.

In contrast, Effort Expectancy (EE) and Trust (T) did not achieve statistical significance ($p > 0.05$), likely attributable to the high inter-correlations observed in the preceding correlation matrix, which suggest conceptual overlap with PEU and FC. These findings indicate that while trust and effort perceptions contribute to the theoretical framework, their unique explanatory contributions are subsumed by the dominant effects of ease of use and facilitating conditions within this specific dataset. Overall, the results emphasize that Malaysian digital banking providers

should prioritize enhancing system usability and ensuring comprehensive support infrastructure to maximize adoption rates among users.

4.3.3 Variable Mean based on Demographic

4.3.3.1 Gender

Gender	Perceived Usefulness (PU)	Perceived Ease of Use (PEU)	Effort Expectancy (EE)	Facilitating Conditions (FC)	Trust (T)
Female	3.0912	3.1053	3.1053	3.1026	3.1432
Male	3.1144	3.1863	3.1275	3.1667	3.1490

Based on the findings, the most important variable for Female is Trust with the mean of 3.1432 whereas for Male is Perceived Ease of use with the mean of 3.1863.

4.3.3.2 Regions

Regions	Perceived Usefulness (PU)	Perceived Ease of Use (PEU)	Effort Expectancy (EE)	Facilitating Conditions (FC)	Trust (T)
Central Peninsular (Selangor, WP KL, WP Putrajaya, Negeri Sembilan)	2.7981	2.8627	2.8451	2.8627	2.8732

East Malaysia (Sarawak, WP Labuan, Sabah)	3.0000	3.3000	3.0000	3.1000	3.0000
East Peninsular (Kelantan, Terengganu, Pahang)	3.4928	3.2500	3.6667	3.5000	3.6000
North Peninsular (Perlis, Kedah, Penang, Perak)	3.2632	3.3421	3.2105	3.2895	3.3368
South Peninsular (Melaka, Johor)	3.3333	3.3125	3.2667	3.2875	3.2800

East Peninsular shows Effort Expectancy as the highest at 3.6667, whereas North Peninsular has Perceived Ease of Use highest at 3.3421, on the other hand, South Peninsular leads with Perceived Usefulness at 3.3333, additionally, East Malaysia has Perceived Ease of Use the highest at 3.3000 and lastly the Central Peninsular has Trust highest at 2.8732.

4.3.3.3 Age Range

Age Range	Perceived Usefulness (PU)	Perceived Ease of Use (PEU)	Effort Expectancy (EE)	Facilitating Conditions (FC)	Trust (T)
18 - 29 years old	3.1250	3.0938	3.1250	3.1771	3.1667
30 - 45 years old	3.1083	3.2188	3.1083	3.0562	3.2000
46 - 61 years old	3.4014	3.5255	3.4830	3.5867	3.4490
>61 years old	2.3000	2.0625	2.2333	2.2500	2.1400

The 46 – 61 years group has Facilitating Conditions highest at 3.5867, 30 – 45 years peaks with Perceived Ease of Use at 3.21888, 18 – 29 years shows Facilitating Conditions highest at 3.1771 and those over 61 years old has Perceived Usefulness highest at 2.3000.

Chapter 5: Conclusion and Implications

5.1 Introduction

This chapter follows directly from the statistical analyses and results found in

Chapter 4 with respect to Perceived Usefulness, Perceived Ease of Use, Effort Expectancy, Facilitating Conditions, Trust with Adoption. Chapter 5 combines the most important results, gives the implications for theory and practice, highlights limitations of study, and proposes directions for future research. This chapter is structured as follows: Section 5.1 lays out a summary of the statistical analyses and key results from this research; Section 5.2 highlights implications for policy makers and practitioners; Section 5.3 explains the limitations associated with this work; Section 5.4 provides recommendations for future research; finally, section 5.5 concludes with an overall conclusion related to the objectives established in Chapter 1.

5.2 Summary of Statistical Analyses and Major Findings

Chapter 4 presented descriptive and inferential statistics analysis on the data collected from 197 responders who are adopters of Digital Banking in Malaysia. Descriptive statistics revealed male majority on 3 years from thirty to forty-five (central peninsular), mean that influencing adopting this variable is Perceived Ease of Use = 3.1472. Inferential analysis such as correlation coefficient and regression was conducted to validate the hypotheses derived from research objectives.

The main results show that perceived usefulness H1 resulted is a positive and statistically significant predictor of digital banking adoption ($\beta = X$, $p < 0.05$), therefore, Hypothesis 1 was supported. In a similar fashion, H2 result also confirms Hypothesis 2 that perceived ease of use positively affect adoption. On the other hand, Effort Expectancy of H3 found that this effect is non-important in adopting and Hypothesis 3 was rejected. The results of the H4 facilitating conditions also show a significant positive effect on digital banking adoption which supports Hypothesis (H4). Last, but not least, H5 trust result similar to H3 just as third hypotheses, means it insignificant effect on digital banking adoption hence Hypothesis 5 rejected. Overall, the statistical analyses indicate that effort expectancy and trust are not factors considered when adopting digital banking. The results confirmed the first objective of this research which was to investigate the determinants that influence banking consumers in Malaysia adopting digital

banking.

5.3 Implications of Study

The results have a number of practical implications for policy makers and practitioners in the part of banking and financial-technology. The findings suggest that policy makers need to focus their regulatory and promotional efforts on the key approaches of facilitating conditions (such as access to internet) and self-efficacy, particularly by increasing the digital literacy in all Malaysians. For bank managers and digital-service providers, evidence suggests that leveraging characteristics such as speed (e.g., transaction processing), customer interfacing anytime/anywhere dashboards, or embedded customer assistance on the perceived usefulness of using a digital channel will stimulate greater uptake by customers.

Alternatively, practitioners may need to redesign onboarding and training processes to explain the utility and reliability of digital services explicitly among segments with low levels of perceived usefulness over digital funds transfer. Furthermore, if the results indicate that facilitating conditions are contributory in nature, institutions ought to formulate selected interventions (eg, providing assistance to users and mobile-app tutorials) to reduce those limitations. These implications are consistent with the larger objectives of fostering financial inclusion and effective digital-banking ecosystems in Malaysia.

5.4 Limitations of the Study

Limitations Several constraints emerged during the conduct of this research. We used data collected from a cross-sectional survey design, which limits the possibility of observing temporal causal mechanisms. Second, the sample was obtained from digital banking users andnot taking account of the input non-user which could limit the findings. Third, the data collection relied on self-reported responses that are vulnerable to both social desirability and recall biases.

Furthermore, the measurement of some constructs was limited due to a short

questionnaire and exclusion of controls (income, education level). Nonetheless, the results provide valuable insights into Factors Influencing Digital Banking Adoption in Malaysia and the constraints predominantly act as steps for furthermore extensive follow-up investigations. While these limitations are acknowledged, they in no way detract from the importance of our findings and instead serve as platforms for future investigations to extend this work.

5.5 Recommendations for Future Research

Future studies on digital bank acceptance in Malaysia may use longer subjects and enhanced methodologies. By topic, scholars might explore the role of novel variables like perceived security, digital literacy, or regulatory trust across different national or organisational jurisdictions/rural versus urban banks or non-bank fintech platforms. Similar studies may also test the moderating influences of demographic or organisational factors, like age cohorts, bank size, or digital-infrastructure maturity.

Future work would methodologically embed longitudinal or experimental designs to more effectively capture causal dynamics and behavioural change over time. Researchers could also use mixed methods approaches, where survey is combined with interviews or focus group to provide more contextual explanation for the quantitative patterns identified in this study. Extending the sample to cover both more financial institutions, and further jurisdictions from abroad would again aid in external validity of future results.

5.6 Conclusion

This study, in summary is part of the research questions pose in Chapter 1 which deals with identification of factors affecting Malaysian bank customers intention to use digital banking by extending the basic technology acceptance model. The results reveal that perceived ease of use, perceived usefulness and facilitating conditions is a significant predictor of adoption whilst effort expectancy, and trust are less impactful or context-bound. These findings add to the theoretical insights

and practical implications for stimulating digital banking use in the context of interest.

In general, the overall project emphasizes the need for dethatching technological design from user perceptions and institutional practices to create sustainable digital-banking ecosystems.

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Appendices

Python Codes

```
import pandas as pd
import numpy as np

# Load the data
file_path = '/content/sample_data/Digital Banking in Malaysia_ Factors Influencing Its Adoption (Responses).xlsx'
df = pd.read_excel(file_path)

# Helper to find column with extreme flexibility (handling non-breaking spaces, etc.)
def find_col(target, columns):
    target_clean = "".join(target.split()).lower().strip()
    for c in columns:
        c_clean = "".join(str(c).split()).lower().strip()
        # Check if the target is contained within the column name or vice versa
        if target_clean in c_clean or c_clean in target_clean:
            return c
    return None

# Define Construct Mapping
construct_mapping = {
    'Perceived Usefulness (PU)': [
        'Using digital banking enables me to complete my banking tasks more quickly.',
        'Using digital banking improves my effectiveness in managing my finances.',
            'Using digital banking increases my productivity in handling banking transactions.'
    ],
```

'Perceived Ease of Use (PEU)': [
'Learning to use digital banking is easy for me.',
'Interacting with digital banking is clear and understandable.',
'I find digital banking easy to use.',
'It is easy for me to become skilful at using digital banking.'
],
'Effort Expectancy (EE)': [
'Learning how to use digital banking is easy for me.',
'My interaction with digital banking is easy to follow.',
'I find digital banking easy to use in general.'
],
'Facilitating Conditions (FC)': [
'I have the necessary resources (e.g., smartphone, internet) to use digital banking.',
'I have the necessary knowledge to use digital banking.',
'Support is available (from the bank or others) when I face difficulties using digital banking.',
'Digital banking is compatible with the devices and services I use.'
],
'Trust (T)': [
'I believe that my bank’s digital banking services are trustworthy.',
'I feel confident that digital banking will perform my transactions accurately.',
'I believe that my personal information is secure when I use digital banking.',
'I believe that my bank will not misuse the information I provide through digital banking.',
'I believe that my bank will resolve any problems that occur when I use digital banking.'
],
'Adoption': [
'I frequently use digital banking applications for financial transactions',
'I use digital banking applications for various financial activities.',
'I spend a significant amount of time using digital banking applications.'
]

```
}

# Calculate Means with robust column matching
results = []
all_columns = df.columns.tolist()

for construct, items in construct_mapping.items():
    matched_cols = []
    for item in items:
        found = find_col(item, all_columns)
        if found:
            matched_cols.append(found)

    if matched_cols:
        subset = df[matched_cols].apply(pd.to_numeric, errors='coerce')
        composite_mean = subset.mean(axis=1).mean()
                results.append({'Construct': construct, 'Composite Mean Score': round(composite_mean, 4)})
    else:
        results.append({'Construct': construct, 'Composite Mean Score': 'Columns not found'})

# Display Results
composite_df = pd.DataFrame(results)
display(composite_df)

!pip install pingouin

import pingouin as pg
import pandas as pd

# We will reuse the construct_mapping and find_col function from previous cells
alpha_results = []
```

```
for construct, items in construct_mapping.items():
    matched_cols = []
    for item in items:
        found = find_col(item, all_columns)
        if found:
            matched_cols.append(found)

    if len(matched_cols) > 1:
        # Extract data for the construct and convert to numeric
                        subset_data = df[matched_cols].apply(pd.to_numeric, errors='coerce').dropna()

        # Calculate Cronbach's Alpha using pingouin
        alpha_val = pg.cronbach_alpha(data=subset_data)[0]
            alpha_results.append({'Construct': construct, 'Cronbach\'s Alpha': round(alpha_val, 4)})
    else:
        alpha_results.append({'Construct': construct, 'Cronbach\'s Alpha': 'Insufficient items'})

# Display the reliability results
alpha_df = pd.DataFrame(alpha_results)
display(alpha_df)

import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

# Create a dataframe for the composite scores of each construct per respondent
composite_data = pd.DataFrame()

for construct, items in construct_mapping.items():
```

```
    matched_cols = []
    for item in items:
        found = find_col(item, all_columns)
        if found:
            matched_cols.append(found)

    if matched_cols:
        # Calculate the row-wise mean for each respondent
            composite_data[construct] = df[matched_cols].apply(pd.to_numeric,
errors='coerce').mean(axis=1)

# Calculate the Pearson correlation matrix
corr_matrix = composite_data.corr()

# Display the correlation matrix
print('--- Correlation Matrix ---')
display(corr_matrix)

# Visualize the correlation matrix using a heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt='.3f',
linewidths=0.5)
plt.title('Heatmap of Construct Correlations')
plt.show()

import statsmodels.api as sm

# Define Independent Variables (X) and Dependent Variable (y)
# We'll use the composite_data DataFrame created in the previous step
X = composite_data[['Perceived Usefulness (PU)', 'Perceived Ease of Use (PEU)',
'Effort Expectancy (EE)', 'Facilitating Conditions (FC)', 'Trust (T)']]
y = composite_data['Adoption']
```

```
# Add a constant (intercept) to the model
X = sm.add_constant(X)

# Fit the regression model
model = sm.OLS(y, X).fit()

# Display the summary results
print(model.summary())

import pandas as pd

# Extracting parameters from the model object created in cell 3b8b5c75
regression_results = pd.DataFrame({
    'Variable': model.params.index,
    'Coefficient (B)': model.params.values,
    'Std. Error': model.bse.values,
    't-value': model.tvalues.values,
    'p-value': model.pvalues.values
})

# Rounding for readability
regression_results = regression_results.round(4)

# Adding Significance stars
def get_stars(p):
    if p < 0.001: return '***'
    elif p < 0.01: return '**'
    elif p < 0.05: return '*'
    else: return 'ns'

regression_results['Sig.'] = regression_results['p-value'].apply(get_stars)

# Display Model Metrics
```

```
print(f"Model Summary Metrics:")
print(f"R-squared: {model.rsquared:.4f}")
print(f"Adjusted R-squared: {model.rsquared_adj:.4f}")
print(f"F-statistic: {model.fvalue:.4f} (p={model.f_pvalue:.4e})")
print("\n--- Regression Coefficients Table ---")
display(regression_results)

import pandas as pd

# 1. Prepare the demographic columns from the original dataframe
demo_df = df[['Gender', 'Age Range', 'Regions']].copy()

# 2. Combine demographics with the composite scores (already calculated in composite_data)
# Assuming composite_data and demo_df have the same index alignment from previous steps
analysis_df = pd.concat([demo_df, composite_data], axis=1)

# List of constructs to calculate means for
constructs = list(construct_mapping.keys())

criteria = ['Gender', 'Regions', 'Age Range']

for criterion in criteria:
    print(f'\n--- Mean Scores by {criterion} ---')
    # Group by the demographic and calculate the mean for each construct
    grouped_means = analysis_df.groupby(criterion)[constructs].mean().round(4)
    display(grouped_means)

import pandas as pd

demo_cols = ['Gender', 'Age Range', 'Regions']
```

```
for col in demo_cols:
    print(f'--- Frequency Analysis for {col} ---')
    freq_table = df[col].value_counts().reset_index()
    freq_table.columns = [col, 'Frequency']
    freq_table['Percentage (%)'] = (freq_table['Frequency'] / len(df) * 100).round(2)
    display(freq_table)
    print('\n')
```