

# **The mediating effect of trust on factors influencing the intention to use FinTech applications among urban working professionals in Malaysia**

by

**Chee Yen Lim**

**(1711636)**

**Submitted in partial fulfilment for the award of the degree of**

**Doctor of Business Administration**



## **DECLARATION SHEET**

This work has not previously been accepted in substance for any degree and is not being concurrently submitted in candidature for any degree.

Signed:

Date: 30 September 2024

### **STATEMENT 1**

This thesis is the result of my own investigation, except where otherwise stated. No correction services have been used in this thesis. Other sources are acknowledged by footnotes giving explicit references. A bibliography is appended.

Signed:

Date: 30 September 2024

### **STATEMENT 2**

I hereby give consent for my thesis, if accepted, to be available for photocopying and for inter-library loan, and for the title and summary to be made available to outside organisations.

Signed:

Date: 30 September 2024

### **STATEMENT 3**

I hereby give consent for my thesis, if accepted, to be available for deposit in the University's digital repository.

Signed:

Date: 30 September 2024

## **ACKNOWLEDGEMENTS**

I would like to express my heartfelt gratitude to my supervisor, Professor Dr. Ilham Sentosa, for his invaluable guidance and advice throughout my DBA research project.

Special appreciation goes to the University of Wales Trinity Saint David for providing me with the opportunity to embark on this DBA project and for offering a supportive learning platform for conducting research.

I would also like to thank the Ethics Committee for their support and endorsement in collecting responses from the public, which was essential for fulfilling the core elements of this research project.

I extend my special thanks to my family members, friends, colleagues, and course mates for their continuous encouragement. This project would not have been fruitful without their involvement, both directly and indirectly.

Lastly, I wish to thank all examiners of this research project for providing constructive feedback to improve this thesis.

This thesis is dedicated to all of you who have played a role in my academic journey.

## ABSTRACT

The integration of financial technology (“FinTech”) applications has transformed the financial services landscape, significantly influencing consumer behaviour and business models worldwide. Despite robust digital economy growth in Malaysia, FinTech adoption among urban working professionals remains slower than in developed nations, hindered by concerns over data security and privacy. This study investigates the factors influencing FinTech adoption in this context, focusing on the mediating role of trust.

Grounded in the Technology Acceptance Model (“TAM”) and extended to include trust as a mediator, the research examines the effects of convenience, perceived usefulness, social influence, and promotions on adoption intention. Trust is conceptualised as users’ confidence in the security, reliability, and data protection of FinTech applications. A self-administered survey of 313 urban working professionals was conducted using a structured questionnaire and analysed with multiple regression and structural equation modelling.

The results reveal that convenience and social influence directly and positively affect FinTech adoption, while the impacts of usefulness and promotions become significant only when mediated by trust. Trust thus emerges as a pivotal factor, bridging the gap between perceived benefits and concerns over security and operational reliability. Demographic analysis further indicates that younger and male users are generally more receptive to FinTech services.

The study recommends that FinTech providers prioritise building trust through enhanced security measures, transparent privacy policies, and responsive customer service. Policymakers are encouraged to strengthen data protection frameworks and invest in digital literacy initiatives to foster a secure and inclusive FinTech ecosystem. Limitations include the focus on urban working professionals in Malaysia. Future research should explore FinTech adoption across diverse populations and examine additional mediators such as financial literacy and cultural factors.

This research contributes to a deeper understanding of FinTech adoption in Malaysia and reinforces the central role of trust in advancing financial inclusion and digital transformation.

**Keywords:** FinTech applications, trust, technology acceptance model, convenience, usefulness, social influence, promotions, FinTech adoption, urban working professionals, Malaysia.

## TABLE OF CONTENTS

<b>DECLARATION SHEET</b>	i
<b>ACKNOWLEDGEMENTS</b>	ii
<b>ABSTRACT</b>	iii
<b>TABLE OF CONTENTS</b>	iv
<b>LIST OF ABBREVIATIONS</b>	viii
<b>LIST OF FIGURES</b>	ix
<b>LIST OF TABLES</b>	x
<b>LIST OF APPENDICES</b>	xii
<b>CHAPTER 1</b>	1
<b>1.0 Introduction</b>	1
<b>1.1 General Introduction</b>	1
<b>1.2 Industry Revolution and FinTech</b>	3
<b>1.3 Background of Research</b>	6
<b>1.4 Problem Statement</b>	9
<b>1.5 Research Significance</b>	12
<b>1.6 Research Scope</b>	13
<b>1.7 Research Objectives</b>	15
<b>1.8 Research Questions</b>	16
<b>1.9 Summary of Chapter</b>	16
<b>1.10 Thesis Structure</b>	17
<b>CHAPTER 2</b>	19
<b>2.0 Literature Review</b>	19
<b>2.1 General Introduction</b>	19
<b>2.2 Definition of Key Concepts</b>	20
<b>2.2.1 FinTech Adoption</b>	20
<b>2.2.2 Convenience</b>	26
<b>2.2.3 Usefulness</b>	27
<b>2.2.4 Social Influence</b>	29
<b>2.2.5 Promotions</b>	31
<b>2.2.6 Trust as a Mediating Factor</b>	33
<b>2.3 Theories in Technology Adoption</b>	38
<b>2.4 Critical Review of FinTech Adoption</b>	50
<b>2.4.1 Current Sentiment in the FinTech Industry</b>	50

2.4.2	Transformations in FinTech: Innovations and Trends	54
2.4.3	Transformations in FinTech: Disruptive Technologies	61
2.4.4	Transformations in FinTech: Impact of Customer Experience	72
2.4.5	Challenges and Complexities Affecting the FinTech Industry	77
2.4.6	Risks Associated with FinTech	83
2.4.7	Evolving FinTech Ecosystem in Malaysia	86
2.4.8	Regulatory Landscape Shaping the FinTech Ecosystem in Malaysia	88
2.5	Research Framework	98
2.6	Formulation of Hypotheses	100
2.6.1	Direct Effect Hypotheses	100
2.6.2	Mediation Hypotheses	100
2.7	Summary of Chapter	101
<b>CHAPTER 3</b>		103
3.0	Research Methodology	103
3.1	General Introduction	103
3.1.1	Saunders' Research Onion Summary	104
3.2	Research Design and Methods	105
3.2.1	Questionnaire Development and Validation	105
3.2.2	Target Population	110
3.2.3	Sample Size & Sampling Method	110
3.2.4	Data Collection Method	112
3.2.4.1	Pilot Study Overview	112
3.2.4.2	Initial Pilot Study (1st Phase)	112
3.2.4.3	Extended Pilot Study (2nd Phase, Pre-Refinement of Questionnaire)	114
3.2.4.4	Refinement of Questionnaire	120
3.2.4.5	Extended Pilot Study (3rd Phase, Post-Refinement of Questionnaire)	122
3.2.4.6	Pilot Study Summary	124
3.2.4.7	Final Data Collection	125
3.2.5	Ethical Issues and Accessibility	125
3.2.6	Data Analysis	127
3.2.6.1	Demographic Analysis	127
3.2.6.2	Reliability Assessment	128
3.2.6.3	Normality Test (Skewness and Kurtosis)	128
3.2.6.4	Pearson Correlation Analysis	128
3.2.6.5	Regression Analysis	128

3.2.6.6	Confirmatory Factor Analysis	129
3.2.6.7	Structural Equation Modelling	129
CHAPTER 4		130
4.0	Findings and Discussions	130
4.1	General Introduction	130
4.2	Context and Rationale	130
4.3	Demographic Profile and Descriptive Analysis	131
4.4	Measurement Model Assessment	135
4.4.1	Reliability Assessment	135
4.4.2	Normality Test (Skewness and Kurtosis)	136
4.4.3	Pearson Correlation Analysis	137
4.4.4	Multicollinearity Test	138
4.5	Regression Analysis	139
4.5.1	Model Fit and Assumptions	139
4.5.2	Regression Coefficients	141
4.5.3	Discussion of Regression Findings	143
4.6	Confirmatory Factor Analysis	147
4.6.1	Convergent Validity and Construct Reliability	147
4.6.2	Discriminant Validity	149
4.7	Structural Equation Modelling	150
4.8	Findings and Discussions	153
4.8.1	The Impact of Convenience in FinTech Adoption	153
4.8.2	The Impact of Usefulness on Adoption Intention	154
4.8.3	The Impact of Social Influence and FinTech Adoption	155
4.8.4	The Impact of Promotions on Adoption Intention	155
4.8.5	The Mediating Role of Trust in FinTech Adoption	156
4.8.6	Summary of Hypothesis Testing	158
CHAPTER 5		160
5.0	Conclusions, Recommendations and Suggestions for Future Research	160
5.1	Overall Conclusions and Implications	160
5.2	Recommendations	165
5.3	Limitations and Suggestions for Future Study	168
5.3.1	Limitations of the Study	168
5.3.2	Interdisciplinary Challenges in FinTech Research	169
5.3.3	Scope and Contextual Limitations	170

<b>5.3.4 Directions for Future Research</b>	173
<b>REFERENCES</b>	176
<b>APPENDICES</b>	201
<b>Appendix 1: Design of the Survey Questionnaire</b>	201
<b>Appendix 2: Reliability of Questionnaire (Pilot Test)</b>	208
<b>Appendix 3: Reliability Testing (Cronbach’s Alpha): Pre-Refinement</b>	218
<b>Appendix 4: Descriptive Statistics</b>	231
<b>Appendix 5: Normality Testing (Skewness and Kurtosis): Pre-Refinement</b>	233
<b>Appendix 6: Pearson Correlations: Pre-Refinement</b>	239
<b>Appendix 7: Regression Analysis: Pre-Refinement</b>	240
<b>Appendix 8: Reliability Testing (Cronbach’s Alpha): Post-Refinement</b>	242
<b>Appendix 9: Normality Testing (Skewness and Kurtosis): Post-Refinement</b>	254
<b>Appendix 10: Regression Analysis (Pre-Refined Questionnaire)</b>	260
<b>Appendix 11: Rotated Component Matrix</b>	262
<b>Appendix 12: Questionnaire (Pre-refinement)</b>	263
<b>Appendix 13: Questionnaire (Post-refinement)</b>	264



## LIST OF ABBREVIATIONS

Abbreviation	Full Term
AI	Artificial Intelligence
AMOS	Analysis of Moment Structures
ATM	Automated Teller Machine
AVE	Average Variance Extracted
BNPL	Buy Now, Pay Later
BNM	Bank Negara Malaysia
CAGR	Compound Annual Growth Rate
CFA	Confirmatory Factor Analysis
COVID-19	Coronavirus Disease 2019
FinTech	Financial Technology
HTMT	Heterotrait-Monotrait Ratio
ML	Machine Learning
P2P	Peer-to-Peer
QR	Quick Response
RO	Research Objective
RPA	Robotic Process Automation
SC	Securities Commission Malaysia
SD	Standard Deviation
SEM	Structural Equation Modelling
SNBL	Save Now, Buy Later
SPSS	Statistical Package for the Social Sciences
TAM	Technology Acceptance Model
UTAUT	Unified Theory of Acceptance and Use of Technology
UNSGSA	United Nations Secretary-General's Special Advocate
G*Power	G*Power (Sample Size Calculation Software)
n	Sample Size
$\alpha$	Cronbach's Alpha
$f^2$	Effect Size
p	Probability Value (Statistical Significance)

## LIST OF FIGURES

List of Figures	Page
Figure 1.1 Example of research model used as a reference for this research study.	13
Figure 2.1 The Theory of Reasonable Action proposed by Fishbein & Ajzen (1975).	39
Figure 2.2 The Theory of Planned Behaviour developed by Ajzen (1991).	40
Figure 2.3 Technology Acceptance Model (“TAM”) proposed by Davis (1986).	41
Figure 2.4 A modified version of TAM proposed by Davis et al. (1989).	42
Figure 2.5 The final version of TAM developed by Venkatesh & Davis (1996).	42
Figure 2.6 TAM2 refined by Venkatesh & Davis (2000).	43
Figure 2.7 TAM3 established by Venkatesh and Bala (2008).	44
Figure 2.8 Innovation Adoption Curve proposed by Rogers (1995).	45
Figure 2.9 TTF developed by Goodhue et al. (1995).	46
Figure 2.10 TRM introduced by Parasuraman (2000).	48
Figure 2.11 UTAUT established by Ventakesh et al. (2003).	50
Figure 2.12 Research Framework.	99
Figure 3.1 Normal P-P plot for (A) convenience, (B) usefulness, (C) social influence, (D) promotions, (E) trust, and (F) intention to use.	116
Figure 3.2 Scatter plots of datasets.	117
Figure 4.1 Scatterplot of standardised residuals vs. predicted values for homoscedasticity analysis (main study).	140
Figure 4.2 SEM of constructs without mediating factor (main study).	152
Figure 4.3 SEM of constructs with mediating factor (main study).	152

## LIST OF TABLES

List of Tables	Page
Table 2.1. Start-up distributions within the FinTech industry categorised based on subcategories.	52
Table 2.2 The distribution of FinTech firms in different categories.	59
Table 2.3 FinTech companies with social media presence in Malaysia categorised by functions.	93
Table 3.1 Questionnaire structure and references to earlier literature (initial 45-item questionnaire).	107
Table 3.2 Survey questionnaire questions by section (initial 45-item questionnaire).	108
Table 3.3 Reliability test of questionnaire during pilot study using Cronbach's alpha (first phase - 50 participants, 45-item questionnaire).	113
Table 3.4 Reliability test of questionnaire using Cronbach's alpha (second phase, pre-refinement pilot - 313 participants, 45-item questionnaire).	114
Table 3.5 Skewness and kurtosis of the data (second phase, pre-refinement pilot - 313 participants, 45-item questionnaire).	115
Table 3.6 Pearson correlations of the datasets (second phase, pre-refinement pilot - 313 participants, 45-item questionnaire) (significant at the 0.01 level; 2 tailed).	118
Table 3.7 Results of the multicollinearity test (second phase, pre-refinement pilot - 313 participants, 45-item questionnaire).	119
Table 3.8 Refined survey questionnaire questions by section (19-item questionnaire).	121
Table 3.9 Reliability test of refined questionnaire using Cronbach's alpha (third phase, post-refinement pilot - 313 participants, 19-item questionnaire).	122
Table 3.10 Results of the multicollinearity test (third phase, post-refinement pilot - 313 participants, 19-item questionnaire).	123
Table 4.1 Demographic data of questionnaire participants.	132
Table 4.2 Descriptive analysis of independent, mediating and dependent variables.	134
Table 4.3 Reliability Test of Questionnaire Using Cronbach's Alpha (main study).	135
Table 4.4 Skewness and Kurtosis of the Data (main study).	136

List of Tables	Page
Table 4.5 Pearson correlations of the datasets (significant at the 0.01 level; 2 tailed).	137
Table 4.6 Results of the multicollinearity test (main study).	138
Table 4.7 Statistics for regression analysis (main study).	139
Table 4.8 ANOVA results for regression analysis (main study).	141
Table 4.9 Regression coefficients (main study).	142
Table 4.10 Convergent validity and construct reliability (main study).	148
Table 4.11 Discriminant validity: HTMT ratios (main study).	149
Table 4.12 Discriminant validity: square root of AVE and correlations (main study).	149
Table 4.13 Unstandardised path coefficients and significance (main study).	151
Table 4.14 Summary of results and hypotheses.	158

## LIST OF APPENDICES

List of Appendices	Page
Appendix 1 Design of Survey Questionnaire	201
Appendix 2 Reliability of Questionnaire (Pilot Testing)	208
Appendix 3 Reliability Testing (Cronbach's Alpha): Pre-Refinement	218
Appendix 4 Descriptive Statistics	231
Appendix 5 Normality Testing (Skewness and Kurtosis): Pre-Refinement	233
Appendix 6 Pearson Correlation: Pre-Refinement	239
Appendix 7 Regression Analysis: Pre-Refinement	240
Appendix 8 Reliability Testing (Cronbach's Alpha): Post Refinement	242
Appendix 9 Normality Testing (Skewness and Kurtosis): Post Refinement	254
Appendix 10 Regression Analysis: Post Refinement	260
Appendix 11 Rotated Component Metrix	262
Appendix 12 Questionnaire (Pre-refinement)	263
Appendix 13 Questionnaire (Post-refinement)	264

# CHAPTER 1

## 1.0 Introduction

### 1.1 General Introduction

Financial technology, also known as “FinTech”, is a blanket term commonly used today that refers to the integration of new technology in innovating traditional-looking finance functions. Some of the common FinTech innovations that remain as part of our daily lives include internet banking, mobile banking, P2P lending, and payments through e-wallets (Suryono et al. 2020). On a broader example, the Starbucks mobile application used by consumers globally is considered part of FinTech owing to its use for mobile payments and customer entitlement to various rewards programmes tailored for its consumers (Akcem, 2023).

The emergence of FinTech-powered applications and platforms has revolutionised the financial services sector, affecting how firms of different sizes manage their finances, make payments, and borrow money. Traditionally, the core functions of incumbent financial service providers are in the areas of lending (i.e. loans and mortgages), remittance (i.e. interbank transfer), and wealth management (i.e. fixed deposits and investments) (Murinde et al., 2022).

The constant evolution and revolution of FinTech have caused a paradigm shift within the financial services industry. In lending for example, the term is no longer associated with merely just loans and mortgages but with many new concepts, such as P2P lending and buy-now-pay-later in the market (Gerrans et al., 2022; McKinsey & Company, 2021). Another form of innovation in the area of lending includes the use of automated underwriting programmes driven by robotic process automation (“RPA”) to increase credit and funding decisions without relying on conventional methods, which are relatively more time-consuming (Chauhan et al., 2022). In the payments space, cryptocurrencies built on blockchain technology have gained

popularity due to their de-centralised nature of bypassing the legacy financial system, including traditional banks and financial institutions, in facilitating borderless payments regardless of the transfer amount (Murinde et al., 2022; Suryono et al. 2020).

Contrary to popular believe, FinTech is not a recent invention. Chen et al. (2021) advocates the introduction of automated teller machine (“ATM”) in the 1960s as one of the first few inventions that has shaped the financial services industry towards the adoption of technology in response to streamlining service delivery and reducing cost. As compared to cash and cheques, which existed before the introduction of ATMs in the 1960s, Chen et al. (2021) regards this as a revolutionary technological development in the payments industry. While many other innovations have continued to transform in the previous decades, most of that can be attributed to advances in technology that are now being used in the banking industry. While some succeeded and remain in use today, others became a legacy and are used as reference points for continuous improvements (Ashta, 2021).

Similar to how ATMs pioneered the FinTech industry, new technologies have emerged in support of FinTech business models, such as RPA, artificial intelligence (“AI”), machine learning (“ML”), and blockchain technology, among other big data applications (Chauhan et al., 2022; Noor et al., 2019; Wang et al., 2021). Each use case is distinct, but the overall goal of disaggregating the financial services industry, which has historically benefited from extensive regulations, is what unites them all, and collectively connected with Industry 4.0 (Soni et al., 2022).

## **1.2 Industry Revolution and FinTech**

The compelling transformations and transitions over the last century have pushed innovation to the best of mankind, starting from the industrial revolution (mechanisation), followed by upscaling using electricity in the second, adoption of computerisation or automation in the third, and more recently, the use of smart systems powered by big data, AI and ML (Bhuiyan et al. 2022; Soni et al., 2022).

FinTech 1.0 was the first phase, spanning from 1866 to 1967, which mainly focussed on international business. The development of international ties among banks and financial institutions was symbolised by this phase (Mohamed & Ali, 2022). Building infrastructure like railroads and bridges has pathed the future by facilitating speed and efficiencies in trade and commerce. In the early 1900s, the United States developed the first transatlantic cable and electronic fund transfer system. The renowned Diner's Club credit card, which debuted in 1950, was the beginning of digital payments using credit cards (Alam et al., 2019).

The interlink between financial services and digitalisation was introduced during the second phase, known as FinTech 2.0, spanning from 1967 to 2008. The world of digital money started in 1967 with the introduction of the first ATM. In 1971, the National Association of Securities Dealers Automated Quotations (“NASDAQ”) launched the first digital stock exchange in the world for trading (Treu, 2022). Through technological advancements, traditional banking institutions started to adopt digital systems during this period, giving birth to many financial services that are still presently being used, such as the SWIFT payment networks and stock exchanges, as well as mobile payments and internet banking (Giglio, 2021). The internet era or the world-wide-web’s explosion came about in the middle of the 1990s. This marked the start of industrialisation with e-commerce business models blooming using FinTech (Malali & Gopalakrishnan, 2020).



Fintech 3.0 and its subsequent versions started in 2008 owing to the development of new financial services and products. However, the 2008–2009 global financial crisis had a significant influence on the financial industry globally, prompting corporations to rethink their strategies and redesign their business models in order to minimise the effects, should another similar catastrophe occur in the future (Duran & Griffin, 2020).

For this reason, customers have become considerably more cautious about the information and services they receive from banks and finance corporations. Within the same period, Bitcoin and Alibaba e-commerce platform was introduced. Digital payments (FinTech 4.0) then expanded quickly across several platforms, including Apple Pay, P2P money transfer systems, and Google Wallet, urging traditional banks to contend with competition brought on by these FinTech innovations (Rahman et al., 2024; Alam et al., 2019).

Numerous significant and far-reaching developments have resulted from the FinTech revolution, introducing many new financial services and products in the market (Murinde et al., 2022; Salampasis & Mention, 2018). However, security and convenience are intertwined due to over reliance and the abundance of FinTech options. As FinTech is said to be the generation replacing traditional banking functions, many companies from the private sector searched for prospects to diversify and expand their businesses into the FinTech industry (Gerrans et al., 2022; Murinde et al., 2022). Many start-up companies were involved in the process of introducing innovative products and services using the state-of-art technology, with an intention of being acquired by larger corporations at a later stage. This acquisition business model has eventually led to a decrease in public confidence due to its security and sustainability (Kitagawa et al., 2020; Xiao, 2021), which will be discussed later in this study.

Financial services and other industries, particularly the manufacturing industry, have been severely impacted by the technologies offered by Industry 4.0 (Dhial et al., 2022). The initial

conceptualisation of integrating data for decision-making has become a norm in how businesses work. These digital technologies aim to solve inefficiencies in processes, which provide businesses an upper hand in today's marketplace to gain competitive advantage and to differentiate from their competitors (Brahma et al., 2020).

Industry 4.0 technologies are promising change agents for sustainability due to their combined effects of efficiency-driven characteristics and digital infrastructure. These technologies can be a powerful tool in identifying processes that contribute to high carbon footprints – total greenhouse gas emissions caused by an array of events brought about by organisations, services, and products (Abdul-Rahim et al., 2022). As the global economy is accelerating towards the reduction of carbon emissions, Industry 4.0 technologies offer solutions that could circumvent this phenomenon that may have resulted from ecological imbalances, including resource depletion and environmental pollution (Vergara & Agudo, 2021).

Governments of all continents have realised the potential of Industry 4.0 technologies, including the use of FinTech, to promote environmental sustainability by de-materialising production and consumption, leading to significantly lower use of natural resources; all in all, to promote environmental protection by reducing energy use (e.g., fuel) and consumption (e.g., carbon emission) (Vergara & Agudo, 2021; Kamali et al., 2021).

Apart from using FinTech for business sustainability and the environment, its services can be expanded to bridge the gap between the rural and developed nations, as proposed by the United Nations Secretary General's Special Advocate (“UNSGSA”) with inclusive finance as part of the agenda (Le et al., 2019). It serves as a convener initiative to raise awareness for development impact, promoting supportive policies for developing digital financial inclusion and reaching neglected populations with the necessary support (Khalid & Kunihibava, 2020). With FinTech, minimising the gap of unbanked consumers is now possible, particularly the

low-income households and minority groups. This is because FinTech services are capable of enabling financial access through microfinance and crowdfunding, providing convenient financing to help enhance their economic possibilities, thus, realising the efforts of financial inclusion as articulated by the UNSGSA (Hasan et al., 2022; Le et al., 2019).

While these advantages are logically coherent, they might pose challenges when it comes to actual implementation. The many controversial issues, such as security risks and operational reliability, have led customers to be hesitant about FinTech adoption leading to low adoption rates (Abdul-Rahim et al., 2022). Despite knowing the perceived benefits, such as economic efficiency, fast and seamless transactions, financial savings, and convenience, consumers are still vigilant due to insecurity portrayed by the perceived risks of using FinTech applications (Kamali et al., 2021).

FinTech is inevitably linked to cyber-related risks, broadly categorised into risks related to compromised data privacy and security, financial losses due to fraud and scams, unclear legal and statutory regulations, and risks related to the operational effectiveness of FinTech providers. Many of these vulnerabilities are frequently brought about by poor management of FinTech providers in addressing the risk of data abuse or misuse (Albarrak & Alokley, 2021).

### **1.3 Background of Research**

Despite knowing the various risks attached to FinTech, many FinTech start-ups focussed only on its benefits while neglecting the associated risks, thus hindering the public in adopting the technology. Some businesses grabbed the opportunity due to funding availability but needed to prepare for the consequence and backlash from the community post-implementation (Hodson, 2021). Although FinTech applications are developed using the state-of-art technologies, the lack of credentials or “trust” behind those applications may posit a barrier for

customers to adopt owing to the rampant reports of scams, identity thefts, and data leakage. Therefore, many FinTech applications today are either supported or financed by credible organisations to gain public confidence (Meyliana & Fernando, 2019). However, there has been little to no research conducted so far investigating "trust" as a mediating factor in the adoption of FinTech. For this reason, this study adopts the knowledge from an earlier published model, the technology acceptance model ("TAM"), introduced by Davis (1989), as the baseline to determine the effect of FinTech adoption among urban working professionals in Malaysia mediated by "trust".

Malaysia's FinTech market has seen continued development across various sectors, including capital markets, banking and payment systems, and insurance (SC, 2023; BNM, 2022). In the capital markets, the Securities Commission Malaysia ("SC") has been at the forefront of digital initiatives, licensing and regulating innovative FinTech activities such as equity crowdfunding, digital asset exchanges, P2P financing, and digital investment management (SC, 2023). The SC has also launched the FIKRA Islamic FinTech accelerator programme and the Digital Innovation Fund to support FinTech innovation (SC, 2023).

In the banking and payments sector, BNM has set out a vision to advance the digitalisation of the financial sector in its Financial Sector Blueprint 2022-2026 (BNM, 2022). Notable developments include the quick response ("QR") payment linkage between Malaysia and Singapore, the real-time payment systems linkage between Malaysia's DuitNow and Singapore's PayNow, and the framework for digital insurers and takaful operators (BNM, 2022; BNM, 2024b). The rise of Buy Now, Pay Later ("BNPL") arrangements has led regulators to identify the need for better consumer protection, resulting in the consultation of a proposed Consumer Credit Act (BNM, 2022). An alternative approach, the Save Now, Buy Later

(“SNBL”) scheme, is also becoming more common in the Malaysian FinTech landscape (BNM, 2022).

Urban working professionals in Malaysia are an ideal population to be investigated for its FinTech adoption as they are the largest group of individuals exposed to the use of FinTech applications. This is largely contributed by the various assistance and support offered by the Malaysian government in driving the adoption of FinTech, driven by the goal of achieving cost reductions amounting to one percent of the country's gross domestic product (BNM, 2022). According to the Central Bank of Malaysia or BNM, it is predicted that Malaysia’s e-payment per capita will increase, with a compound annual growth rate (“CAGR”) of more than 15%, as part of Malaysia's Financial Sector Blueprint to accelerate the digital transformation plan (BNM, 2016; BNM, 2022). The Malaysian government has also invested heavily in promoting FinTech in Malaysia, ensuring that businesses not only prioritise the perceived benefits of FinTech innovations but also integrate security measures to address public's concerns and improve accessibility to all individuals. This is in line with the financial inclusion agenda that was mentioned by UNSGSA in the preceding section, where technology-based innovation must fulfil the following criteria: (i) easy accessibility, (ii) high uptakes, (iii) responsible usage, and (iv) high satisfaction (BNM, 2016; BNM, 2022).

Nevertheless, its adoption rate could have been more promising compared to other neighbouring countries. It is postulated that the public still perceives that FinTech applications' risks outweigh the benefits (Tun-Pin et al., 2019). This is particularly true during the pre-pandemic phase, as indicated by Lyons et al. (2022), which showed that the public is sceptical regarding the adoption of FinTech for many reasons, predominantly trust and confidence in the service provider. Interestingly, a recent study has shown an improving trend post-pandemic, where it is deduced that the increased FinTech adoption rate is a direct result of the

implementation of social distancing and a push for contactless payment by the government, in curbing the rising COVID-19 infection cases (Rabbani et al., 2020).

Unfortunately, the higher rate of Fintech adoption has resulted in a rise in reported instances of scams and financial losses (Najaf et al., 2021). These findings are derived from the MyCERT portal, which monitors various cyber security events, including spam, malicious codes, cyber harassment, fraud, vulnerability reports, intrusion attempts, and denial of service. According to the MyCERT report, the potential financial loss suffered from cyber incidents in the past five years reached an estimated sum of approximately RM51 billion (BNM, 2022). In order to ensure the sustainability of FinTech in Malaysia, it is imperative for both FinTech providers and the government to meticulously reassess their policies, enhancing regulatory measures to effectively counter cybercrimes. This should be coupled with the implementation of practical strategies for mitigating such threats, all the while instilling a sense of "trust" among the public towards embracing FinTech (Lysons et al., 2022; Tun-Pin et al., 2019).

#### **1.4 Problem Statement**

As FinTech gains prominence as a promising innovative industry for many developing nations to enhance their financial services, customers remain cautious and apprehensive due to the recurring incidents of fraud, identity thefts, and data breaches. In order to establish credibility and build trust, Meyliana & Fernando (2019) advocate that a contemporary approach would be for FinTech applications to be supported or funded by reputable organisations. Despite this, there is a significant gap in research specifically investigating the role of trust as a mediating factor in the adoption of FinTech applications. This gap highlights the need for a focused examination of how trust influences FinTech adoption, particularly within specific demographic and regional contexts.

Perceived trust stands out as the most significant factor influencing a lender's willingness to extend credit, with studies revealing that perceived risks exert an unfavourable influence on this 'trust' perception. Across various research endeavours, including those centred around mobile banking, perceived trust has consistently emerged as a substantial predictor of individuals' perceptions and intentions to partake in specific behaviours. Moreover, perceived trust serves a pivotal role as a mediator between associated benefits and anticipated outcomes, as underscored by research conducted by Tang (2019) and Wiczorek & Meyer (2019). Tang (2019) asserts that an individual's perception of security and privacy risks associated with the use of e-commerce and related technologies is reflected in their assessment of perceived trust. Wiczorek & Meyer (2019) defines trust as having the confidence to rely on a partner. According to Ryu & Ko (2020), perceived trust quantifies an individual's willingness to believe that online transactions will fulfil expectations without introducing any risks. In the realm of FinTech, trust is even more crucial and important for customers, mainly due to the inherent uncertainty often associated with FinTech providers as compared to e-commerce or e-banking platforms typically operated by well-known banks and financial institutions.

While FinTech applications have gained significant traction in Malaysia, their adoption among urban working professionals remains lower compared to that in developed nations. According to the Department of Statistics, Malaysia, only 58% of urban professionals actively use FinTech services beyond basic mobile banking, whereas in countries such as Singapore and the United Kingdom, adoption exceeds 80% (DOSM, 2023). Furthermore, a survey by Teoh & Yap (2021) found that 27% of Malaysian respondents were hesitant to be early adopters of FinTech services, with 68% of Malaysians citing security concerns and a lack of trust. Despite substantial government investments, including the RM393.8 billion allocated in the 2024 budget to support SME digitalisation and cybersecurity (MOF, 2023), adoption levels remain moderate rather than widespread (Urus & Mohamed, 2021; Gambe & Estopace, 2022).

Cybersecurity risks, regulatory uncertainties, and perceived complexity are among the key deterrents to broader adoption (IMF, 2020; Urus & Mohamed, 2021; FMT, 2024).

The slow pace of adoption has several implications. FinTech is a critical driver of financial inclusion and digital transformation, providing efficiencies in payments, credit access, and wealth management (BNM, 2023). Lower adoption rates may hinder Malaysia's ability to compete with regional FinTech hubs such as Singapore and Hong Kong, where digital financial ecosystems are more advanced (IMF, 2020). Businesses and consumers alike may miss opportunities to optimise financial decision-making and fully leverage digital finance solutions. Beyond convenience and usefulness (Tun-Pin et al., 2019; Wu & Peng, 2024), external factors such as promotional strategies and social influence also impact FinTech adoption (Kiew et al., 2022; Hoque et al., 2024). Marketing incentives and peer recommendations can encourage adoption, but trust remains a decisive factor in whether users engage with these financial technologies.

To better understand these challenges, this study examines the mediating role of trust in influencing FinTech adoption among urban working professionals in Malaysia. Using TAM (Davis, 1989), this research investigates how convenience, perceived usefulness, promotions, and social influence affect the behavioural intention to adopt FinTech applications, with trust serving as a key mediating factor. While convenience and usefulness shape users' willingness to engage with FinTech, external influences such as promotional strategies and social persuasion also play a role in adoption decisions. However, trust remains a critical element that can either enhance or hinder the effectiveness of these factors. Addressing trust-related barriers and understanding its interplay with other adoption drivers may provide valuable insights for improving adoption strategies and supporting Malaysia's digital economy agenda.



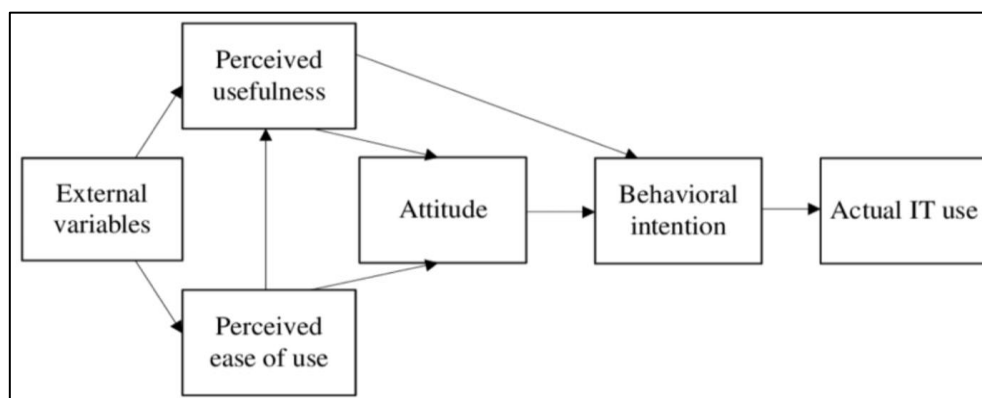
## 1.5 Research Significance

Upon completion of this research study, FinTech providers and start-ups will be better equipped to refine their product and service positioning through enhanced adoption strategies. The anticipated outcomes will also enrich the existing body of knowledge by shedding light on the emerging nexus of ‘trust’ as the critical success factor mediating between perceived benefits and intention to use FinTech applications among urban working professionals in Malaysia. The significance of the relationships between the different independent variables (collectively, perceived benefits) and the dependent variable (adoption of FinTech among urban working professionals in Malaysia), holds immense significance, as it underpins the sustainable development of FinTech applications (Abdul-Rahim et al., 2022). Consequently, a call is warranted for additional empirical substantiation concerning the repercussions of perceived benefits associated with FinTech adoption among urban working professionals in Malaysia.

Moreover, this study will introduce a novel perspective on the societal impact of trust by examining its role as a mediator in FinTech adoption among urban working professionals in Malaysia. Given the established link between trust and FinTech adoption, the research anticipates that addressing trust will significantly enhance the traction of FinTech applications, complementing the well-researched perceived benefits (Meyliana & Fernando, 2019). While much research has investigated trust as a mediating factor in FinTech adoption, studies are often fragmented and context-specific. This study aims to fill the gap by focusing on Malaysia, particularly urban working professionals, and by integrating trust with TAM to offer a comprehensive understanding of its influence on FinTech adoption within this specific regional and demographic context.

## 1.6 Research Scope

This research investigates the technological acceptance of FinTech applications among urban working professionals in Malaysia, by incorporating the mediating role of ‘trust’ as a critical success factor. It does so by considering the perceived benefits associated with FinTech applications, encompassing convenience, usefulness, promotional aspects, and social influence. Within the context of this research, FinTech is referred to as financial technology applications offered by non-banking entities, distinct from the digital platforms typically offered by conventional banking establishments such as mobile banking or internet banking. The research framework for this study is constructed based on an adapted version of the TAM (Davies, 1989), as illustrated in Figure 1.1 below:



**Figure 1.1** Example of research model used as a reference framework for this research.

In essence, the model presents a three-stage progression where external elements (such as system design features) trigger cognitive responses (perceptions of usefulness and ease of use), which subsequently lead to a behavioural response in terms of attitude and intention towards actual use of technology. TAM outlines behaviour as an outcome of perceived usefulness, perceived ease of use, and behavioural intention (Davis, 1989).

An extended study by Davies (1993) discovered that the attitude towards behaviour, serving as an emotional evaluation of the probable consequences of behaviour, can supplant behavioural intention. The likelihood of a behaviour occurring increases with the intensity of the emotional response. The fact that perceived usefulness might directly impact actual use emphasises the significance of the variable in behaviour prediction (Huang & Ren, 2020). While perceived ease of use does not directly determine behavioural intention, it supports the influence of perceived usefulness. According to this concept, if an application is expected to be user-friendly, the user is more likely to perceive it as beneficial, consequently fostering technology adoption (Ventre & Kolbe, 2020).

The development of TAM and its related metrics for gauging technology acceptance has proven to be valuable in practice (Davies, 1989; Davies, 1993). Understanding the cognitive aspects governing the effect of system characteristics on technology acceptance was made easier by establishing the constructs that showed a strong and substantial link with behavioural intention (Huang & Ren, 2020; Mathew & Soliman, 2021). Therefore, TAM is applied in this research to study the effect of FinTech adoption among urban working professionals in Malaysia. This is akin to prior studies carried out by Tun-Pin et al. (2019), Abdul-Raham et al. (2022), and Shahzad et al. (2022). In line with this, the study by Ahmed et al. (2020) on cloud computing adoption also highlights the importance of perceived usefulness and personal innovativeness as key factors influencing behavioural intention, which parallels their relevance to FinTech adoption. However, subjective norm was found to be insignificant in cloud computing adoption, suggesting that in both contexts, individual perceptions, rather than peer influence, may play a more significant role in technology acceptance. Nonetheless, this study deviates slightly by introducing the novel element of ‘trust’ as a mediating factor, which has not been previously explored.

## **1.7 Research Objectives**

The primary objectives of this research are to investigate the effects of perceived benefits on the intention to adopt FinTech applications among urban working professionals in Malaysia and to develop an extended TAM that incorporates ‘trust’ as a mediating variable between perceived benefits and the intention to adopt FinTech applications. This study also aims to examine whether trust plays a significant role in influencing the intention to adopt FinTech applications, given the perceived benefits, and to empirically assess the resultant conceptual model.

Therefore, the specific research objectives for this study are to determine:

1. The relationship between Convenience and Intention to Use FinTech applications among urban working professionals in Malaysia.
2. The relationship between Usefulness and Intention to Use FinTech applications among urban working professionals in Malaysia.
3. The relationship between Promotions and Intention to Use FinTech applications among urban working professionals in Malaysia.
4. The relationship between Social Influence and Intention to Use FinTech applications among urban working professionals in Malaysia.
5. Whether Trust mediates the relationship between these independent variables and Intention to Use FinTech applications among urban working professionals in Malaysia.

## **1.8 Research Questions**

To address the primary and specific research objectives outlined above, this study seeks to answer the following research questions:

1. What is the relationship between Convenience and Intention to Use FinTech applications among urban working professionals in Malaysia?
2. What is the relationship between Usefulness and Intention to Use FinTech applications among urban working professionals in Malaysia?
3. What is the relationship between Promotions and Intention to Use FinTech applications among urban working professionals in Malaysia?
4. What is the relationship between Social Influence and Intention to Use FinTech applications among urban working professionals in Malaysia?
5. Does trust mediate the relationship between Convenience, Usefulness, Promotions, Social Influence, and Intention to Use FinTech applications among urban working professionals in Malaysia?

## **1.9 Summary of Chapter**

This chapter introduces FinTech and its association with Industry 4.0 using advanced technologies, including blockchain, AI, ML, and big data. It is worth noting that FinTech may be deemed as a relatively new term by the public, but it is, in fact, a dynamic integration of intricate concepts of conventional banking functions, including lending, moving, and holding of funds. The paradigm shifts towards the contemporary way of moving funds using FinTech is no stranger to businesses as it is used daily for payments, e-commerce transactions, and accounting.

FinTech has impacted the community in different ways, notably leading merchants to embrace contactless payment methods. This trend has unprecedentedly gained momentum, particularly in the wake of the global Covid-19 pandemic. Payments using FinTech applications have become an accepted norm in Malaysia due to its perceived benefits. However, a prevailing scepticism persists among a significant part of the Malaysian population regarding its reliability, largely attributed to the status of numerous FinTech companies being start-ups and the potential lack of robust government backing. This context underscores the core objective of this research, where the mediating role of ‘trust’ is examined as a critical success factor in the adoption of FinTech among urban working professionals in Malaysia.

## **1.10 Thesis Structure**

This thesis is organised into five main chapters, outlined as follows:

### *Chapter 1: Introduction*

This chapter provides an overview of the research enquiries to be explored and outlines the framework within which the research questions and objectives will be addressed. It sets out the context for understanding the significance of how ‘trust’ as a mediator influences the perceived benefits in driving FinTech adoption among urban working professionals in Malaysia.

### *Chapter 2: Literature Review*

In this chapter, an examination of literature is conducted on the fundamental definitions relevant to this research. It offers a holistic view of the previous studies concerning TAM theories and their association with stimulating FinTech adoption within the Malaysian context. Each essential definition is critically reviewed with existing literature, thus identifying the research gap leading to the purpose of this research study.

### Chapter 3: Research Methodology

This chapter details the research methodology used in conducting this research project, along with the rationale behind each approach chosen for data collection, validation, and subsequent analysis. To gather responses, a questionnaire is used and statistically analysed to ascertain the significance of the datasets in substantiating the research questions and hypotheses. The findings from the analysis are then deliberated upon in the next chapter.

### Chapter 4: Findings and Discussion

In this chapter, an exploration of the analysis findings is presented based on the responses collected through a structured questionnaire inspired by previous scholarly works. A comparative examination of these results against established literature is conducted, yielding valuable insights that can serve as reference points for future research.

### Chapter 5: Conclusions, Recommendations and Suggestions for Future Research

This chapter provides the conclusions and recommendations of the research project that would potentially benefit FinTech providers or start-ups in formulating the right strategy to better position their products and services for sustained business outcomes.

## CHAPTER 2

### 2.0 Literature Review

#### 2.1 General Introduction

In recent years, new technologies such as ML and AI have revolutionised the financial services industry. These technologies have led to a paradigm shift in how financial functions are conducted, including bill payment, investment management, as well as corporate and consumer banking (Wang et al., 2021). For instance, repetitive or routine tasks such as fraud detection and risk assessment are being automated using ML and AI. This can free up human resources to focus on more value adding activities. Additionally, these technologies have been used to personalise financial products and services to meet the needs of individual customers. As a result of these changes, the financial services industry is becoming more efficient, personalised, and customer-centric. This is leading to new opportunities for businesses and consumers alike.

FinTech has an extensive history within the realms of banking and finance, as outlined in the preceding introductory chapter, despite it being a buzzword in the past decade or so. According to Suryono et al. (2020), Fintech is a financial service that combines money and technology, and it is made possible by cutting-edge information and communications technology. ATMs, credit cards, online banking, and, more recently, mobile banking and e-wallets have all been made possible due to FinTech innovations. In addition to online transactions, Fintech also offers services such as P2P lending, crowdsourcing, budgeting, financial planning, and investments (Gerrans et al., 2022; Murinde et al., 2022).

The latest FinTech developments are supported by the fusion of new and old technologies, such as blockchain, AI, ML, and big data (Chauhan et al., 2022; Chen et al., 2021; Noor et al., 2019). These technologies enable the development of increasingly sophisticated and comprehensive



financial products and services. Most researchers agree that FinTech has great potential in addressing numerous business challenges through process automation (Chauhan et al., 2022; Chen et al., 2021; Noor et al., 2019). However, Ashta (2021) argues that the key challenge to FinTech service providers is developing a successful FinTech adoption model that will see mass migration from traditional financial services to FinTech's innovative products and services. As such, factors impacting FinTech adoption will be discussed in detail in the following section and used as a basis for developing the framework that will steer the course of this research investigation.

## **2.2 Definition of Key Concepts**

### **2.2.1 FinTech Adoption**

The emergence of FinTech start-ups and the recent advancement of technology are revolutionising the way financial services are offered. Philippon (2016), an early contribution to the FinTech literature, explores how innovations in the field have not only reduced the cost of accessing financial services but also exposed new vulnerabilities in cybersecurity and introduced legal and regulatory challenges. This is reinforced in the study conducted by Thakor (2020), which found that FinTech innovations may not fit with the traditional financial intermediation theory. Thakor's (2020) study further contends that FinTech innovations hold the potential to bring about disruption by introducing more efficient, cost-effective, and secure ways of transmitting financial information. This, in turn, can reduce dependencies on traditional financial intermediaries, as these new technologies enable direct interactions and transactions between savers and borrowers, bypassing the need for intermediaries like banks. However, it is important to note that while FinTech has the potential to reshape the financial landscape, the extent of its impact can vary based on various factors including regulatory frameworks, consumer adoption, and technological advancements (Thakor, 2020).

The study by Tang (2019) suggests that in consumer lending, especially in the context of P2P lending, visual impressions based on a borrower's photos can influence financial transactions. Borrowers who come across as more reliable or trustworthy through their appearances may have an increased likelihood of obtaining loans, as indicated by the ratings assigned to their photos. This indicates that non-financial factors, such as appearance-based impressions, can play a role in lending decisions. Tang (2019) observes that P2P lending platforms, that often cater to individuals who might be considered small and marginal bank customers, effectively offer an alternative source of funding for such individuals in place of traditional banks. This reflects the role of P2P lending companies in serving segments of the population that might have limited access to traditional banking services.

The intricacies of P2P lending platforms, specifically investigating the trade-offs faced by investors in relation to unfavourable selection challenges were studied in the work of Vallee & Zeng (2019). By examining the interplay between inexperienced investors and their more sophisticated counterparts, the study emphasises the evolving role of technology in mediating lending interactions. The findings reveal the maturation of lending platforms, with heightened screening efforts by experienced investors as well as a reduction in the volume of information disseminated to external investors. This study contributes to the discourse on FinTech adoption by revealing the complexities of investor decision-making within the P2P lending landscape. Vallee & Zeng (2019) also explored further into borrower preferences for different loan terms on P2P lending platforms and the associated default rates. By leveraging a natural experiment facilitated by LendingClub, one of the pioneering P2P lending platforms, the study unveils how varying loan term options impact borrower decisions and subsequent default rates. This research provides a window into the influence of technology-enabled lending solutions on borrower choices and the implications for default risk management. It aligns with the FinTech

adoption discourse by exploring the ways in which technology-driven platforms shape borrower preferences and behaviours.

The rise of FinTech lenders has sparked renewed interest in the similarities and differences between these technology-driven companies and "shadow banks." Shadow banks are financial intermediaries that engage in credit intermediation but operate outside the regulatory framework that governs traditional banks. In contrast, FinTech companies leverage technology to offer financial services, such as lending, payments, and investment management. The growth of FinTech lenders has been fuelled by factors such as the increasing availability of data and computing power, the widespread use of mobile devices, and regulatory changes following the financial crisis. While FinTech lenders have the potential to disrupt the traditional financial system, it is crucial to consider the risks associated with these new players (Cornelli et al., 2023).

The rapid expansion of digital lending by FinTech and BigTech companies has significantly reshaped the credit landscape, particularly in countries with higher GDP per capita, where traditional banking sector mark-ups are high, and regulatory frameworks are less stringent. Cornelli et al. (2023) observe that these new forms of lending thrive in environments with advanced investor protection, efficient judicial systems, and well-developed bond and equity markets. Rather than replacing traditional credit, FinTech and BigTech lending complements it, offering alternative avenues that coexist with conventional financial institutions. This synergy between traditional and digital lending underscores the transformative impact of FinTech on global financial markets, particularly in enhancing accessibility and efficiency in credit provision.

Further, the advantages and disadvantages of FinTech companies and shadow banks in mortgage lending highlight their differing growth dynamics. Cornelli et al. (2023) found that

FinTech lenders have primarily grown due to their use of alternative information to set rates and their ability to originate loans online, reducing both the cost and time of origination. On the other hand, shadow banks have expanded mainly in geographic and socioeconomic areas hardest hit by increased post-crisis regulation (Croux et al., 2020). Fuster et al. (2019) noted that FinTech lenders in the mortgage business process applications 20% faster than other lenders, without a corresponding increase in default rates, indicating the efficiency of their technology-driven approach.

Blockchain is another famous FinTech-related technology that has been the subject of several studies in finance (Kumar et al., 2023). Chiu & Koepl (2019) discussed the problems related to blockchain forking in the context of asset trading settlement. They argued that the benefit of blockchain-based settlement technology is faster and more flexible settlement, but forking can also lead to other equilibriums. Shanaey et al. (2020) examined the negative aspects of cryptocurrencies like Bitcoin. According to Shanaey et al. (2020), the cryptocurrency industry is one of the largest unregulated sectors, and that about 46% of Bitcoin transactions, equivalent to approximately \$76 billion, are linked to illegal activities. Griffin & Shams (2020) found that purchases with Tether, a digital currency pegged to the US Dollar, coincides with market downturns and subsequently led to substantial surges in Bitcoin prices. They mapped the blockchains of Bitcoin and Tether to find that one major player on Bitfinex, a cryptocurrency exchange, is purchasing significant amounts of Bitcoin after market downturns.

Recent research has also focused on how FinTech is affecting wealth management and investments. A study of robo-advisory by D'Acunto & Rossi (2021) found that robo-advisory adopters and non-adopters are comparable in terms of demographics and prior interactions with human advisors. D'Acunto & Rossi (2021) also found that the three main behavioural biases; disposition effect, trend-chasing, and rank effect, have decreased among adopters. Rossi &

Utkus (2020) found that customers with limited financial knowledge, as well as those with substantial cash holdings and high trading volume, benefited the most from robo-advisory using data from one of the largest robo-advisors in the United States, Vanguard's Personal Advisory Services.

FinTech is an interdisciplinary field, and researchers from fields other than finance have also investigated the effects of technological innovation on the supply of financial services. Earlier research by Gomber et al. (2018) examines FinTech innovation and disruption from the standpoint of information systems. They argue that FinTech is a disruptive technology that is transforming the financial services industry. Another earlier study conducted by Arner et al. (2015) examines the legal and regulatory challenges that FinTech companies face. They argue that regulators are facing challenges in developing a regulatory framework that is flexible enough to foster innovation while being open enough to uphold confidence and trust of the market, investors, and ultimately the customers.

The adoption of FinTech technologies has transformed the way businesses perform financial transactions. However, the lack of regulations has opened up new risks, such as the possibility of money being siphoned for illegal purposes. According to a financial services regulatory update by PwC (2022), many FinTech companies have not been subject to the same level of regulatory scrutiny as traditional banks. This has created a poor perception among the public that FinTech applications are unreliable and that customers are at risk of having their personal information abused and misused for illegal activities, or even scammed. A study by Najaf et al. (2021) found that the lack of regulations in the FinTech industry is a major concern for businesses and consumers. The study found that businesses are worried about the security of their data and the risk of fraud, while consumers are concerned about the lack of transparency and accountability in the industry.

To address these concerns, many FinTech companies are working with financial institutions to develop regulatory frameworks that will protect businesses and consumers. The work of Barroso & Laborda (2022) and Abdul-Rahim et al. (2022) found that collaboration between traditional financial institutions and FinTech companies is mutually beneficial. Barroso & Laborda (2022) emphasises the impact of emerging technologies and regulatory challenges, while Abdul-Rahim et al. (2022) highlights the exchange of resources, expertise, innovation, and agility that enhance both parties' capabilities.

Transitioning to the Malaysian context, it is essential to understand how these global trends intersect with the specific factors influencing FinTech adoption within the country. Malaysia's financial sector is characterised by a rapidly growing middle class, a government commitment to digital transformation, and a strong mobile penetration rate. These factors provide a fertile ground for FinTech innovation (Beirne et al., 2022). The regulatory environment in Malaysia plays a pivotal role in FinTech adoption. The Securities Commission Malaysia and Bank Negara Malaysia have introduced progressive regulations that facilitate FinTech development while ensuring consumer protection and financial stability. These regulatory initiatives have attracted both domestic and foreign FinTech companies (BNM, 2022). Comparing the Malaysian context with global trends, it is evident that Malaysia's regulatory support, mobile-centric consumer behaviour, and expanding urban working professionals are influencing the rapid adoption of FinTech solutions. However, the unique challenges faced by Malaysian consumers and businesses, as highlighted in local studies, underscore the importance of tailoring FinTech offerings to suit to the Malaysian market, in particular the expanding urban working professionals.

### 2.2.2 Convenience

Convenience is an important factor that influences consumer intention and behaviour towards the use of new technology. It is often associated with perceived usability and simplicity, which can affect the speed of the learning process. Convenience is said to have a significant impact on the adoption of information technology, and it is one of the factors that promotes the acceptance of many FinTech applications, such as mobile banking (Tapanainen, 2020).

Amnas et al. (2023) investigated the factors influencing customers' intention to use FinTech services, with a particular focus on the role of trust. Integrating insights from the Unified Theory of Acceptance and Use of Technology 2 (“UTAUT2”) framework and the trust theoretic model (“TTM”), the study revealed several key factors influencing FinTech adoption, with convenience emerging as a significant determinant. Effort expectancy, a component of UTAUT2, was found to have a substantial impact on the intention to use FinTech services. This suggests that users are more inclined to adopt and regularly use FinTech platforms when they perceive these services to be convenient and require minimal effort. Habit, another determinant identified in the study, significantly influences behavioural intention to use FinTech services. This implies that individuals tend to develop routines around the convenience and accessibility of FinTech platforms, making them a natural choice for financial tasks. Furthermore, facilitating conditions, which encompass the availability of infrastructure, support, and resources that facilitate the use of FinTech, were also found to have a positive relationship with behavioural intention to use FinTech. This underscores the importance of a convenient and enabling environment in driving FinTech adoption. While convenience itself was not explicitly measured as a separate variable in this study, the factors such as effort expectancy, habit, and facilitating conditions indirectly highlight the significance of convenience in users' decisions to adopt and use FinTech services (Amnas et al., 2023).

Moreover, a case study of Access Bank in Ghana and Nigeria found that perceived convenience had a positive impact on consumers' behavioural intentions to use FinTech. The study revealed that consumers were more likely to use Access Bank's FinTech services if they found them to be convenient (Ahiabenu, 2022).

The work of Ali et al. (2021) found that perceived usability is positively correlated with mobile banking adoption. This means that the more convenient the mobile banking application is perceived to be, the more likely people are to adopt it. The authors concluded that this is because convenience makes the application easier to use and more accessible, which reduces the perceived risk and effort of using it. The study also found that convenience is associated with the notion that users do not need any special knowledge to use the application (Ali et al., 2021). This is because a user-friendly interface with clear guidelines makes the application easy to learn and use. These findings align with those of Sheng (2021), who found that mobile technology that is focused on user convenience can improve adoption. This study also looked at the development of FinTech in China and found that mobile banking applications that were easy to use and convenient were more likely to be adopted by consumers (Sheng, 2021).

Similarly, a preliminary study on FinTech in Malaysia found that customers' attitudes towards FinTech adoption were influenced by convenience and the perceived ease of use (Tun-Pin et al., 2019). This study surveyed 200 Malaysian consumers and found that those who perceived FinTech to be convenient and easy to use were more likely to be willing to adopt it.

### **2.2.3 Usefulness**

Perceived usefulness is a person's belief that using a particular system will improve their performance in a position or task. It is a key factor in the TAM, which is a model that explains how people adopt new technologies. Perceived usefulness has been shown to be a key



motivator for customers to adopt new technologies in the technological sector (Singh et al., 2020). This is because new technologies can help people to perform tasks more effectively and efficiently.

The study by Almashhadani et al. (2023) explores FinTech adoption in Jordan during and post-COVID-19 pandemic, integrating and extending the TAM and UTAUT theories to predict behavioural intention to use FinTech. The study identifies six predictors hypothesised to impact behavioural intention: perceived usefulness, perceived ease of use, social influence, personal innovativeness, financial risks, and privacy risks, with COVID-19 lockdowns acting as a moderator (Almashhadani et al., 2023). The findings reveal that perceived usefulness and personal innovativeness significantly influence behavioural intention, while privacy risks show no significant impact. Moreover, the study demonstrates the moderating role of COVID-19 lockdowns on the relationship between several predictors and behavioural intention, highlighting the pandemic's impact on increasing FinTech adoption in Jordan.

Wu & Peng (2024) investigated the determinants of FinTech adoption among rural residents in China, where perceived usefulness emerged as a critical mediator shaping behavioural intentions towards FinTech adoption. A study in Taiwan (Lin et al., 2020) highlighted customers' reliance on perceived usefulness when contemplating FinTech adoption before online purchases. Practical functionalities of FinTech, such as real-time account monitoring and instant fund transfers, were deemed most pertinent due to their direct impact on individuals' financial well-being (Meyliana & Fernando, 2019).

Noonpakdee (2020) found that the Thailand's banking industry has made FinTech applications appropriate for use at the workplace due to its perceived usefulness. This is because FinTech can help employees search for information more rapidly and easily, without having to spend unnecessary time browsing through large amounts of data. Ali et al. (2021) also found that the

perceived usefulness of FinTech is a key factor in consumers' intentions to adopt it. They found that consumers are more likely to adopt FinTech if they believe that it will help them save time and money, and make better financial decisions. Other researchers have also found that consumers' perceptions of the usefulness of FinTech are important (Al-Okaily et al., 2021; Lim et al., 2019; Singh et al., 2020). These studies suggest that FinTech companies need to focus on making their products and services as useful as possible in order to attract and retain customers.

Perceived usefulness positively affects the propensity to use FinTech applications because customers tend to assess their satisfaction after using a technology platform to perform financial-related transactions (Lim et al., 2019). Lim et al. (2019) found that users of FinTech applications usually evaluate their satisfaction levels based on the utility and the strengths of the system or product. This is consistent with many research studies where technology usefulness is found to be one of the most reliable predictors for customer satisfaction. For example, the study by Lim et al. (2019) found that perceived usefulness was the strongest predictor of customer satisfaction with regards to online banking services. The relationship between perceived usefulness and propensity to use FinTech has not yet been empirically tested in this study, but it is theoretically related. This means that it is likely that the two variables are correlated, but more research is needed to confirm this.

#### **2.2.4 Social Influence**

Venkatesh et al. (2003) describes social influence as the extent to which an individual believes that significant individuals in their life, such as family members, friends or colleagues, think they should adopt the new system. The UTAUT, a widely used technology acceptance model formulated by Venkatesh et al. (2003) pointed out that social influence has a favourable impact on individuals' inclination to adopt technology within the UTAUT framework. Furthermore, a

multitude of studies substantiate that social influence also has a positive effect on individuals' behavioural outcomes. While many studies found positive relationships between subjective norms and behavioural intention, Singh et al. (2020) argues about the complex nature of social influence in FinTech adoption.

A recent study by Hoque et al. (2024) shed light on the role of social and facilitating influences in FinTech adoption, particularly in regions like Chattogram, Bangladesh. The study identified image, compatibility, and experiences of FinTech use as significant predictors of FinTech user intention, with perceived social norms having a non-informative effect. Interestingly, perceived behavioural control was found to negatively influence females' adoption of Fintech, indicating a potential gender gap in FinTech user intention.

Irimia-Diéguez et al. (2023) sheds further light on social influence, integrating the TPB and the Theory of Reasoned Action (“TRA”) frameworks to predict FinTech adoption among small and medium enterprises. Irimia-Diéguez et al. (2023) found that subjective norms and attitudes significantly influence the intention to use Fintech services. These findings are consistent with studies by Al-Okaily et al. (2020) and Wang et al. (2019) in the FinTech sector. According to Hassan et al. (2022), there is a strong interest among potential followers in learning about emerging technologies, specifically mobile payments and e-commerce, which are integral to the FinTech industry. In the context of new technology adoption, individuals are greatly influenced by their social networks who embrace FinTech and its associated benefits, as these individuals typically spend a substantial amount of their time with their social circles (Chan et al., 2022). Tun-Pin et al. (2019) investigated the factors influencing the intention to adopt FinTech in Malaysia using the UTAUT model and found a significant and positive relationship between social influence and the intention to adopt FinTech. In addition, Xie et al. (2021)

emphasises that social impact plays a crucial role in shaping an individual's perspective and experience with novel FinTech products.

It is essential to note that not all studies align with these findings. For instance, a study conducted by Bajunaied et al. (2023) in Saudi Arabia, presented contrasting results. This research suggests that social influence has an insignificant impact on consumers' behavioural intention towards FinTech services in Saudi Arabia (Bajunaied et al., 2023). The unique cultural and social norms in Saudi Arabia, deeply rooted in subjective norms and strong beliefs, may play a more dominant role in shaping technology adoption decisions (Bajunaied et al., 2023). These divergent findings underscore the importance of considering 'trust' as a mediating factor when examining the influence of social factors on FinTech adoption behaviour, particularly in the case of urban working professionals in Malaysia.

### **2.2.5 Promotions**

Nangin et al. (2020) associates promotions with perceived delight, and describes promotions as an incentive that influences an individual's adoption of technology. According to Meidawati et al. (2022), promotions play a significant role in influencing the public's interest in adopting e-wallet services in Indonesia. They advocate that promotions are effective in raising awareness about e-wallets and informing people about the advancements in payment systems. E-wallet companies employ creative and attractive promotional methods to capture people's attention and generate interest in their products (Meidawati et al., 2022).

Windasari et al. (2022) investigates the impact of various factors, including promotions, on the adoption of digital-only banking services among generation Y and generation Z individuals. The study suggests that while promotions are important in driving adoption of digital-only banking services, it is just one of several factors that influence customers' decision-making

process. According to Windasari et al., (2022), effective promotional strategies should be complemented by other elements such as user-friendly interfaces, rewards, and positive customer feedback to enhance the overall customer experience and encourage sustained usage of digital banking platforms.

Nguyen & Nguyen (2022) explores the impact of promotional advantages on the intention to use mobile wallets (a form of FinTech), highlighting the role of various factors such as demographics, social influence, and compatibility. It discusses how promotional incentives may not directly impact the intention to use mobile wallets, but rather influence factors like social influence and compatibility, which in turn affect usage behaviour. One of the key findings is that promotional advantages have a strong effect on social influence, as consumers are more likely to recommend mobile wallets to others when enticing promotional campaigns are in place (Nguyen & Nguyen, 2022). This word-of-mouth recommendation can be a powerful tool for service providers to encourage adoption.

A similar study conducted by Kiew et al. (2022) investigates the factors influencing the adoption of e-wallets in Malaysia, particularly in light of the accelerated growth of cashless and contactless digital payments due to the COVID-19 pandemic. This study highlights the significant impact of promotions on e-wallet adoption. Attractive promotions, such as coupons, discounts, and cashbacks, are found to be instrumental in attracting new users and retaining existing ones. These promotions make e-wallet usage more appealing to consumers by offering incentives to spend less and avail of financial benefits.

According to a study conducted in Thailand by Jenweeranon (2020) on mobile banking, individuals are more likely to embrace new technology when they perceive it as rewarding, particularly with new promotions, as it encourages socialisation and advocacy. Furthermore, it was found that one of the crucial factors leading consumers in Taiwan to use online financial

services is perceived enjoyment. Consumers prefer to feel glad and pleasant when trying a new system, especially when it is perceived as beneficial and pleasurable (Lin et al., 2020). The adoption of new technology is greatly influenced by perceived enjoyment, as individuals are more likely to develop a habit when they find an action enjoyable. This is also supported by a similar study conducted by Hamzah et al. (2022) within the context of Malaysia.

### **2.2.6 Trust as a Mediating Factor**

FinTech and mobile technologies are key drivers in modern business models and service delivery. The development and implementation of these models are guided by basic technological frameworks, with mobile technology playing a strategic role in providing consumers easy and efficient access to financial services (Arner et al., 2020). However, trust is crucial in the adoption of FinTech services (Nangin et al., 2020). This study emphasizes the role of perceived ease of use and promotional efforts in building customer trust, with findings indicating that trust significantly and positively impacts FinTech usage. Higher levels of trust are linked to a greater likelihood of adopting and using FinTech applications.

Ali et al. (2021) examined the adoption of Islamic FinTech and provided insights into the mediating role of trust. Their findings indicate that perceived benefits, perceived risks, and trust influence the intention to adopt Islamic FinTech. Importantly, the study highlights that perceived benefits have a strong impact on building trust, suggesting that users who perceive tangible advantages in Islamic FinTech services are more likely to trust the platform. This indicates that trust acts as a mediator between perceived benefits and the intention to adopt FinTech.

Scholars have also explored the perceived risks and uncertainties surrounding innovation. Financial organisations in the FinTech sector face various risks, including financial, legal,

security, and operational concerns (Ryu & Ko, 2020). The gap between high expectations for FinTech growth and its actual realisation is often attributed to customer hesitation due to the unpredictable nature of the technology. Ryu & Ko (2020) found that factors like uncertainty and the quality of information technology strongly influence intentions to continue using FinTech services. Moreover, information quality was found to be positively related to trust.

Perceived trust is also a critical factor in determining consumers' willingness to engage in financial transactions, as shown in studies by Tang (2019) and Wiczorek & Meyer (2019). Tang (2019) describes perceived trust as an individual's assessment of the security and privacy risks associated with online transactions, which directly impacts their readiness to engage in such transactions. Similarly, Wiczorek & Meyer (2019) advocate that trust is fundamental in successful financial interactions, requiring confidence in both technology and the reliability of service providers. Zhao et al. (2024) further emphasise that the absence of trust presents a major challenge to achieving stable and effective financial systems.

Arli et al. (2020) explored trust in the context of cryptocurrencies, identifying knowledge of cryptocurrencies, trust in government, and transaction speed as key factors influencing consumer trust in these digital assets. Service providers must focus on building strong relationships between FinTech users and businesses to foster trust. The trust of adopters is significantly influenced by FinTech service providers, mobile operators, and merchants (Cojoianu et al., 2021; Ryu & Ko, 2020).

Leong et al. (2020) define trust as an individual's willingness to believe in the reliability of service providers, encompassing perceptions of dependability and confidence in both people and technology. Trust, in this context, plays a crucial role in shaping consumer behaviour, particularly in the adoption of technology. Zhao & Liu (2022) found that consumers' trust in

FinTech services is influenced by system quality, information, and service, with security and privacy being critical to fostering positive attitudes and intentions towards FinTech usage.

Ventre & Kobe (2020) argue that trust in mobile technology plays a pivotal role in the adoption of financial technologies, particularly when it comes to financial transactions conducted via smartphones. Factors such as perceived benefits, security, adherence to financial regulations, and the reliability of service providers are key determinants that influence trust in mobile FinTech applications (Ventre & Kobe, 2020). Furthermore, the risks associated with insecure FinTech ecosystems can significantly undermine user confidence, which highlights the importance of building robust, secure platforms for FinTech services. The dynamic preferences of younger generations, such as Gen Z, further illustrate the evolving nature of trust in the digital financial landscape.

Research also shows that behavioural intention is positively influenced by perceived trust across various digital contexts, including e-commerce, internet banking, mobile banking, and mobile payments (Ryu & Ko, 2020). Trust serves to mitigate uncertainty, particularly in situations where one party depends on another to act in their best interest (Kowalski et al., 2021). Dawood (2021) found that mobile perceived trust is the most influential factor in determining behavioural intention for online payments, while Kiew et al. (2022) identified trust as crucial in the adoption of e-wallets in Malaysia, where users need to trust the system to ensure their money is safe.

Indiani et al. (2024) reinforced trust's mediating role in online environments. The study shows that while consumer demographics do not moderate the intention-purchase relationship, they do influence the trust-purchase relationship (Indiani et al., 2024). Trust, therefore, plays a central role in decision-making processes, especially in high-risk digital contexts like FinTech, where overcoming barriers to adoption relies on building trust.



Similarly, Chawla et al. (2023) identified perceived trust as a significant factor in the adoption of FinTech products, particularly among digital natives in the post-COVID-19 era. The study demonstrated that perceived trust, along with perceived security and perceived risks, significantly influenced customer intentions to adopt FinTech. Trust, in particular, was driven by aspects such as company credibility and the user-friendly nature of the technology (Chawla et al., 2023). This further emphasises its role as a mediator in FinTech adoption. Moreover, perceived security played a crucial role, as concerns over cyber risks and data protection directly impacted users' willingness to adopt FinTech. These insights further reinforce the importance of trust as a mediating factor in the adoption of FinTech, especially as users navigate the risks and benefits of FinTech (Chawla et al., 2023).

Building on this, Amnas et al. (2024) explored the role of digital financial literacy as a mediator in the relationship between FinTech and financial inclusion, as well as the moderating effect of perceived regulatory support. The work of Amnas et al. (2024) highlights that trust, alongside service quality and perceived security, is essential in promoting FinTech adoption. In addition, digital financial literacy also emerged as a key mediator, helping users overcome barriers to financial inclusion, while regulatory support played a significant moderating role in strengthening the relationship between FinTech adoption and financial inclusion. These findings suggest that enhancing digital financial literacy and ensuring regulatory support can further solidify trust in FinTech, making it more accessible and inclusive for users (Amnas et al., 2024).

Nangin et al. (2020) also highlighted that perceived ease of use and promotional efforts are key factors in building customer trust, which in turn significantly impacts FinTech adoption. Trust is influenced by factors such as ease of use, security measures, cultural considerations, brand image, and regulatory compliance. Recognising and cultivating trust is essential for FinTech

providers aiming to secure user adoption and foster long-term customer relationships. However, the generalisability of these findings is limited by the study's focus on Jakarta and constraints due to the pandemic, suggesting the need for broader research across different regions.

Cojoianu et al. (2021) and Meyliana & Fernando (2019) highlight the importance of customer trust in mobile banking, where privacy and security concerns are paramount due to the sensitive financial information involved. Roh et al. (2023) contribute to this understanding by showing that trust is a mediating factor in the adoption of AI-enabled robo-advisors in FinTech, where perceived security and privacy concerns play a key role. A study by Bajunaied et al. (2023) in Saudi Arabia identifies privacy as a critical factor contributing to the increasing penetration of FinTech services. Zakariyah et al. (2023) found that perceived trust and social norms are crucial in driving the adoption of FinTech in *waqf* (charitable Islamic endowment) institutions in Malaysia, reinforcing trust's importance in financial transparency and efficiency. Jafri et al. (2024) emphasise the role of trust in the adoption of FinTech by demonstrating how users' trust in mobile platforms is influenced by the perceived quality of service, security, and the regulatory framework. The findings point to trust as an essential enabler of FinTech adoption, especially in the rapidly evolving digital landscape.

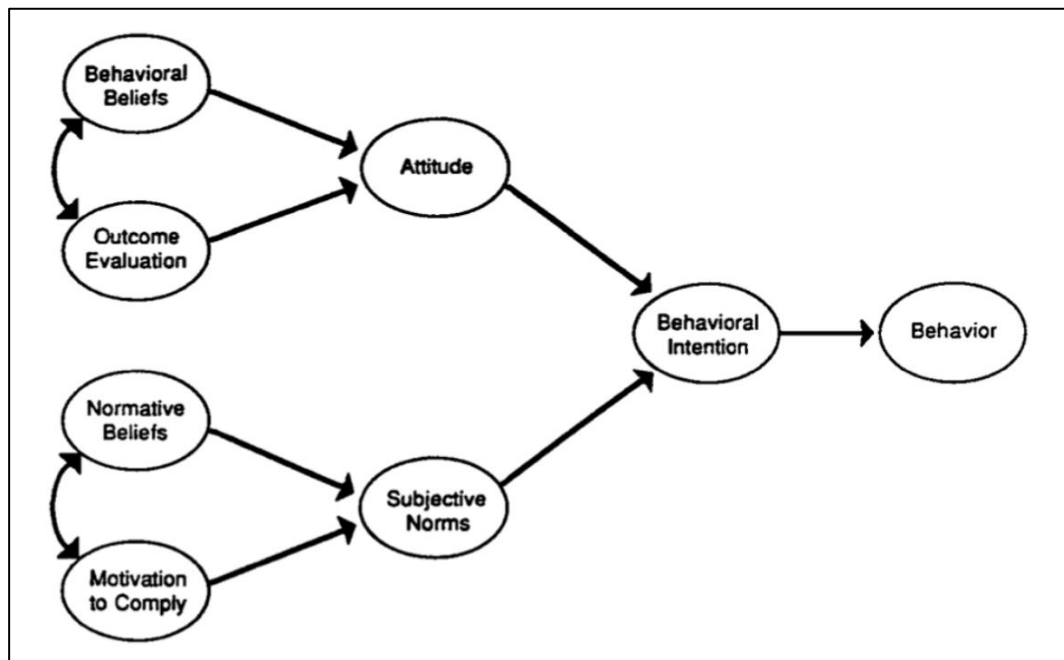
Similarly, Mawadi et al. (2023) explored trust's mediating role in the context of reverse logistics and customer satisfaction at Shopee Indonesia (an online shopping app where people in Indonesia can buy and sell things like clothes, electronics, and more). Their findings showed that while reverse logistics significantly impacted customer satisfaction, trust did not play a significant mediating role between reverse logistics and satisfaction. This highlights the contextual importance of trust, showing that its mediating effect may vary depending on the

sector or type of digital service being considered. In FinTech, however, trust remains central to the adoption and satisfaction process, as seen in other digital financial services contexts.

In conclusion, the collective body of research highlights the multifaceted role of trust in influencing consumer behaviour and attitudes toward FinTech adoption. Trust is a key mediator in the adoption of FinTech among urban working professionals in Malaysia, shaping perceptions of security, privacy, and reliability. Service providers must prioritise building strong relationships and addressing security challenges to foster greater trust, thereby enhancing the likelihood of FinTech adoption.

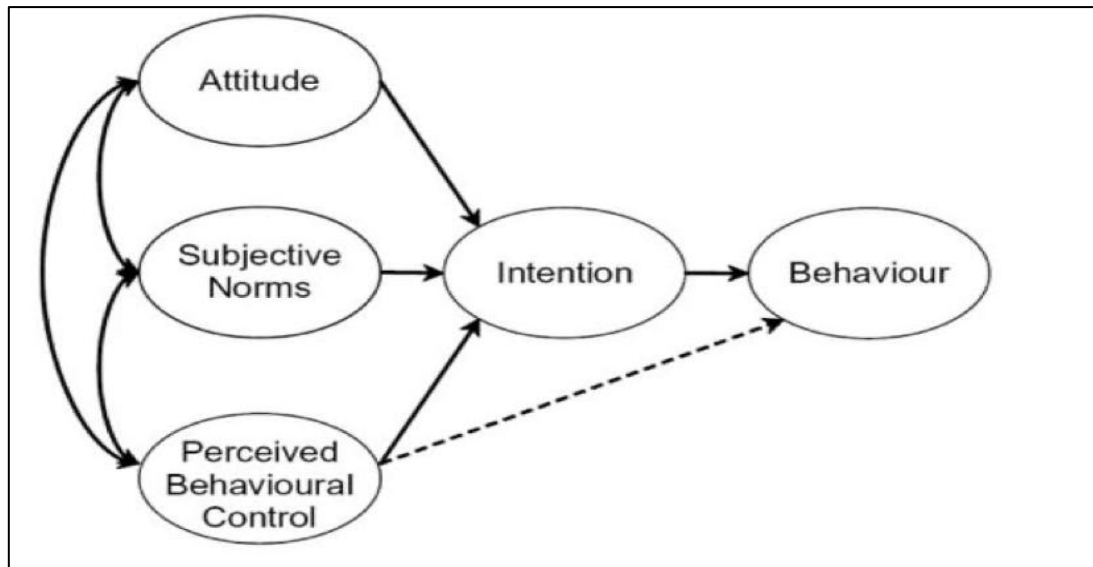
### **2.3 Theories in Technology Adoption**

One of the most influential theories, the Theory of Reasoned Action (Fishbein & Ajzen, 1975), focuses on factors that impact a person's attitudes towards behaviour, as depicted in Figure 2.1. The authors define "attitude" as an individual's assessment of an item, "belief" as a connection between an object and an attribute, and "behaviour" as an outcome or goal. A set of ideas about the thing being acted upon forms the basis of affective attitudes (e.g., credit cards are convenient). The second component is the individual's subjective norms regarding how their peers feel about a particular behaviour. For instance, "My peers use credit cards, and it's a status that I should have."



**Figure 2.1** The Theory of Reasonable Action proposed by Fishbein & Ajzen (1975).

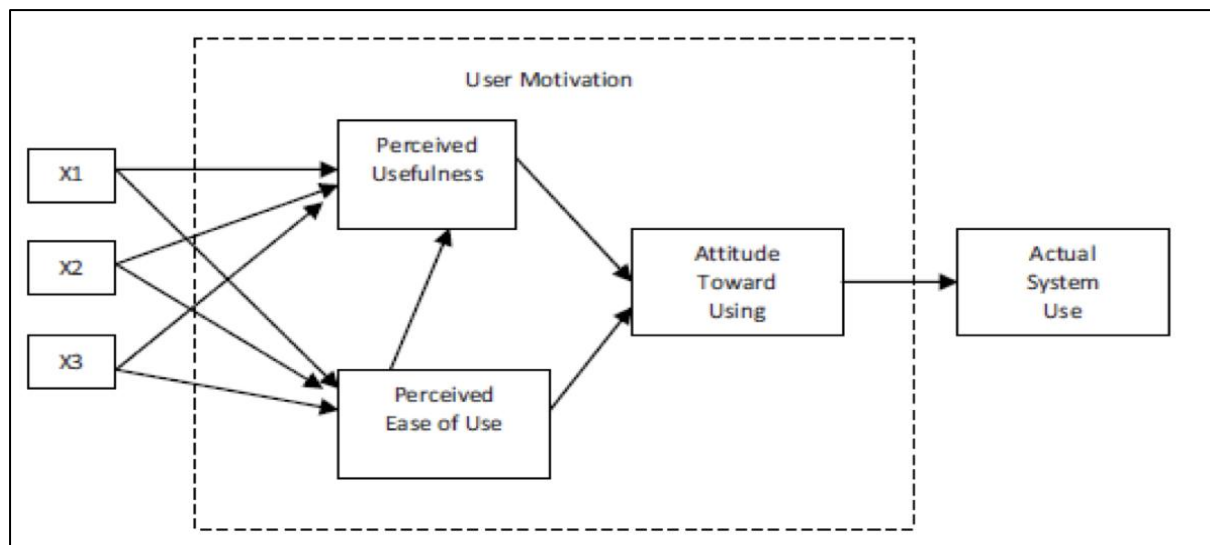
The subsequent model, the Theory of Planned Behaviour (Ajzen, 1991), shares similarities with the previously mentioned Theory of Reasoned Action, encompassing overlapping components such as attitude and subjective norms. Ajzen (1991) introduced a modification to the model by integrating a novel element of perceived behavioural control in connection to the intention to use and behaviour, as illustrated in Figure 2.2. Using the example of credit card use, a pertinent question arises: “Can I apply for a credit card, and what are the associated requirements?”



**Figure 2.2** The Theory of Planned Behaviour developed by Ajzen (1991).

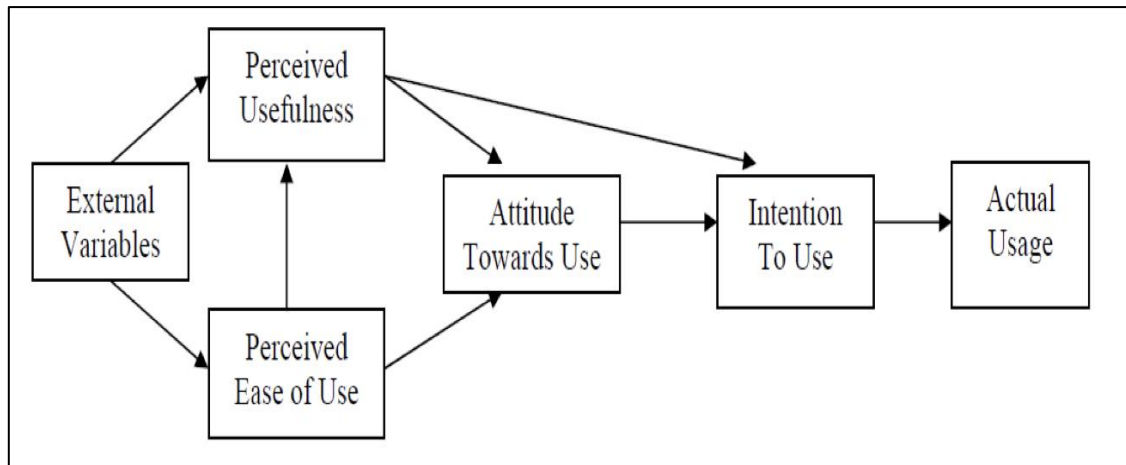
Years later, Taylor & Todd (1995) introduced the Decomposed Theory of Planned Behaviour, which upholds the same components as measured by Fishbein & Ajzen (1975) and Ajzen (1991). However, this model enhances the focus on influencing behavioural intention and actual behaviour adoption as the outcomes. All three models, including the Theory of Reasoned Action, Theory of Planned Behaviour, and Decomposed Theory of Planned Behaviour, have been extensively referred to in studies examining existing products in the market, considering societal perspectives, also known as the subjective norm.

During the same timeframe, another model emerged to simulate consumer acceptance of technology or information system, the well-known Technology Acceptance Model (“TAM”) developed by Davis (1986) for his doctoral project, as depicted in Figure 2.3.



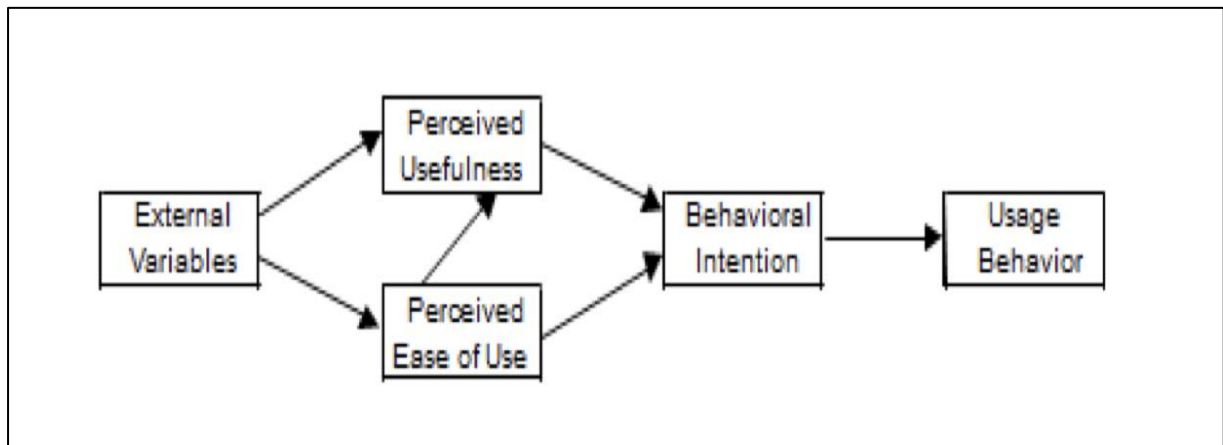
**Figure 2.3** Technology Acceptance Model (“TAM”) proposed by Davis (1986).

Subsequently, Davis et al. (1989) made refinements to their model by introducing the element of "Intention to Use," positioned between "Attitude Towards Use" and "Actual Usage," as shown in Figure 2.4. TAM seeks to clarify the fundamental factors that influence user behaviours across a diverse range of end-user computing technologies and user demographics. Within the foundational TAM model, two specific beliefs were investigated: Perceived Usefulness (“PU”) and Perceived Ease of Use (“PEU”). The concept of PU reflects the subjective belief that utilising a specific system, such as a single-platform e-payment system, will enhance one's actions. On the other hand, PEU relates to how straightforward one expects the target system to be for use (Davis et al., 1989). TAM acknowledges the existence of external variables that may impact an individual's belief in a system.



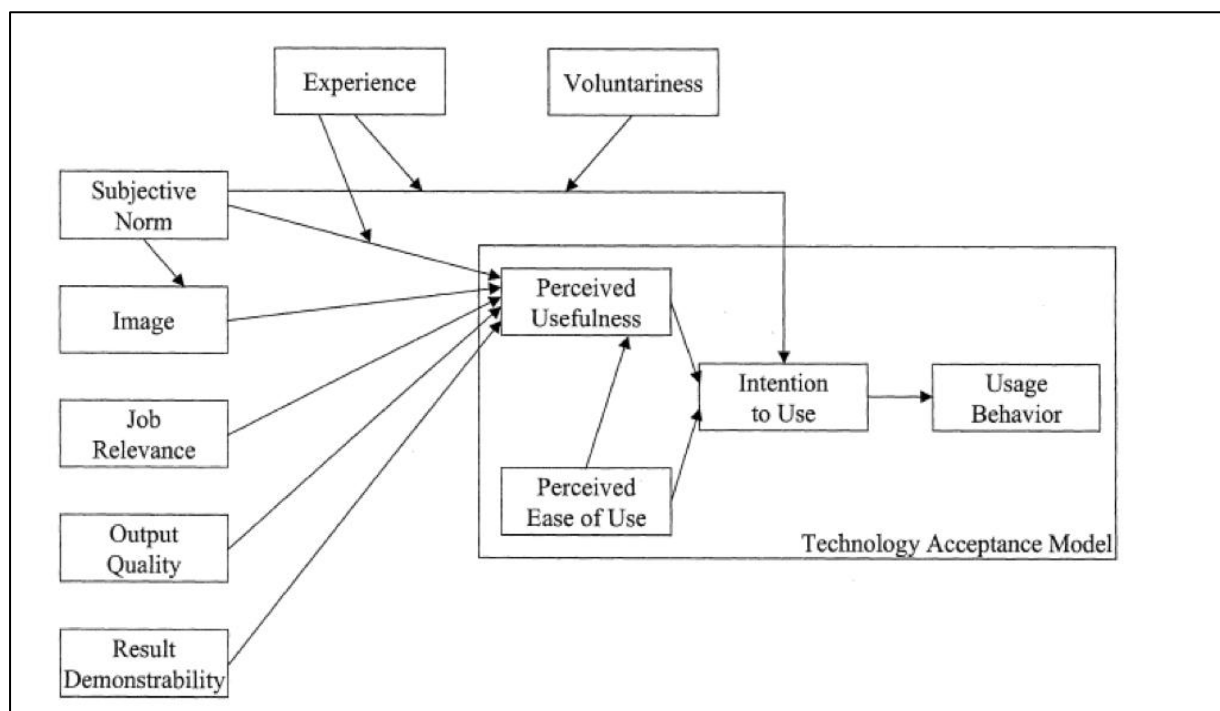
**Figure 2.4** A modified version of TAM proposed by Davis et al. (1989).

Venkatesh & Davis (1996) made a significant contribution to the initial TAM by revealing that both PU and PEU play pivotal roles in influencing behavioural intention. This discovery prompted the development of the final version of TAM, as depicted in Figure 2.5. Notably, their work demonstrated that the inclusion of PEU as a distinct factor negated the need for the attitude component in the model.



**Figure 2.5** The final version of TAM developed by Venkatesh & Davis (1996).

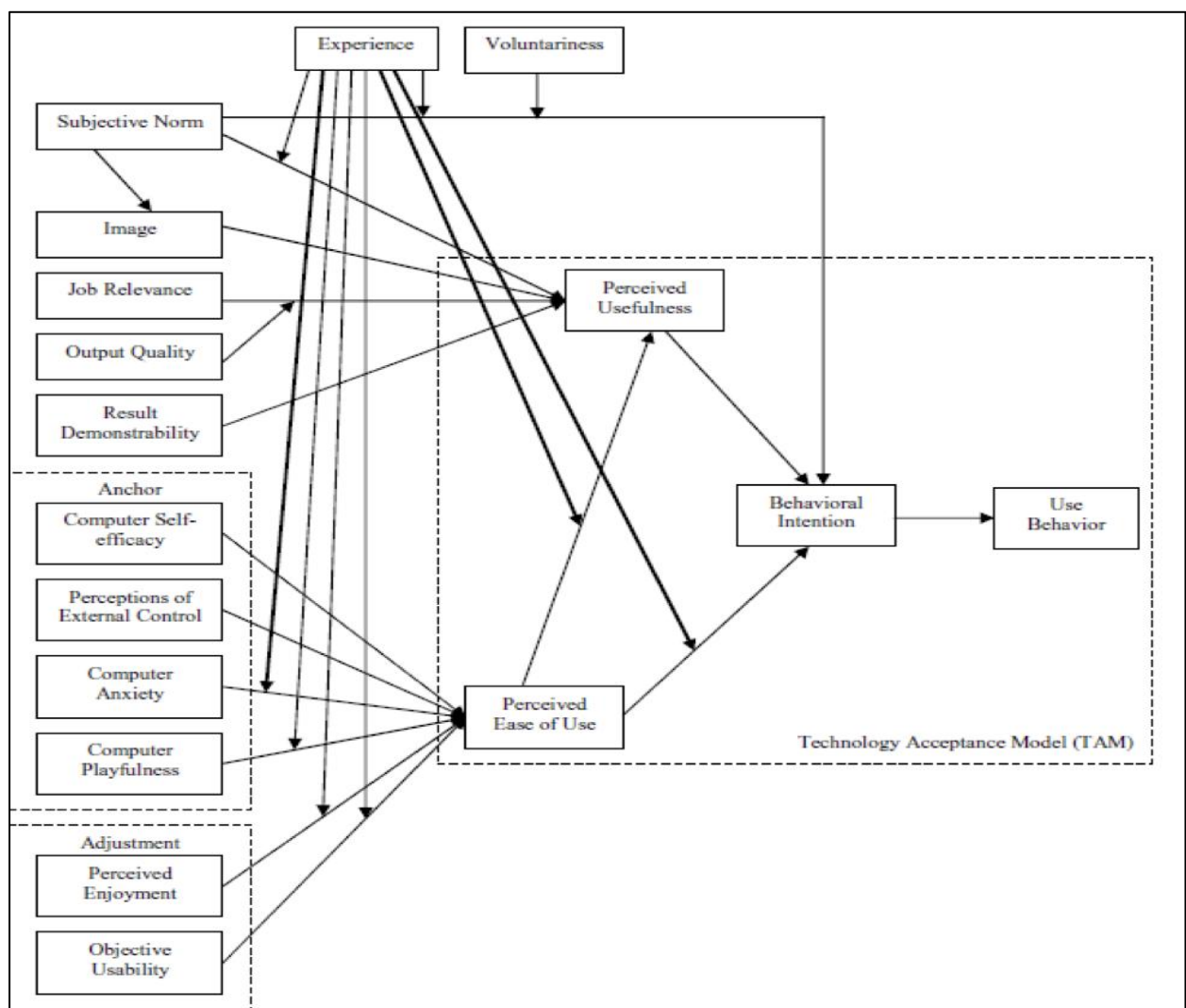
Technology Acceptance Model 2 (“TAM2”) was then introduced by Venkatesh & Davis in their paper "A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies" in 2000. TAM2, as depicted in Figure 2.6, is an extension of the original TAM proposed by Davis in 1989. TAM2 incorporates additional variables to enhance the model's explanatory power in predicting technology acceptance and usage behaviour. In TAM2, Venkatesh and Davis (2000) introduced two key external factors: subjective norm and cognitive instrumental processes. These additions aim to provide a more comprehensive understanding of the factors influencing users' acceptance of technology. The TAM2 model builds on the original TAM by addressing some of its limitations, particularly its focus on individual beliefs and attitudes. By incorporating social and cognitive factors, TAM2 offers a more nuanced perspective on the complexities of technology acceptance.



**Figure 2.6** TAM2 refined by Venkatesh and Davis (2000).

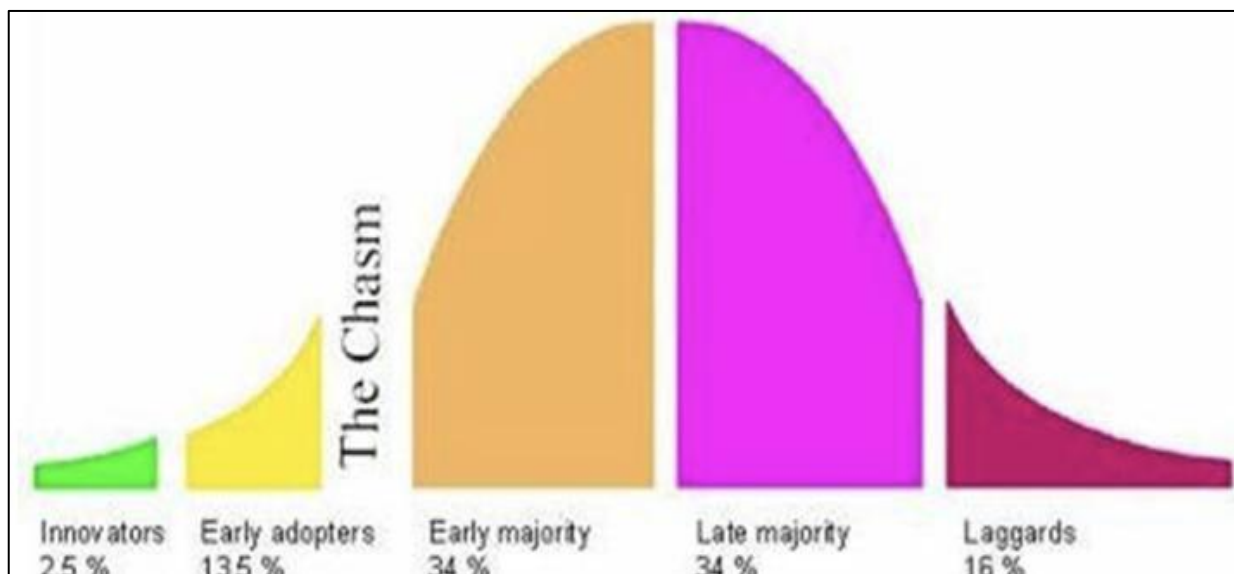


As the study of technology adoption become more complex, and acknowledging that the earlier models primarily address “use behaviour”, the TAM models were further modified to cater for technology implementation environments. The initial models were again refined by combining TAM2 and the model of the PEU drivers, as shown in Figure 2.7. The individual differences, system characteristics, social impact, and facilitating factors, which are determinants of PU and PEU, were used by the authors to design TAM3. The TAM3 research paradigm was tested in actual IT implementation environments (Venkatesh & Bala, 2008).



**Figure 2.7** TAM3 established by Venkatesh & Bala (2008).

Not long after the inception of the TAM, a subsequent model, the Diffusion of Innovation theory, was developed in a study conducted by Rogers (1995). The aim of the author was to investigate the acceptance and adoption of technological innovations based on stages of acceptance; encompassing innovators, early adopters, early majority, late majority, and laggards. This theory addresses the assimilation of innovations within both individuals and organisations, synthesising evidence from over 500 research studies. It explains how innovation is disseminated over time among the constituents of a social system through specific channels, a process termed ‘diffusion’ by the author. This involves members of a social system communicating an innovation through various channels over time, including stages of understanding, persuasion, decision, implementation, and confirmation (Rogers, 1995). The bell-curved adoption model is depicted in Figure 2.8.

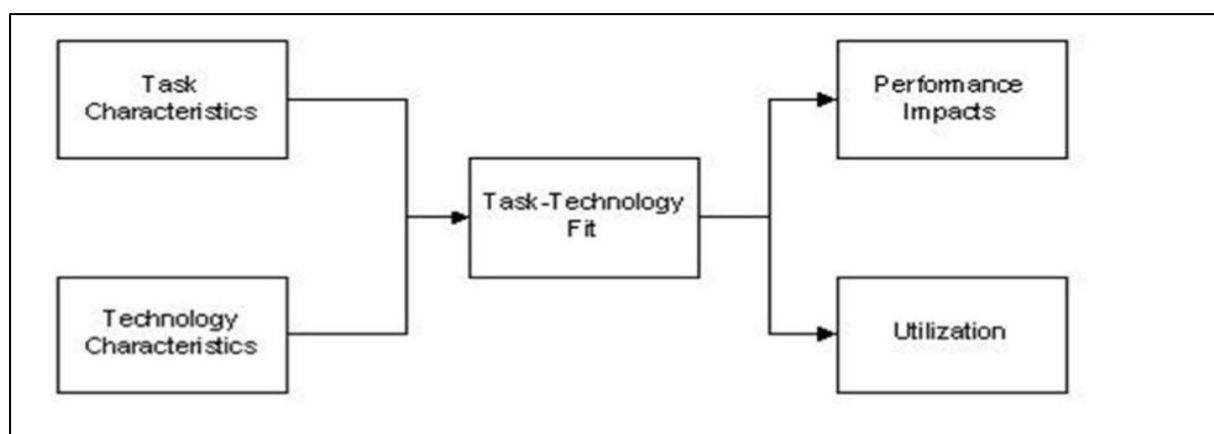


**Figure 2.8** Innovation Adoption Curve proposed by Rogers (1995).

Technology readiness denotes an individual’s predisposition to adopt and utilise new technologies to achieve personal and professional goals. Tsikriktsis (2004) segmented technology consumers into five readiness categories: explorers, pioneers, sceptics, paranoids, and laggards, based on individual technology readiness scores. This segmentation aligns with

Rogers's (1995) S-shaped adoption curve, which includes innovators, early adopters, early majority, late majority, and laggards. As the study is market-focused, the diffusion of innovation or technology readiness is essential for an organisation's implementation success. Roger's (1995) model is better suited for analysing the spread of innovations across different social groups and over time. However, it may not provide sufficient depth in understanding the specific motivations and barriers faced by individual consumers when deciding to adopt FinTech applications and services.

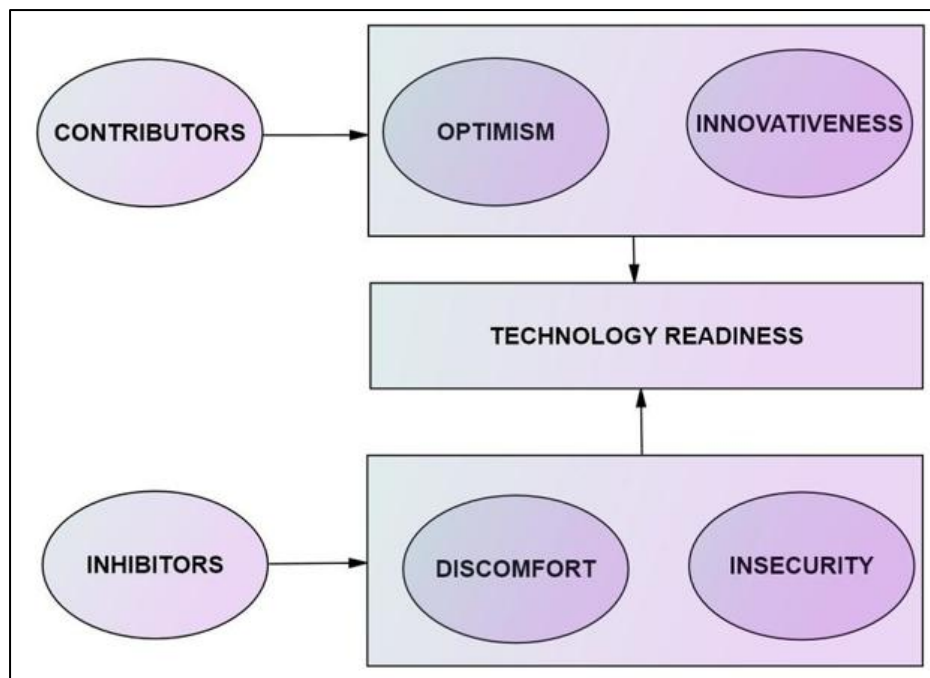
Another related model, the Task-Technology Fit ("TTF") model conceptualised by Goodhue et al. (1995), emphasises individual impact, where "individual impact" refers to enhanced effectiveness, efficiency, and/or quality. A favourable task-technology fit increases the likelihood of usage and performance impact by closely aligning with user demands and preferences for the task. This paradigm is well-suited for examining actual technology usage, especially when testing new technology to gather feedback, as depicted in Figure 2.9. Task-technology fit is valuable for evaluating technological applications already available in the market, such as those in the Google Play Store or Apple App Store.



**Figure 2.9** TTF developed by Goodhue et al. (1995).

The TTF model is primarily concerned with the fit between existing technologies and user tasks. It might not adequately address the evaluation of emerging FinTech technologies or services where the exact nature of tasks and benefits may not be fully defined. While the TTF model acknowledges the importance of task-technology fit, it may not fully capture the broader context of user needs and motivations. Factors such as perceived value, trust, and security, which are crucial for FinTech adoption, are explicitly addressed by the model.

In 2000, Parasuraman introduced the Technology Readiness Model (“TRM”), which provides a framework for understanding the factors that influence an individual's propensity to adopt new technologies. The TRM evaluates four key dimensions of technology readiness: optimism, innovativeness, discomfort, and insecurity (Parasuraman, 2000). Optimism reflects how much individuals see technology as a tool for increased control, flexibility, and efficiency in their activities. Innovativeness signifies a readiness to experiment with and adopt new technologies ahead of the curve, showcasing a proactive and forward-thinking attitude towards technological advancements. Discomfort denotes feelings of being overwhelmed or intimidated by technological tools, which can act as a barrier to adopting and effectively using new technologies. Insecurity captures feelings of distrust or uncertainty towards technology, which can adversely affect the adoption process and limit engagement with new technological solutions.



**Figure 2.10** TRM introduced by Parasuraman (2000).

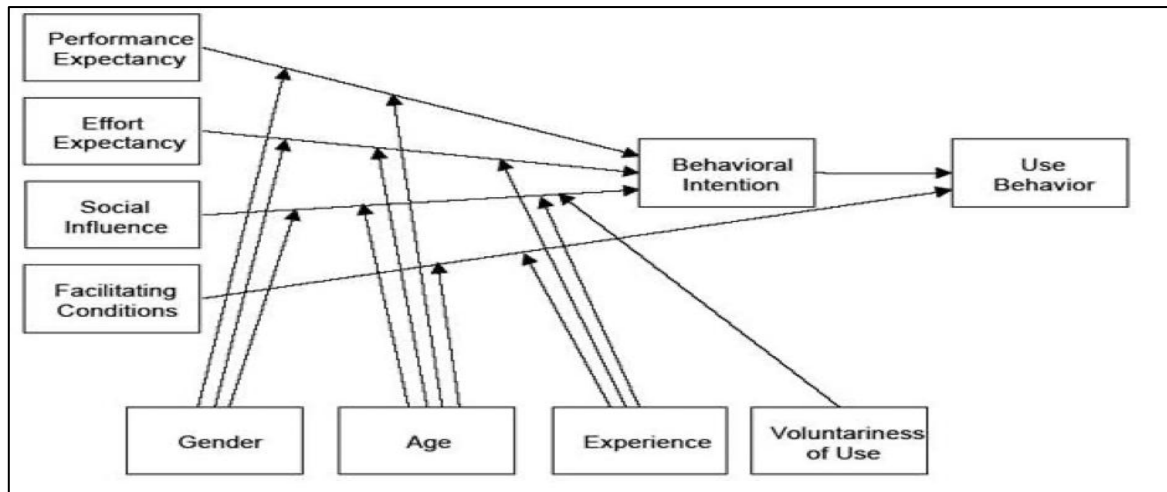
While the four factors proposed by Parasuraman (2000) are important, they might not fully capture the complexities of FinTech adoption, which is often influenced by external factors like social norms, trust, and perceived risks. The TRM is a general model of technology adoption that might not adequately capture the unique characteristics of FinTech applications and services. Unlike traditional technologies, FinTech often involves financial transactions, raising critical concerns about security, privacy, and trust.

The TRM's focus on individual psychology overlooks these specific risks and challenges inherent to FinTech. To fully comprehend FinTech adoption, it is essential to consider the broader context, including the regulatory environment, consumer protection measures, and the competitive landscape. By examining these factors alongside individual characteristics, a more comprehensive understanding of FinTech adoption can be achieved.

Finally, the Unified Theory of Acceptance and Use of Technology (“UTAUT”), developed by Venkatesh et al. (2003), represents a significant advancement in the understanding of technology adoption, building upon the foundations laid by earlier TAM iterations. UTAUT is an integration and extension of influential theories, including TRA, TAM, and the Social Cognitive Theory. UTAUT integrates four key determinants, namely performance expectancy, effort expectancy, social influence, and facilitating conditions, to comprehensively address users' behavioural intentions. Performance expectancy focuses on users' beliefs in a technology's ability to enhance job performance. Effort expectancy delves into the perceived ease associated with its use. Social influence explores the impact of social factors, such as norms and support, on the decision to adopt technology. Facilitating conditions address perceptions of the availability of necessary infrastructure and support for technology use.

Behavioural Intention, a crucial component of UTAUT, signifies an individual's readiness to engage in the behaviour, particularly their intention to use technology. This intention, in turn, influences ‘use behaviour’, representing the actual utilisation of the technology. UTAUT also recognises the impact of individual characteristics, such as gender, age, and experience, on technology acceptance. UTAUT's broad applicability and successful validation across diverse contexts and technologies contribute significantly to a comprehensive understanding of the dynamics of technology adoption.

A notable distinction in the UTAUT model is the omission of the social environment component, acknowledging its limited impact on voluntary situations. This refinement is illustrated in Figure 2.10, emphasising the model's adaptability and responsiveness to the nuanced dynamics of technology adoption. UTAUT's incorporation of these dimensions and the elimination of less impactful elements contribute to its robustness as a theoretical framework for comprehending the intricacies of users' technology acceptance behaviours.



**Figure 2.11** UTAUT established by Ventakesh et al. (2003).

## 2.4 Critical Review of FinTech Adoption

### 2.4.1 Current Sentiment in the FinTech Industry

The previous section has highlighted the rapid surge in excitement and scholarly interest surrounding FinTech over the years. Meanwhile, investors have long foreseen the potential of FinTech, and this anticipation is substantiated by a study conducted by Chemmanur et al. (2020). The study utilised data from the Venture Scanner database, providing insights into funding trends for FinTech start-ups spanning from their inception to the year 2020. Notably, a significant proportion of these start-ups, particularly those founded in or after 2014, has attracted substantial investments. It is crucial to consider, however, that despite the influx of investments, only a select few have managed to endure. This phenomenon may be attributed to various factors, including a nuanced understanding of market demand and the pivotal element of "trust" in securing public confidence (Arli et al., 2020).

According to a report by Boston Consulting Group, Global Fintech 2023: Reimagining the Future of Finance, FinTech companies have secured over US\$500 billion in funding over the last ten years. Notably, from 2019 onward, they have accounted for approximately 20% of global venture capital investments. This influx of capital has come from a diverse range of investors, including generalists, technology-focused private investors, and hedge funds, expanding beyond the traditional financial services specialists who historically supported these ventures (BCG, 2023).

The payments sector, specifically consumer payments, payments backend and infrastructure, and point-of-Sale (“POS”) payments, are the most geographically diversified subcategories, as shown in Table 2.1 (Chemmanur et al., 2020).



**Table 2.1** Start-up distributions within the FinTech industry categorised based on subcategories. Table adopted from a study conducted by Chemmanur et al. (2020).

Name of subcategory	Number of countries	Number of companies	Number of investors	Amount raised
Banking infrastructure	32	198	577	\$5.81B
Business lending	30	266	1,021	\$26.73B
Consumer and commercial banking	21	102	393	\$9.43B
Consumer lending	37	382	1,308	\$48.46B
Consumer payments	42	216	732	\$37.77B
Crowdfunding	24	90	232	\$913.75M
Equity financing	25	153	357	\$2.45B
Financial research and data	13	97	251	\$1.86B
Financial transaction security	16	122	514	\$4.38B
Institutional investing	21	228	513	\$3.85B
International money transfer	18	90	378	\$3.68B
Payments backend and infrastructure	41	261	780	\$35.9B
Personal finance	34	288	813	\$8.14B
Point of sale payments	38	206	661	\$11.31B
Retail investing	29	201	596	\$5.3B
Small and medium business tools	32	331	993	\$15.981B

Start-ups from 42 different nations are featured in the ‘consumer payments’ category, including MyCheck, a prominent FinTech company specialising in payment and integration technologies for the hospitality sector. The ‘payments backend and infrastructure’ subcategory encompasses start-ups from 41 nations, featuring notable American companies like Stripe and a substantial presence from Europe and Asia, where the payments technology start-up scene has witnessed significant growth. In the ‘POS payments’ segment, start-ups from 38 nations are represented, with iZettle, a Swedish business offering cutting-edge products in point of sale, payments, finance, and partner applications, serving as an exemplary illustration in this domain.

‘Consumer lending’ emerges as the largest subcategory, featuring well-known FinTech firms such as SoFi and CommonBond. SoFi operates as a P2P lending platform connecting individuals who may face challenges obtaining credit through conventional means with investors seeking to build a microloan portfolio (Campbell et al., 2021). In contrast, CommonBond is a FinTech lender specialising in assisting individuals in refinancing their student loans (Imerman & Fabozzi, 2020). All transactions on their web-based platform are executed swiftly, and decisions are made expeditiously. CommonBond effectively maintains low and competitive interest rates by securitising student loans funded through their platform, thereby freeing up cash for issuing new loans. The ‘business lending’ subcategory, representing 8% of the businesses in the database, is also noteworthy, featuring well-known brands such as Kabbage, an Atlanta-based company facilitating capital provision to small and medium-sized enterprises (Ben-David et al., 2020).

In the financial services sector, constituting 9% of FinTech companies, Credit Karma from San Francisco offers services such as access to credit scores and reports, tax preparation, and information on various financial products, generating revenue through referral fees (Chemmanur et al., 2020). This San Francisco-based enterprise was founded in 2007, unveiling

its web-based service in 2008, and has offered a mobile application since 2012 for convenient access to its services (Galvin et al., 2018).

Crowdfunding, representing the smallest subcategory in the database, contributes to just under 3% of all companies and features platforms such as Kickstarter and Indiegogo. The case study titled "Crowdfunding: A Tale of Two Campaigns" extensively examines both crowdfunding sites, which collectively secured US\$66.5 million in venture capital. These platforms empower small businesses to raise modest amounts of capital from numerous individuals in exchange for incentives and/or product samples (Abedeldayem and Aldulaimi, 2022).

Start-ups within the 'consumer lending' sector have secured the highest funding, surpassing US\$48 billion. Following closely are Consumer Payments and Payments Backend and Infrastructure, with funding amounts reaching approximately US\$38 billion and US\$36 billion respectively. 'Business lending' claims the fourth position, having amassed almost US\$26 billion in funds raised, after which the funding amounts experience a significant decline. 'Retail and institutional investing' have collectively raised over US\$9 billion (Chemmanur et al., 2020). Notable retail investment firms in this category include Betterment and Wealthfront, both robo-advisors, along with the micro-investing platform Acorns (Poornima, 2022). Among institutional businesses facilitating alternative investments is San Diego-based Artivist. 'Crowdfunding' records the least amount raised, accumulating less than US\$1 billion in total funding.

#### **2.4.2 Transformations in FinTech: Innovations and Trends**

The FinTech industry has undergone transformative changes driven by technological innovations, regulatory developments, and evolving consumer demands. This evidence review explores key trends and innovations in the FinTech sector, drawing insights from reputable

sources such as Forbes Innovation, Fintech News Malaysia, and Statista, among others. FinTech trends represent the latest advancements in financial technology, often driven by emerging technologies such as AI & ML and blockchain (OECD, 2021). According to a report by Statista, the FinTech industry continues to experience remarkable growth, with the global market expected to reach US\$332.3 billion by 2027.

Embedded finance, the integration of banking services into non-financial products and platforms, stands out as a transformative trend (KPMG, 2023). This innovative approach allows consumers to access financial services seamlessly through various touchpoints. For instance, individuals can purchase insurance through their favourite e-commerce platform or obtain a loan through a ride-hailing app. While this enhances accessibility and convenience for consumers, the implementation of embedded finance presents intricate challenges, particularly regarding data privacy and security concerns (Ozili, 2022). Ozili (2022) argues that striking the right balance between user convenience and robust security measures remains a critical consideration in this evolving landscape.

Open banking is a transformative framework that enables consumers and businesses to share their financial data securely with third-party providers. Sieber (2021) estimated that around 87% of countries had implemented some form of open banking as of early 2021. This trend has unlocked new opportunities for fintech companies to develop innovative financial products and services. The global open banking market, valued at US\$7 billion in 2018, is predicted to reach US\$43 billion by 2026 (Research and Markets, 2022). Robo-advisors, for example, leverage open banking to access customer data and deliver personalised investment advice (Poornima, 2022). According to Chan et al. (2022), open banking empowers consumers with greater control over their financial data, fostering the development of personalised digital payment

solutions. However, this trend requires significant investments in technology and security infrastructure while navigating challenges related to data privacy (Babin and Smith, 2022).

Blockchain, a distributed ledger technology, continues to revolutionise the FinTech landscape (Kumar et al., 2023). Its applications extend beyond cryptocurrencies, encompassing decentralised finance (“DeFi”) and streamlined cross-border payments. Some banks are leveraging blockchain to enhance the efficiency and security of traditional financial processes (Mosteanu & Faccia, 2021). According to Kumar et al. (2023), the technology's distributed and transparent nature holds promise for reducing the need for intermediaries in financial transactions, thereby cutting costs (BCG, 2023). Despite these advantages, the complexity of blockchain, its nascent development stage, and regulatory hurdles pose challenges that the industry is actively addressing (Robiady et al., 2021).

AI and ML are pivotal in enhancing the efficiency and accuracy of various financial services (Boukherouaa et al., 2021; OECD 2021). From fraud detection to risk assessment and personalised financial advice, these technologies enable FinTech companies to streamline operations and deliver tailored solutions. AI-powered chatbots, for instance, facilitate customer support and financial enquiries, contributing to improved customer experiences (Edelman & Abraham, 2022). Nevertheless, the deployment of AI and ML in FinTech necessitates addressing concerns related to data privacy, security, and algorithmic fairness (OECD, 2021).

Cyber security has emerged as one of the most critical trends in FinTech, driven by the increasing targeting of financial companies by cyber criminals (PwC, 2023; BNM, 2022). FinTech firms are making substantial investments in cyber security to safeguard customer data and financial assets (PwC, 2023). The incorporation of AI in cyber security measures, such as fraud detection, plays a crucial role in staying ahead of evolving threats (Najaf et al., 2021).

While these measures are vital for thwarting fraud and financial losses, they require continuous adaptation and investment to outpace the sophistication of cyber criminals (PwC, 2023).

The BNPL trend has also gained significant traction, especially among younger consumers, allowing them to make purchases and pay for them in instalments (Gerrans et al., 2022). According to Guttman-Kenney et al. (2023), while BNPL enhances affordability and credit history for consumers, there are potential risks associated with overspending, leading to debt. Timely payment is crucial to avoid negative impacts on credit scores. The popularity of BNPL services indicates a shift in consumer preferences towards alternative financing methods, challenging traditional concepts of credit and lending (McKinsey & Company, 2021).

Digital-only banks, often referred to as neobanks, represent a paradigm shift in banking services (Barosso and Laborda, 2022). Offering a range of financial services online, including current accounts, savings accounts, and loans, these banks prioritise convenience, user-friendly interfaces, and competitive fees. Their accessibility 24/7, intuitive websites, and mobile apps position them as formidable competitors to traditional banks. However, the study of Ziouache & Bouteraa (2023) argue that challenges exist, such as the potential need for more physical branches and a comprehensive suite of financial products compared to their traditional counterparts.

Using data from the Venture Scanner database again, Chemmanur et al. (2020) examined the innovation (patenting) activities of 1,309 U.S.-based FinTech companies between 1983 and 2018. This sample comprises companies from various industries, including blockchain, consumer finance, and insurance technology. Among the 1,309 FinTech companies, 21 (or 1.6% of the sample) underwent an initial public offering, and 230 (17.6%) were subsequently purchased (Table 2.2).

Comparing and contrasting the innovation activities of established players (conventional intermediaries) with newcomers is an intriguing subject in FinTech study (FinTech start-ups). According to Chen et al. (2019), the IoT, robo-advising, and blockchain industries have been the main drivers of many of the valuable patents in the financial industry (Zhao et al., 2022). The authors also discovered that businesses outside the financial sectors, mostly technology businesses, lead the bulk of patent applications.

A notable achievement in the FinTech revolution, encompassing crowdfunding and blockchain, has spurred extensive research in the FinTech domain. Nevertheless, the prevailing association of perceived trust with perceived risk acts as a deterrent, impeding the broader acceptance among the general public (Baber, 2020; Liu, 2021). In the following section, crowdfunding and blockchain will be used as primary FinTech illustrations in discussing the critical role of trust in influencing the adoption of FinTech.

**Table 2.2** The distribution of FinTech firms in different categories. Table adopted from a study conducted by Chemmanur et al. (2020).

Category	Frequency	Percent
Auto insurance	13	0.99
Banking infrastructure	42	3.21
Blockchain innovations	89	6.8
Business lending	63	4.81
Consumer insurance management platforms	6	0.46
Consumer lending	104	7.94
Consumer payments	21	1.60
Consumer and commercial banking	18	1.38
Crowdfunding	34	2.60
Digital asset big data	3	0.23
Digital asset business services	5	0.38
Digital asset exchanges	21	1.60
Digital asset financial services	22	1.68
Digital asset gambling	1	0.08
Digital asset infrastructure	7	0.53
Digital asset mining	1	0.08
Digital asset news and data services	1	0.08
Digital asset payments	12	0.92
Digital asset trust and verification services	5	0.38
Digital asset wallets	11	0.84
Employee benefits platforms	12	0.92



**Table 2.2** (Cont'd) The distribution of FinTech firms in different categories. Table adopted from a study conducted by Chemmanur et al. (2020).

Category	Frequency	Percent
Enterprise / commercial insurance	19	1.45
Equity financing	36	2.75
Financial research and data	29	2.22
Financial transaction security	50	3.82
Health / travel insurance	49	3.74
Institutional investing	95	7.26
Insurance comparisons / market place	29	2.22
Insurance data / intelligence	32	2.44
Insurance education / resources	1	0.08
Insurance infrastructure / backend	63	4.81
Insurance user acquisition	14	1.07
International money transfer	15	1.15
Life, home, property, and casualty insurance	19	1.45
P2P insurance	2	0.15
Payments backend and infrastructure	65	4.97
Personal finance	88	6.72
Point of sales payments	37	2.83
Product insurance	5	0.38
Retail investing	49	3.74
Small and medium business tools	121	9.24
<b>Total</b>	<b>1,309</b>	<b>100.00</b>

### 2.4.3 Transformations in FinTech: Disruptive Technologies

Disruptive technologies are innovations that significantly alter the way businesses, industries, or consumers operate, often displacing established products or services. In the context of FinTech, disruptive technologies such as AI, blockchain, mobile payments, P2P lending, and crowdfunding platforms have transformed traditional financial services by offering more efficient, accessible, and cost-effective alternatives. Clayton Christensen's theory of disruptive innovation, as outlined in his seminal works, including *The Innovator's Dilemma* and *The Innovator's Solution*, provides a framework for understanding how disruptive technologies impact industries, including FinTech. According to Christensen (1997), disruptive technologies initially emerge at the lower end of the market, catering to less demanding or niche segments with simpler, more affordable solutions. In the FinTech sector, innovations such as blockchain technology, P2P lending platforms, and digital currencies exemplify this pattern by offering alternatives to traditional financial intermediaries and services (Christensen, 1997; Christensen & Raynor, 2003). These technologies often begin by addressing gaps in the market or providing services that are more accessible to underserved populations.

Over time, as these disruptive technologies advance and improve, they can move upmarket and challenge established financial institutions by providing enhanced convenience, lower costs, and superior customer experiences (Christensen, 1997). Consequently, traditional financial institutions may struggle to adapt due to their focus on sustaining innovations that cater to their most demanding customers, thereby failing to fully embrace or invest in emerging disruptive technologies (Christensen & Raynor, 2003). To remain competitive, established firms must recognise the potential of these disruptions and strategically integrate them into their business models (Christensen, 1997).

Alam (2024) advocates that the convergence of AI and blockchain technologies are driving transformative changes across various sectors, including finance and energy trading, by increasing operational efficiency, transparency, and automation. However, this does not imply that AI and blockchain are the only disruptive technologies. According to Bajwa et al. (2022), FinTech innovations such as online payments and P2P lending platforms are reshaping financial services by enhancing transaction security, efficiency, and customer experience.

Solanki & Sujee (2022) elaborate on the broader implications of FinTech as a disruptive innovation. Their study reveals that while FinTech has indeed introduced significant disruptions in areas like P2P lending, crowdfunding, and digital payments, it also faces challenges such as cyber security risks and regulatory gaps. The authors argue that despite FinTech's innovation and potential to reshape traditional financial sectors, its role is complex, blending disruptive elements with sustaining innovations and highlighting the need for traditional institutions to adapt to or counteract these changes effectively. Thus, while FinTech continues to drive transformation, its ultimate impact will depend on overcoming existing challenges and the ability of both new and traditional players to navigate the evolving landscape of financial technology.

Building on the insights from Solanki & Sujee (2022), Zhao (2023) further complements this by exploring how these converging technologies, through their synergy, are reshaping the financial industry, fostering innovations that enable faster, more secure transactions and improved risk management. Aldboush & Ferdous (2023) focus on the ethical and privacy considerations surrounding the use of big data and AI in FinTech, highlighting the importance of safeguarding customer trust. Their study advocates the need for FinTech companies to adopt ethical practices, such as ensuring data privacy, transparency, and corporate digital responsibility, to maintain and enhance trust among consumers. These ethical considerations

are crucial in navigating the challenges posed by disruptive technologies and ensuring their successful integration into the financial sector.

Kabengele & Hanh (2021) argue that mobile payment systems have already been significantly altering the conventional roles of banks in payment systems, especially in developing countries. The global adoption of mobile money is impacting traditional banks' ability to generate revenue through credit and debit cards. Although research on mobile payments is fragmented, it shows promise in significantly affecting economic outcomes in developing countries and highlights the disruptive nature of this innovation (Kabengele & Hanh, 2021). Mobile money systems provide new opportunities for financial transfers and can influence economic results in less wealthy nations, as evidenced by the rapid rise of mobile money in Africa.

Solanki & Sujee (2022) explore the disruptive nature of FinTech within Industry 4.0, highlighting its impact on traditional financial processes through technologies like blockchain, AI, ML and big data. Their findings emphasise that while FinTech has disrupted niche areas such as P2P lending, crowdfunding, and digital currencies, traditional financial institutions remain robust in core areas, for instance retail banking. However, the unregulated nature of many FinTech entities, particularly those not governed by traditional financial regulations, raises significant concerns about customer security and trust.

Kumari & Nagarjan (2022) contribute to the discussion by examining the impact of FinTech and blockchain technologies on banking and financial services, emphasising their role in transforming investment standards, enhancing security, and improving financial tracking. This paper reviews the impact of FinTech and blockchain technology on the banking and finance sector. It highlights how financial institutions are undergoing significant changes to adapt to digital advancements, with FinTech driving major transformations. Kumari & Nagarjan (2022) asserts that blockchain technology, with its focus on decentralisation and equity, can offer a

more efficient banking alternative by enabling faster money transfers, enhanced security, and transparent financial tracking. It also argues that FinTech developments are likely to reshape investment standards and improve customer experiences in banking. Meanwhile, Kumari & Nagarjan (2022) also acknowledges that while blockchain technology holds promise, it still faces challenges and is not seen as a rival to central banks or cryptocurrencies.

Larsson et al. (2024) explores the evolving dynamics between FinTech companies and traditional banks in countries like Denmark, Estonia, the Netherlands, and Sweden. The study challenges the traditional view that FinTechs are purely disruptive forces in the financial sector. Instead, it introduces the concept of a "coopetitive" market ecosystem where both traditional banks and FinTech companies engage in both competition and cooperation. This ecosystem is known for its shared infrastructure and mutual interdependence, where FinTechs act as catalysts for innovation and transformation in the financial industry. This concept of a "coopetitive" ecosystem complements and extends the ideas discussed by Bajwa et al. (2022), Zhao (2023), Alam (2024), and Kumari & Nagarjan (2022).

The notion of a "coopetitive" market ecosystem proposed by Larsson et al. (2024) illustrates how the relationship between traditional financial institutions and FinTechs is not solely adversarial but also collaborative. This interdependence is crucial for fostering trust among consumers and institutions, which is a key factor in the adoption of FinTech solutions. The emerging "coopetitive" environment provides a framework for understanding how trust is built and maintained in a landscape where innovation and collaboration coexist. While Larsson et al. (2024) introduces the concept of a "coopetitive" market ecosystem where FinTechs and traditional banks coexist, Bhattacharjee et al. (2024) explores further into the broader disruptive effects of FinTech on traditional financial services and advocates the need for these institutions to adapt to technological change. Bhattacharjee et al. (2024) adds another layer by addressing

the regulatory challenges and the balance between innovation and consumer protection, which are critical to fostering trust in the rapidly evolving FinTech landscape.

The integration of FinTech and BigTech lending into global financial markets is a prime example of how disruptive technologies are transforming traditional credit systems by enhancing efficiency, accessibility, and trust, particularly in well-regulated environments (Cornelli et al., 2023). The study also advocates the crucial role of technological advancements in fostering trust and adoption within the financial sector (Cornelli et al., 2023). Zarifis & Cheng (2024) has also provided a comprehensive analysis of the evolving landscape of FinTech, particularly focussing on how AI is being integrated into different business models within the financial services industry. The study identifies five distinct FinTech business models that leverage AI for growth and innovation, each representing a unique approach to incorporating AI into financial services. A central theme across all five models is the importance of trust (Zarifis & Cheng, 2024). However, the manner in which trust is built varies significantly depending on the business model and the point in the value chain. According to Zarifis & Cheng (2024), traditional financial institutions typically build trust through their financial services, relying on established reputations and regulatory frameworks. In contrast, tech-focused companies often build trust through their existing non-financial services, which subsequently extends to their financial offerings (Zarifis & Cheng, 2024).

Synthesising these insights, it becomes clear that while FinTech has the potential to disrupt traditional financial systems significantly, its success hinges on the ability to build and maintain trust with customers, especially in the face of regulatory challenges. The unregulated nature of many FinTech firms, as highlighted by Solanki & Sujee (2022), makes the trust-building strategies discussed by Zarifis & Cheng (2024) even more critical. These strategies ensure that FinTech firms can navigate the complexities of customer security and regulatory scrutiny while

continuing to innovate and grow (Cornelli et al., 2023; Zarifis & Cheng, 2024). Together, these studies illustrate that trust is not just an operational concern but a foundational element of any successful FinTech business model.

FinTech is increasingly seen as an alternative to traditional financial intermediaries. However, further research is needed to understand how it fundamentally differs from other FinTech innovations. FinTech platforms, including those used for crowdfunding, are often regarded as new intermediaries with less regulation rather than eliminating intermediaries altogether (Papadimitri et al., 2021). For example, a borrower might secure a loan through a traditional bank while the lender receives a note from the crowdfunding platform. Similarly, investment banks set up platforms to enable fundraisers to raise money from investors, making the underlying processes of these P2P platforms and conventional banking intermediaries quite similar (Dömötör et al., 2023).

One notable advantage of FinTech over traditional banks is its reduced regulatory constraints, which potentially lowers transaction costs. However, this advantage is based on a preliminary perspective, as there is insufficient ex-post analysis to confirm its accuracy. Although transaction costs may be slightly reduced by FinTech platforms, this does not necessarily mean that FinTech is a more "efficient" method for capital aggregation and reallocation compared to traditional financial intermediation, due to the lack of comprehensive data on this topic (Thakor, 2020). Moreover, recent FinTech research highlights the persistence of asymmetric information issues within these platforms, suggesting that some form of intermediation remains necessary (Feyen et al., 2021). Nguyen & Vaubourg (2021) argue that intermediation is a crucial element of finance since it supports various important, interconnected goals, including asset accumulation, market creation, risk management, and information clearing. Thus, while

FinTech may appear to bypass traditional financial intermediaries for capital raising, its fundamental objectives align closely with those of financial intermediation.

The evolving landscape of financial intermediation is witnessing significant disruptions and innovations, particularly with the rise of FinTech and technologies like blockchain. Financial intermediaries have traditionally performed crucial roles such as mediating between surplus and deficit units, managing risks, accumulating assets, and achieving economies of scale. However, the emergence of FinTech has introduced new models like crowdfunding, which bypass traditional intermediaries and offer P2P alternatives. Crowdfunding, particularly in its investment-based form, has become a popular alternative to traditional financing, enabling fundraisers to avoid complex regulatory frameworks and reduce transaction fees (Biancone et al., 2019). At the same time, technologies like blockchain are challenging the need for centralised intermediaries altogether. Blockchain's decentralised ledger system has the potential to disrupt the traditional financial infrastructure by facilitating trust and transparency without the need for middlemen, as seen in applications like Bitcoin and other cryptocurrencies (Kowalski et al., 2021). The role of intermediaries is further complicated by the rise of innovative payment services and the potential for financial services to become disintermediated through FinTech (Das, 2019). As traditional intermediaries adapt or compete with these new technologies, the financial sector is poised for a transformation that may redefine the functions and importance of intermediaries in the future (Breidbach et al., 2020).

Financial intermediaries are also expected to face disruption from emerging developments in AI, ML, and robo-advisors. These technologies drive the creation of innovative financial products and may lead to the emergence of new financial intermediaries or offer clients and investors direct access channels, potentially reducing the need for traditional intermediaries. AI-driven systems, including self-learning machines, are being developed to enhance and



automate financial processes. The work by Bhattacharjee et al. (2024) provides a comprehensive review of the disruptive impact of FinTech on traditional financial services. Bhattacharjee et al. (2024) asserts how technological advancements such as digital technology, data analytics, and AI are revolutionising the financial landscape. It explores the origins, evolution, and key drivers of FinTech's growth and reveals how innovations like P2P lending, robo-advisors, mobile payment systems, and blockchain-based cryptocurrencies are reshaping the industry. This study also addresses the democratisation of finance, allowing greater access to financial services for underserved populations and small businesses, which is crucial in understanding how trust is built in FinTech ecosystems.

The role of financial intermediaries and the potential changes brought about by FinTech innovations represent a critical area for future research. Despite FinTech's disruptive influence, intermediaries continue to play a vital role in finance. It is essential to analyse and explain these evolving dynamics to benefit all stakeholders, including incumbents, new entrants, and regulators. The landscape is characterised by both competition and cooperation between traditional and new intermediaries. Financial intermediaries perform essential economic functions, such as mediating between surplus and deficit units, facilitating saving and capital investment, managing risks, accumulating assets, and achieving economies of scale. Cornelli et al. (2023) highlight the importance of examining how FinTech advancements might impact these core functions of financial intermediation. Traditional intermediaries have historically benefited from economies of scale due to their size and the volume of business, leveraging cost advantages through effective knowledge management and the integration of financial, economic, and legal expertise. However, their monopolistic tendencies can stifle innovation, reduce efficiency, and hinder improvements in customer experience. As FinTech developments are primarily driven by technology companies rather than banks, Thakor (2020) believe they pose a significant challenge to the conventional role of financial intermediaries.

The evolving landscape of financial intermediation continues to witness significant disruptions and innovations, particularly with the rise of FinTech and technologies like blockchain. Traditional financial intermediaries have played crucial roles in mediating between surplus and deficit units, managing risks, and achieving economies of scale. According to Biancone et al. (2019), investment-based crowdfunding has also gained popularity as it allows fundraisers to circumvent complex regulatory frameworks and reduce transaction fees. In light of this rapid expansion of alternative financing methods, a potential future research project could focus on predicting how traditional funding sources will change in terms of cash quantities over the medium and long term. Notably, crowdfunding research is the only stream within FinTech that exhibits clear, albeit weak, interrelations. Other areas of FinTech research need to be more cohesive, as there are currently few local and international connections (Robiady et al., 2021). Although blockchain is rapidly developing, it stands out as a promising area that requires further study among the dispersed FinTech research.

Blockchain technology not only supports crowdfunding but also challenges the necessity for centralised intermediaries. For instance, while crowdfunding enables P2P financial transactions without middlemen, Bitcoin offers a different mechanism for transferring wealth. Financial intermediaries typically act as centralised agents; blockchain can eliminate this necessity by facilitating trust and transparency without intermediaries (Kowalski et al., 2021). The potential of blockchain to revolutionise financial services is significant; it can streamline transactions by reducing the layers of intermediaries. For example, the average time for a global bank transfer currently stands at three days due to the involvement of multiple intermediaries. A blockchain could enhance this process by providing a transparent, distributed ledger that eliminates the need for third-party reconciliation (Kumar et al., 2023; Osmani et al., 2020).

Sharin et al. (2023) highlight blockchain's transformative potential in FinTech, focusing on its core features of decentralisation, security, immutability, transparency, and efficiency. These attributes allow blockchain to disrupt financial services by reducing intermediaries, lowering costs, enhancing transaction speed, and increasing trust in digital platforms. Key areas of impact include payment systems, digital identities, and smart contracts, where blockchain provides secure, transparent, and real-time solutions (Sharin et al., 2023). As FinTech continues to evolve, blockchain is expected to play a crucial role in addressing issues like fraud, inefficiency, and trust, driving future innovation and growth in the industry.

As financial institutions become increasingly aware of blockchain's capabilities, they are compelled to explore new options. This trend suggests that some traditional financial intermediaries can become more efficient and transparent, allowing them to persist in the financial industry by reducing the number of intermediaries and, consequently, transaction costs (Ozili, 2022). We are currently witnessing a transformation in financial intermediation driven by FinTech, with both new and established intermediaries adopting innovative strategies. This evolution is characterised by competition and collaboration between traditional and new entrants, although academic research often lags behind these rapid industrial changes (Barroso & Laborda, 2022; Abdul-Rahim et al., 2022).

Despite the growing importance of these developments, many unresolved issues remain in the financial sector. For instance, further research is needed to understand how P2P platforms differentiate themselves from conventional fundraising sources. One critical challenge in P2P networks is information asymmetry, which could potentially be addressed through blockchain innovations (Gomber et al., 2018). Moreover, the role of miners in the Bitcoin ecosystem presents another fascinating area for research. Miners validate transactions and build the blockchain, earning transaction fees and newly minted Bitcoins in the process. As blockchain

technology evolves, it can be categorized into three stages: Blockchain 1.0 (digital currencies like Bitcoin), Blockchain 2.0 (smart contracts), and Blockchain 3.0, which focuses on broader applications (Lutfiani et al., 2022). Despite the potential for blockchain to reshape the financial sector, there remains a shortage of comprehensive business studies examining its implications. Many publications address the concept of blockchain from various disciplines, including accounting, management, and finance, yet descriptive research exploring new hypotheses about blockchain phenomena is limited.

Since 2016, numerous studies have outlined the foundational concepts of blockchain and its transformative potential in finance. For example, Garanina et al. (2022) describe blockchain as a public ledger that can revolutionize settlement and back-office activities. Similarly, Lutfiani et al. (2022) highlight that blockchain can address issues such as trust deficits and high transaction costs in banking. DeFi, powered by blockchain, fosters greater transparency and inclusiveness, catering to urban professionals seeking innovative financial solutions (Kumar et al., 2023; Chen & Bellavitis, 2020). However, DeFi must also navigate challenges like regulatory uncertainties and scalability issues to fully realise its potential. There are still many unanswered questions regarding cryptocurrencies, such as their volatility, utility as digital currency, and behaviour as speculative investments (Lutfiani et al., 2022).

The excitement surrounding blockchain technology indicates a significant potential to transform the financial sector, prompting market participants and infrastructure providers to investigate its applications (Sharin et al., 2023; Liu, 2021). While the groundwork for a blockchain-based financial ecosystem is being laid, it remains to be seen which specific banking sector elements will benefit most from this transformative technology. The interplay of traditional and new financial intermediaries, influenced by innovations like blockchain and AI, continues to redefine the future of financial services (Kumar et al., 2023).

#### **2.4.4 Transformations in FinTech: Impact of Customer Experience**

The loss of confidence in traditional financial institutions following the financial crisis, combined with the rapid evolution of technology, has served as a significant driver for "BigTech" companies (such as Meta, Google, and so forth) and start-ups to create more user-friendly products, particularly utilising mobile and wireless technology (Meyliana & Fernando, 2019; Baber, 2020). During this period, there was a substantial increase in mobile app downloads, surging from 100 billion in 2014 to 195 billion in 2018, with a projected figure of 215.7 billion in 2019 (Chemmanur et al., 2020). According to Statista, a leading research platform that provides statistical data and business intelligence, an anticipated 299 billion global app downloads were projected for 2023, marking a significant increase from the roughly 247 billion worldwide app downloads recorded in 2020.

FinTech companies have been able to harness readily available data and construct simple mobile interfaces by developing mobile applications and big data analytics (for example, Credit Karma) (Galvin et al., 2018). This has allowed them to provide consumers with free financial information. Borrowers and depositors can now complete numerous common operations with the touch of a button on a smartphone app, making banking simpler and more convenient as they no longer need to visit a branch physically (Di Maggio et al., 2022). For instance, the United Services Automobile Association (USAA) pioneered mobile deposit in 2009, while Quicken Loan's 2016 introduction of RocketMortgage currently offers fully online mortgages (Johnson et al., 2019). Closer to home, GXBank has received the green light from the authorities to initiate operations effective from September 1, 2023. GXBank, an exclusively digital bank, will address customer needs through diverse channels, including a dedicated banking app and round-the-clock customer support accessible via various platforms.

FinTech firms have excelled in delivering a considerably enhanced experience for their users by incorporating user-friendly interfaces and leveraging insights from big data analytics. In order to ensure the products offered are innovative and customer centric, there has been a noticeable increase in the demand for customer experience (“CX”) and user experience (“UX”) designer roles within FinTech companies in recent times (Javed et al., 2022). Many financial applications created by FinTech companies, either as standalone applications or through licensing agreements with established incumbents, possess innovative features from location tracking and push notifications. These functionalities enhance customer interaction significantly. For example, a payment application can identify when a consumer passes by his or her favourite coffee shop and offers a 50% discount on iced specialty drinks. Subsequently, a push notification from the application encourages the customer to enter the store, resulting in increased sales for the payment application.

Another illustration from the FinTech sector involving retail investors is the utilisation of event alerts on mobile devices to initiate trading. Users of a share trading application can receive a push notification when a company whose shares they own or are monitoring releases its earnings (Burke, 2021). According to Burke (2021), the company's study on whether they anticipate earnings to meet or fall short of analyst estimates may be referenced. As the earnings announcement approaches, investors can decide whether to buy, sell, or hold onto their positions. This scenario enhances the likelihood of a transaction, similar to the example in payments technology, and the aggregation of user data can be employed to calculate and even predict the effectiveness of this technology (Hassan et al., 2022).

It is evident that FinTech start-ups have spearheaded many recent technological innovations, particularly in the development of mobile apps. While these start-ups are not necessarily new to the market, the mobile apps developed are increasingly more customer focussed and socially

conscious (Vergara & Agudo, 2021). FinTech businesses worldwide take pride in advancing financial inclusion and literacy (Alexander, 2021). The educational component is seamlessly integrated into the FinTech products currently available in the market. Consequently, customers can even learn about wealth planning and budgeting and utilise technology for banking or investment purposes (Suseendran et al., 2020).

On the contrary, incumbents often carry a conservative reputation, historically prioritising profits and share prices over customer satisfaction. Following the financial crisis, they have been labelled as "greedy fat cats" exploiting the market's financial illiteracy by charging hefty fees to maximise earnings. Some have sought to alter this perception by adopting technology through licenses from FinTech firms or internal development (Vergara & Agudo, 2021; Suseendran et al., 2020). Originating from the idea attributed to Milton Friedman in the 1970s is the famously associated concept of shareholder wealth maximisation. In his influential essay "The Social Responsibility of Business is to Increase its Profits" (1970), Friedman argued that the primary responsibility of a business is to its shareholders. He contended that businesses should focus on maximising profits within the legal and ethical framework. In traditional decision-making, other stakeholders, such as employees, suppliers, and customers, have little impact (Elrick & Thies, 2018).

While incumbent CEOs may claim that their customers are the foremost stakeholders, their actions do not consistently align with such assertions. Some FinTech startups, as evidenced by the innovative financial services they have introduced, seem to prioritise the needs of specific customers, deviating from the strict shareholder value maximisation approach discussed earlier (Murinde et al., 2022).

Consumer trust in financial service providers, such as banks and asset managers, holds paramount significance. According to findings from the "Voice of the Consumer Survey," a

collaborative study by Capgemini and LinkedIn in 2017, almost half of the surveyed customers (44.8%) opt for the services of at least one FinTech provider alongside traditional firms for their investment management. Furthermore, nearly one-third of the surveyed customers (29.4%) reported using at least one FinTech provider, in addition to traditional banks, for their banking requirements. In this survey, participants were tasked with rating, on a scale of 1 to 7, the level of trust they have in traditional financial service firms, major "Big Tech" companies, and non-traditional FinTech firms. A score of 1 signifies complete mistrust, while a 7 indicates a very high level of trust. Respondents initially answered the question without any conditions, and subsequently, those who had a satisfactory experience were included. The survey revealed intriguing findings, with an unconditional response showing that 23.6% of customers trust FinTech and Big Tech companies, while 36.6% trust traditional financial institutions (Chemmanur et al., 2020).

In instances where customers may not have used the services of a FinTech application or have had unfavourable experiences due to limited exposure, it suggests that FinTech companies may face challenges in garnering high levels of confidence. However, after a positive encounter, consumer trust in both traditional institutions and FinTech companies surpasses the 50% mark. In fact, customers exhibit higher faith in FinTech companies, with 56.3% expressing trust compared to 52.9% who have faith in traditional financial services companies (Chemmanur et al., 2020). This underscores the conditional nature of trust, requiring time and positive experiences for customers to trust new entrants in markets such as investments or banking (Avarmaa et al., 2022).

The survey also investigated how trust and positive CX vary across different dimensions. In terms of security and fraud prevention, 74.3% of customers expressed greater comfort with incumbents as opposed to only 5.4% with FinTech companies. Incumbents are preferred in



terms of service quality, with 47.3% of consumers favouring them compared to merely 21.6% for FinTech firms. However, FinTech companies outshine the incumbents in areas such as value, speed, efficiency, transparency (associated with trust), convenience, and UX. Particularly noteworthy is the overwhelming preference for FinTechs in UX, with 67.6% of customers reporting a better experience with FinTech companies compared to just 9.5% with the incumbents (Chemmanur et al., 2020).

The prevailing trend in developed markets and nations involves FinTech companies delivering value by attracting and retaining customers through user-friendly technology and top-notch UX design. According to Popelo et al. (2021), the decline in trust in traditional banks following the financial crisis, coupled with the increasing adoption of mobile technologies, provided an excellent opportunity for FinTech companies to offer financial services through smartphone apps and other technological channels. However, Vasquez & San-Jose (2022) argue that recent surveys indicate that customers are more inclined to trust traditional banks given their robust mechanisms in addressing fraud and cyber security risks. It will be intriguing to observe the advancements made by FinTech companies focusing on emerging technologies in this area in the coming years. FinTech companies do hold the potential to bring about a significant transformation for underserved populations around the world. However, for FinTech's full potential to be realised in these regions, national governments must modernise their respective regulatory frameworks to align with contemporary needs. Encouragingly, some policymakers are beginning to accelerate their efforts; nevertheless, there is still a substantial amount of work ahead to achieve comprehensive regulatory adaptation. (Fenwick et al., 2020).

According to Berkmen et al. (2019), various issues related to financial access, the availability of financial tools, and the efficiency of financial markets in developing nations, particularly in Latin America, are discussed. These markets exhibit common challenges such as low credit-

to-GDP ratios, high service costs, reliance on unconventional financing sources, and significant unbanked populations, despite considerable regional variations (Chemmanur et al., 2020). Lashitew et al. (2019) advocates that FinTech has the potential to enhance the functioning of markets for the general population in these underserved regions. For instance, mobile operators can now provide banking-related features directly on customers' phones, and e-commerce platforms offer a variety of mobile payment options.

While these technologies have been widely adopted in Asia and Africa for over a decade, Latin America lags behind. Notably, the perceived ease of use has a significant impact, with systems becoming more user-friendly and enjoyable through digital features. The launch of banking services by M-Pesa in Kenya, for instance, has already garnered over 30 million customers across ten nations (Natile, 2020). According to Hassan et al. (2022), the adoption of mobile payment technologies in China has expanded so rapidly that it has outpaced the rate seen in the United States. In contrast, Latin America falls behind. Remittances constitute 1.5% of GDP in the region and up to 15% in countries such as El Salvador, Haiti, Honduras, and Jamaica (Worrell, 2020). Despite the region's significant share of global remittances, the market is still dominated by expensive traditional banks and money transfer companies, while mobile money usage remains relatively low (Ahmad et al., 2020).

#### **2.4.5 Challenges and Complexities Affecting the FinTech Industry**

Earlier research predominantly concentrated on exploring the advantages and effects of digital finance on both financial inclusion and innovation. While FinTech companies have made significant strides in reshaping the financial landscape, they are not without their challenges and flaws. According to Mohsin et al. (2022), FinTech companies encounter similar challenges to traditional financial institutions in their efforts to digitise financial services. Common issues include cyber security, limited customer readiness, particularly in rural areas, and the necessity

for regulatory bodies to bolster consumer and investor protection amid the rapid evolution of FinTech. Evolving customer expectations drive the demand for seamless digital banking solutions to address daily needs (Mohsin et al., 2022; PwC, 2023a).

PwC's 26<sup>th</sup> Annual Global CEO Survey revealed that 63% of CEOs in Malaysia believe the most significant potential source of disruption in their industry is regulatory change. Following this, more than half of those surveyed expressed concerns around changing customer preferences, disruptions in the supply chain, technological shifts, and shortages in skills and labour (PwC, 2023a). FinTech companies often struggle with keeping up because they need to be fast and skilled to improve their current solutions. This is especially challenging due to the regular updates in rules and regulations across different jurisdictions (PwC, 2023).

FinTech companies operate in a complex regulatory landscape, facing uncertainties and evolving regulations across different jurisdictions. This dynamic regulatory environment can significantly impact the adoption of FinTech solutions, and understanding the nuances is crucial. According to a report by the World Bank, the lack of regulatory clarity is identified as a significant barrier to the growth of FinTech (World Bank, 2019). Regulatory uncertainties create a sense of insecurity among potential users. Concerns about the legality and compliance of FinTech services can deter individuals and businesses from adopting FinTech applications. Users, especially in jurisdictions with ambiguous or stringent regulations, may exhibit hesitancy in adopting FinTech services. According to the World Bank (2019), legal uncertainties contribute to a lack of trust among potential users. The Financial Stability Board highlights the need for regulatory frameworks that balance innovation and risk management to foster the growth of FinTech (FSB, 2019). Clear and supportive regulations play a pivotal role in providing a conducive environment for FinTech adoption. Well-defined regulatory frameworks reassure users and businesses, fostering trust and confidence.

Alam et al. (2019) further suggest that regulators need to be vigilant about the limitations of existing regulatory approaches and be proactive in identifying new functions of technology-enabled finance that might require regulation. Bains & Wu (2023) examines the regulatory approaches of countries like Singapore and the United Kingdom, providing insights into how clear regulations positively impact FinTech ecosystems. Jurisdictions with progressive and transparent regulatory environments have witnessed a comparatively more rapid adoption of FinTech applications, where users in such regions feel more secure in engaging with these technologies. According to the International Monetary Fund, collaborative efforts among nations to create standardised and transparent regulatory frameworks contribute to a more conducive environment for FinTech adoption on a global scale. This suggests that regulatory clarity is crucial for fostering trust and encouraging adoption. However, achieving such regulatory clarity requires significant collaboration and standardisation efforts among nations, which can be challenging.

On the other hand, Khan et al. (2023) illustrates the potential downside of FinTech adoption, particularly in the context of the Gulf Cooperation Council (GCC) economies. Their research indicates that the introduction of regulatory sandboxes, which are intended to foster innovation, has led to increased financial instability. This highlights the challenge of balancing innovation with financial stability. The study emphasises the need for continuous regulatory updates and adaptive risk management, indicating that the dynamic nature of FinTech requires regulators to be constantly vigilant and responsive to emerging risks. Thus, the challenges include maintaining financial stability while fostering innovation, ensuring regulatory clarity, and the need for continuous adaptation to the rapidly evolving technological landscape (Chaudhry et al., 2022). The work of Sampat et al. (2024) identifies several complexities and challenges from the perspective of FinTech developers, particularly in developing countries like Nigeria. These include customer vulnerability due to poor technological infrastructure, data

management challenges, and ethical issues related to privacy. Furthermore, the lack of skilled developers and inadequate regulatory frameworks pose significant obstacles to FinTech integration and adoption.

In addition to the challenges highlighted above, Firmansyah et al. (2023) shed further light on the complexities surrounding FinTech adoption. Their systematic literature review identifies various factors influencing fintech adoption, including trust, financial literacy, and the dynamic nature of customer behaviour. These factors contribute to the intricate landscape of FinTech adoption, where customer perceptions, regulatory frameworks, and technological advancements intertwine. The study also emphasises the importance of maintaining customer trust, particularly in virtual FinTech interactions, which is crucial for long-term sustainability. These insights add depth to the discussion on FinTech adoption challenges, underscoring the multifaceted nature of the FinTech landscape and the need for adaptive strategies to navigate its complexities.

In Indonesia, Rufaidah et al. (2023) examined FinTech adoption within the agricultural sector and identified the challenges as diverse. Despite the emergence of FinTech providers in Indonesia, farmers encounter significant hurdles in accessing these financial services. The reliance on informal and non-formal sources of capital persists due to factors such as familiarity, ease of terms, and trust, highlighting the entrenched nature of traditional financial practices. Moreover, FinTech providers face an uphill battle in overcoming negative perceptions and rigid structures that deter farmers from engaging with them. Additionally, the exploitation of farmers through lower purchase prices, disguised as benevolent gestures, underscores the need for transparent and equitable financial solutions. While agricultural FinTech holds promise in addressing these challenges by offering tailored services, its adoption is hindered by limited technology access and awareness among farmers. Rufaidah et al. (2023)

advocates that concerted efforts are required to enhance financial literacy, raise awareness about FinTech solutions, and improve IT infrastructure.

In the Malaysian setting, Jamhor et al. (2021) undertook an investigation into the challenges and complexities of FinTech within the Malaysian financial landscape. While FinTech presents advantages, Jamhor et al. (2021) argues that it also entails drawbacks and risks. These risks encompass three categories within the fintech business: risks to consumers, risks to financial services firms, and threats to financial stability (Chaudhry et al., 2022). In terms of risks to consumers, Jamhor et al. (2021) cited the lack of understanding of FinTech design and function, potential mis-selling of products, and concerns about data privacy and security. The study also referred to statistics showing an increase in cyber-crime incidents, such as personal data breaches and financial fraud, posing significant threats to consumer data and financial security. Moreover, the digital divide can limit access to FinTech services, especially in rural or underserved areas. Inclusive strategies are necessary to ensure broader access (Rufaidah et al., 2023). Financial service firms face challenges related to technological advancements, skills shortages, and regulatory complexities (Jamhor et al., 2021). The study emphasised the need for firms to adapt quickly and acquire talent proficient in modern technologies like ML and data analytics to stay competitive in the FinTech landscape. Furthermore, threats to financial stability were highlighted, including the concentration of power among successful FinTech firms and vulnerability to cyber-attacks (Chaudhry et al., 2022; Jamhor et al., 2021; Najaf et al., 2021). The study emphasised the importance of robust measures to mitigate cyber risks and maintain consumer trust.

However, times are improving, with many publications raising similar concerns from different viewpoints. Governments worldwide know that the financial industry's future must rely on FinTech following the digital revolution, with the increased expectations for real-time updates

or personalisation features by customers. This warrants financial institutions to actively participate in discussions on integrating FinTech with financial operations and the government's support to gain the public's confidence and trust in adopting FinTech (Berkmen et al., 2019; Fenwick et al., 2020).

The literature review above reveals several critical findings regarding the adoption of FinTech among urban professionals in Malaysia, emphasising the role of trust as a mediating factor. One of the primary barriers to the adoption of FinTech is the issue of cyber security (Chaudhry et al., 2022; Jamhor et al., 2021; Najaf et al., 2021). Urban professionals, despite being more technologically savvy, remain cautious about potential data breaches and financial fraud. Therefore, regulatory frameworks play a critical role in fostering trust in FinTech solutions. The literature reviewed indicates that jurisdictions with transparent and progressive regulations experience higher adoption rates of FinTech applications. In Malaysia, regulatory complexities pose significant challenges, asserting the importance of establishing clear and supportive regulatory frameworks to reassure users and promote trust. Such regulatory clarity can help mitigate uncertainties and provide a more conducive environment for FinTech growth.

The rapid evolution of FinTech also necessitates a skilled workforce proficient in modern technologies such as ML and data analytics. The shortage of such skills in the Malaysian FinTech sector is a notable challenge, impacting the ability of firms to innovate and stay competitive. Consumer readiness, particularly in understanding and trusting FinTech technologies, remains a challenge. Urban professionals require assurance regarding the reliability and security of FinTech services. Trust is a critical success factor, influenced by transparent communication, effective data protection measures, and a seamless user experience. Building consumer trust involves not only securing data but also providing clear and consistent information about the benefits and risks associated with FinTech services.

Technological advancements present both opportunities and challenges for FinTech firms. Firms must adapt quickly and leverage new technologies to enhance their offerings and build consumer trust. This requires continuous investment in research and development to stay ahead of technological trends and innovations. The need to balance innovation with financial stability is highlighted as a significant challenge (Chaudhry et al., 2022). While fostering innovation is crucial, it should not compromise financial stability. Continuous regulatory updates and adaptive risk management practices are necessary to address this balance and ensure sustainable growth in the FinTech sector. Maintaining this balance is essential for the long-term success and stability of the FinTech industry (Chaudhry et al., 2022).

These findings collectively highlight the importance of trust as a mediating factor in the adoption of FinTech among urban professionals in Malaysia. By addressing cyber security concerns, ensuring regulatory clarity, overcoming skill shortages, and fostering consumer readiness, stakeholders can build a secure, inclusive, and innovative financial landscape that meets the needs and expectations of urban professionals.

#### **2.4.6 Risks Associated with FinTech**

In addition to the challenges and complexities discussed in the preceding section, FinTech introduces a variety of risks that require careful consideration and management. This section discusses the additional risks associated with FinTech, providing a comprehensive analysis supported by evidence from existing literature and case studies.

Operational risks in FinTech arise from internal processes, people, systems, or external events that can disrupt services. These risks are often linked to technological failures, human errors, or inadequacies in internal controls. According to the study by Bains & Wu (2023), operational risks in FinTech can lead to significant financial losses, customer dissatisfaction, and



reputational damage. For instance, the case of the TSB Bank's IT failure in the United Kingdom highlighted how a system upgrade gone wrong can leave customers unable to access their accounts for days, causing severe trust and operational issues. Across the value chain of digital financial services, new operational risks in the digital space can emerge, as highlighted by Wang et al. (2021), emphasising the need for robust risk management strategies.

The digital nature of FinTech services makes them a prime target for fraud and identity theft. The increasing sophistication of cyber criminals poses significant threats to both consumers and financial institutions. The FSB (2019) reports that as FinTech companies handle vast amounts of sensitive data, they become attractive targets for cyber-attacks. High-profile breaches, such as the 2019 Capital One data breach, where sensitive information of over 100 million customers was compromised, illustrate the severity of these risks. Such breaches can lead to financial losses, legal consequences, and erosion of consumer trust (FSB, 2019).

Systemic risk refers to the potential for a disturbance in one institution to spread and impact the broader financial system. FinTech's interconnected nature with traditional financial systems can amplify these risks. The World Bank (2019) identifies the concentration of market power among a few dominant FinTech firms as a potential source of systemic risk. The collapse of a major FinTech firm due to operational failures or cyberattacks could have far-reaching consequences, affecting not only the FinTech ecosystem but also the stability of the entire financial system.

Navigating the complex and evolving regulatory landscape is a significant challenge for FinTech companies. Regulatory and compliance risks arise from the potential for regulatory changes or enforcement actions that can disrupt business operations. According to PwC (2023a), 63% of CEOs in Malaysia consider regulatory change the most significant potential source of disruption in their industry. FinTech firms must continuously adapt to new

regulations, which can be resource-intensive and complex, especially when operating across multiple jurisdictions. The dynamic regulatory environment demands constant vigilance and adaptability from FinTech companies to ensure compliance and mitigate risks. The necessity for open dialogue between regulators, the FinTech industry, and academia is crucial to ensure a shared understanding of FinTech activities and effective regulatory measures (Croxxson et al., 2022).

The handling of vast amounts of personal and financial data by FinTech companies introduces substantial data privacy risks. Mismanagement of data can lead to breaches that compromise user privacy and security. The collection and analysis of enormous amounts of consumer and transaction data, commonly referred to as "big data," come with their own set of advantages and hazards. While big data can enhance service delivery and personalisation, it also poses risks related to data security, privacy, and ethical considerations (Wang et al., 2021). The study by Mohsin et al. (2022) highlights that concerns about data privacy are among the top reasons consumers hesitate to adopt FinTech solutions. As such, ensuring robust data protection measures and compliance with data privacy regulations, such as the Personal Data Protection Act, 2010 in Malaysia or the General Data Protection Regulation in Europe, is crucial to maintaining consumer trust and preventing legal repercussions.

FinTech companies often rely on third-party service providers for various functions, such as cloud computing, payment processing, and cybersecurity. This reliance introduces third-party risks, where the vulnerabilities or failures of these external partners can impact the FinTech firm's operations. The case of the SolarWinds cyberattack in 2020, which affected numerous organisations worldwide, including financial institutions, illustrates the potential risks associated with third-party dependencies (Coco et al., 2022). Managing these risks requires

rigorous due diligence, continuous monitoring, and robust contractual agreements to ensure third-party compliance with security and operational standards (PwC, 2023a).

While FinTech aims to enhance financial inclusion, there is a risk that it might inadvertently exacerbate financial exclusion for certain populations. The digital divide, particularly in rural or underserved areas, can limit access to FinTech services. As Rufaidah et al. (2023) found in their study on FinTech adoption in Indonesia's agricultural sector, reliance on technology can exclude those without adequate digital literacy or access to digital infrastructure. Inclusive strategies are necessary to ensure that all potential users can benefit from FinTech solutions (Rufaidah et al., 2023).

The FinTech industry, while offering significant benefits, also presents a range of risks that must be managed to ensure sustainable growth and consumer protection. Operational risks, fraud, systemic risk, regulatory challenges, data privacy concerns, third-party dependencies, and financial exclusion are among the critical risks that stakeholders must address. Effective risk management strategies, robust regulatory frameworks, continuous technological innovation, and inclusive approaches are essential to mitigating these risks and fostering a secure and resilient FinTech ecosystem. By understanding and addressing these risks, FinTech companies can build trust and confidence among users, paving the way for broader adoption and integration into the financial system.

#### **2.4.7 Evolving FinTech Ecosystem in Malaysia**

In 2024, Malaysia is poised to witness substantial growth in its FinTech industry, driven by increased digital adoption, supportive government regulations, substantial funding, and a rapidly growing talent pool (Hamid et al., 2024). These factors collectively shape the country's evolving FinTech landscape. Various segments within FinTech, such as digital banking,

Islamic FinTech, InsurTech, WealthTech, and payments, are experiencing rapid development. Mohsin et al. (2022) advocates that the adoption of FinTech solutions among Malaysian consumers and businesses is on the rise with the COVID-19 pandemic accelerating the digitisation of financial services.

The issuance of five digital banking licences in 2022 has intensified competition within the banking sector. New entrants like Boost Bank, AEON Bank, and GXBank are disrupting traditional banking models. In 2024, the imminent launch of two additional digital banks backed by Sea Limited, YTL Digital Capital, and KAF Investment Bank will further enhance market competition and financial inclusion. According to FinTech News Malaysia (2023), Malaysia is at the forefront of digital transformation, evidenced by its development of digital identity solutions such as MyDigital ID and PADU. PADU is Malaysia's centralised platform for government agencies to access and utilise demographic data for policy formulation and targeted programme delivery. These platforms leverage biometric data and demographic information to streamline authentication processes, enhancing security and efficiency compared to traditional methods.

The insurance sector is also undergoing a transformation with the rise of InsurTech and the introduction of Digital Insurance and Takaful Operator ("DITO") licences by the Central Bank of Malaysia (BNM, 2024b). DITO licences aims to address underinsurance and stimulate innovation and expansion across the insurance value chain. Simultaneously, Islamic FinTech is also emerging as a significant segment, catering to the growing demand for ethical financial solutions. These developments collectively contribute to a dynamic and inclusive FinTech landscape in Malaysia.

Venture capital and government support have been instrumental in fostering FinTech innovation in Malaysia. Initiatives such as PENJANA and the National Economic Recovery

Plan have provided crucial funding and incentives for FinTech startups (Government of Malaysia, n.d.). Significant investments from entities like Khazanah Nasional have further bolstered the industry's growth. This influx of capital has enabled FinTech companies to expand their reach, develop new products, and contribute to the overall vibrancy of the FinTech ecosystem.

Amid these developments, the role of trust as a mediating factor in the adoption of FinTech among working professionals in Malaysia becomes increasingly significant. Trust influences the willingness of consumers to embrace new financial technologies, particularly in a rapidly evolving landscape marked by digital-only banks, advanced identity verification systems, innovative insurance solutions, and ethical Islamic fintech offerings. Understanding and enhancing trust in FinTech solutions is critical for driving adoption and ensuring the successful integration of these technologies into the daily lives of Malaysian urban working professionals.

#### **2.4.8 Regulatory Landscape Shaping the FinTech Ecosystem in Malaysia**

Malaysia has witnessed significant regulatory initiatives and developments in its FinTech ecosystem, reflecting the government's commitment to fostering innovation and growth in this sector. Policymakers and regulators have actively supported the FinTech landscape by creating a conducive regulatory environment and encouraging public-private partnerships (Alwi et al., 2019). The Financial Sector Blueprint 2022–2026, published by Bank Negara Malaysia (BNM), outlines the central bank's strategic objectives for the financial sector's development in the coming years. It highlights aspirations to foster an open data ecosystem, implement a national digital identity programme, and establish real-time payment linkages (BNM, 2022).

The regulatory framework for FinTech businesses in Malaysia is primarily overseen by BNM and the Securities Commission (SC) (BNM, 2022; SC, 2023). FinTech activities involving

banking, investment banking, insurance, money changing, remittance, payment systems, or the issuance of payment instruments are regulated by BNM under the Financial Services Act 2013 and the Islamic Financial Services Act 2013 (BNM, 2022). The SC regulates FinTech activities in capital markets, including stockbroking, investment advice, and digital asset offerings, under the Capital Markets and Services Act 2007 (SC, 2023). Malaysia has introduced specific regulations for cryptocurrencies and crypto-assets, with the SC serving as the primary regulator in this area (SC, 2023). The SC has issued the Digital Asset Order and the Digital Asset Guidelines, which classify certain digital currencies and tokens as securities and regulate their issuance through Initial Exchange Offerings (SC, 2023). However, both BNM and the SC emphasise that digital assets are not considered legal tender in Malaysia (BNM, 2022; SC, 2023).

According to BNM data, there were over 7.2 billion electronic payment channel transactions in 2021, representing a 30% increase from the previous year. For easy reference, a list of FinTech companies operating in Malaysia is provided in Table 2.3, categorised according to their financial functions (FinTech News, 2022). Analysing payment trends over time reveals that internet banking and mobile banking have become increasingly popular since 2019. Between 2019 and 2021, there were fewer than 500 million internet banking transactions and more than 2 billion mobile banking transactions, respectively (BNM, 2022).

The BNPL market has also seen remarkable expansion in Malaysia. Hoolah, a Singapore-based BNPL provider operating in Malaysia, Hong Kong, and Singapore, reported a staggering 400% increase in users and a doubling of repeat usage in 2021. Similarly, Atome, another BNPL competitor, experienced a hundred-fold increase in order volume in the first half of 2021, along with a five-fold expansion of its merchant network. Atome operates across nine regions in the Asia Pacific, including Malaysia, Indonesia, and Vietnam, with a monthly growth rate of 20%

in new application downloads and usage (Tan, 2022). In response to the rapid growth and emerging consumer risk concerns in the BNPL market, Malaysian regulators and policymakers have introduced new regulations aimed at governing consumer credit activities, including BNPL arrangements. The Consumer Credit Act seeks to address risks associated with new financial schemes while enhancing consumer protection measures (Alam et al., 2019; BNM, 2022).

The Malaysian government and regulators are generally receptive to FinTech innovation and have introduced initiatives to facilitate the growth of the digital economy, such as the Malaysia Digital Hub and the Orbit co-working space (MDEC, 2023). BNM and the SC have also implemented regulatory sandboxes to enable the testing of FinTech solutions in a controlled environment (BNM, 2022; BNM, 2024a; SC, 2023). These regulatory sandbox initiatives aim to promote innovation and experimentation within the FinTech sector. For instance, the Financial Technology Regulatory Sandbox Framework provides two pathways for participation: the Standard Sandbox and the Green Lane (BNM, 2024a).

The Standard Sandbox involves a two-stage application process, with the first stage focusing on eligibility assessment. To qualify, applicants must identify regulatory impediments, demonstrate the value proposition of their solution, present a viable business plan, address risk management concerns, and showcase the credibility of their management team. Upon approval, participants proceed to the second stage for solution testing. The Green Lane, on the other hand, offers an accelerated track for financial institutions with robust risk management capabilities. These institutions undergo a one-off assessment of their risk management, compliance, and governance capabilities. Upon approval, they can expedite the testing of innovative solutions without going through the full Standard Sandbox process. Throughout the testing period, participants must adhere to reporting requirements and submit progress reports to BNM.

Additionally, they must comply with regulatory standards and consumer protection measures. BNM reserves the right to revoke approvals or terminate testing if adverse developments arise or if participants fail to meet regulatory requirements (BNM, 2024a).

FinTech businesses established outside of Malaysia must comply with relevant Malaysian laws and regulations, which may require the establishment of a local entity to obtain the necessary licences or approvals (SC, 2023). The Personal Data Protection Act, 2010 also applies to FinTech businesses operating in Malaysia, regulating the collection, use, and processing of personal data. In addition to financial regulations, FinTech businesses in Malaysia may also be subject to other regulatory regimes, such as cyber security laws, anti-money laundering and anti-corruption regulations, and general business regulations. For instance, Cyber Security Act, 2024; Anti-Money Laundering, Anti-Terrorism Financing and Proceeds of Unlawful Activities Act, 2001; Malaysian Anti-Corruption Commission Act, 2009.

Innovations and inventions in Malaysia are protected under the country's patent, copyright, and industrial design laws, as well as through confidential information under common law (Patents Act, 1983; Copyright Act, 1987; Industrial Designs Act, 1996). In terms of ownership of intellectual property (“IP”), copyright initially vests in the author, while trademarks are owned by the *bona fide* proprietor who has registered the mark. Patents belong to the inventor, unless the invention was made by an employee or pursuant to a commission, in which case the employer or commissioner would own the rights (Patents Act, 1983; Trademarks Act, 2019; Industrial Designs Act, 1996). Malaysia is also a member of various international IP treaties and conventions, which allows for the enforcement of rights beyond just national registrations. IP in Malaysia can be exploited through licencing or co-development arrangements, as well as through the sale of IP rights.



Collaboration among regulatory authorities, FinTech firms, traditional financial institutions, and other stakeholders is instrumental in driving innovation and addressing regulatory challenges. Public-private partnerships facilitate the sharing of expertise, resources, and best practices, promoting responsible FinTech growth (Alwi et al., 2019). Efforts to align Malaysian FinTech regulations with international standards and best practices have been prioritised to enhance cross-border FinTech activities and promote regulatory consistency and cooperation (BNM, 2022; BNM, 2024a). Monitoring and evaluation mechanisms have been established by regulators to assess the effectiveness of FinTech regulations in achieving their objectives. Regular assessments help identify emerging risks, evaluate regulatory compliance, and inform policy adjustments to maintain regulatory efficiency and effectiveness (PwC, 2022; PwC, 2023a; BNM, 2024a).

**Table 2.3** FinTech companies with social media presence in Malaysia categorised by functions  
(source: FinTech News, 2022).

Functions	Company	Year Founded	LinkedIn	Facebook	Twitter
Payments	AppPay	2017		Yes	
	Billplz	2012		Yes	Yes
	GHL Systems Berhad	1997			
	Imaginary Pay	2016			
	iPay88	2006	Yes	Yes	Yes
	iPayLinks	2015	Yes	Yes	
	MOLPay	2005	Yes	Yes	Yes
	ManagePay Systems Berhad (MPay)	2000	Yes	Yes	Yes
	Ozopay	N/A			
	Mobiversa	2015	Yes	Yes	Yes
	Mobile Money	N/A	Yes		
	PayAzu	N/A	Yes	Yes	Yes
	Revenue Monster	2000	Yes	Yes	
	Soft Space	2012	Yes		
	SenangPay	2015		Yes	
	Webcash	N/A	Yes	Yes	Yes

**Table 2.3** (Con'd) FinTech companies with social media presence in Malaysia categorised by functions (source: FinTech News, 2022).

Functions	Company	Year Founded	LinkedIn	Facebook	Twitter
e-Wallets	Alipay (Zhifubao)	2014	Yes	Yes	Yes
	Boost	N/A		Yes	
	FavePay	N/A		Yes	Yes
	HotWallet	N/A		Yes	Yes
	Kiple	N/A	Yes	Yes	Yes
	MCash	2017		Yes	Yes
	PrimeKeeper	N/A			
	Samsung Pay	N/A	Yes	Yes	Yes
	Touch 'n Go	1997	Yes	Yes	Yes
	VCash	N/A			
	VeCash	N/A	Yes	Yes	Yes
Currency Exchange	Currenseek	2015		Yes	Yes
	eForex	N/A		Yes	
	Moneybay	2015	Yes	Yes	Yes
	MoneyMatch	2015	Yes	Yes	Yes
	SwapIt	N/A		Yes	
	WorldKoins	2015	Yes	Yes	Yes

**Table 2.3** (Con'd) FinTech companies with social media presence in Malaysia categorised by functions (source: FinTech News, 2022).

Functions	Company	Year Founded	LinkedIn	Facebook	Twitter
Blockchain	HelloGold	2015		Yes	
	LuxTag	N/A	Yes	Yes	
	NEM	N/A	Yes	Yes	Yes
	Neuroware	N/A	Yes	Yes	Yes
Islamic Fintech	Ethis Kapital	N/A			
	Sedania As-Salam Capital (As-Sidq)	2009	Yes	Yes	Yes
	Wahed	N/A	Yes	Yes	Yes
Personal Finance	FinPay	N/A	Yes		
	Money Lion	N/A	Yes	Yes	Yes
	PerfectSen	N/A	Yes		Yes
	Smartly	N/A	Yes	Yes	Yes
Crowdfunding	ATA Plus	N/A	Yes	Yes	Yes
	Crowdo	N/A	Yes	Yes	
	Crowdplus	N/A	Yes	Yes	Yes
	Eureeca	N/A	Yes	Yes	Yes
	Funded be Me	N/A	Yes	Yes	Yes
	pitchIN	N/A		Yes	Yes
	Skolafund	N/A	Yes	Yes	Yes

**Table 2.3** (Con'd) FinTech companies with social media presence in Malaysia categorised by functions (source: FinTech News, 2022).

Functions	Company	Year Founded	LinkedIn	Facebook	Twitter
Lending	B2B FinPal	N/A			
	Capital Bay	N/A	Yes	Yes	
	Direct Lending	N/A	Yes	Yes	Yes
	Ethis Crowd	N/A	Yes	Yes	Yes
	Fundaztic	N/A	Yes	Yes	Yes
	Funding Societies	N/A	Yes	Yes	Yes
	LendLend	N/A	Yes	Yes	
	QuicKash	N/A			
KYC	Chekk.me	N/A	Yes	Yes	
	EZMCOM	2006	Yes	Yes	Yes
	Innov8tif	N/A	Yes	Yes	Yes
	Pulse iD	N/A	Yes		
	Solus	N/A	Yes		Yes
	Xendity	N/A			
Comparison Sites	Bank Bazaar	N/A	Yes	Yes	Yes
	CoverGO	N/A	Yes	Yes	Yes
	Get Cover	N/A		Yes	
	Go Insurance	N/A		Yes	
	iMoney	N/A	Yes	Yes	Yes
	Loanstreet	N/A	Yes	Yes	Yes

**Table 2.3** (Con'd) FinTech companies with social media presence in Malaysia categorised by functions (source: FinTech News, 2022).

Functions	Company	Year Founded	LinkedIn	Facebook	Twitter
Comparison Sites	Qompanion	N/A		Yes	Yes
	RinggitPlus	N/A	Yes	Yes	Yes
Insurtech	DraVa	N/A			
	FatBerry	N/A	Yes	Yes	
	Katsana	N/A	Yes	Yes	Yes
	PolicyStreet	2017	Yes	Yes	Yes
	U For Life	2015	Yes	Yes	
Remittance	eRemit	N/A		Yes	
	MoneyMatch	2015	Yes	Yes	Yes
	Tik Fx	N/A		Yes	
	Tranglo	N/A	Yes	Yes	Yes
	TransferFriend	N/A	Yes	Yes	Yes
	Valyou	N/A	Yes	Yes	
Artificial Intelligence	Goals 101	N/A	Yes		
	MyFinB	N/A		Yes	Yes
	Pand.ai	N/A	Yes		
Marketplace	MHUb	N/A		Yes	
	MyCash	N/A	Yes	Yes	Yes
	Re Solutions	N/A	Yes	Yes	

## 2.5 Research Framework

This literature review has provided many insights into the current state of the FinTech landscape globally. Each phase of the industrial revolution, including the first through mechanisation, followed by upscaling using electricity, the third with computerisation or automation, and now the fourth – considerably known as the upgraded version of the third industrial revolution using smart systems powered by sophisticated algorithm-based technologies powered by big data, such as ML and AI (Bhuiyan et al. 2022; Soni et al., 2022).

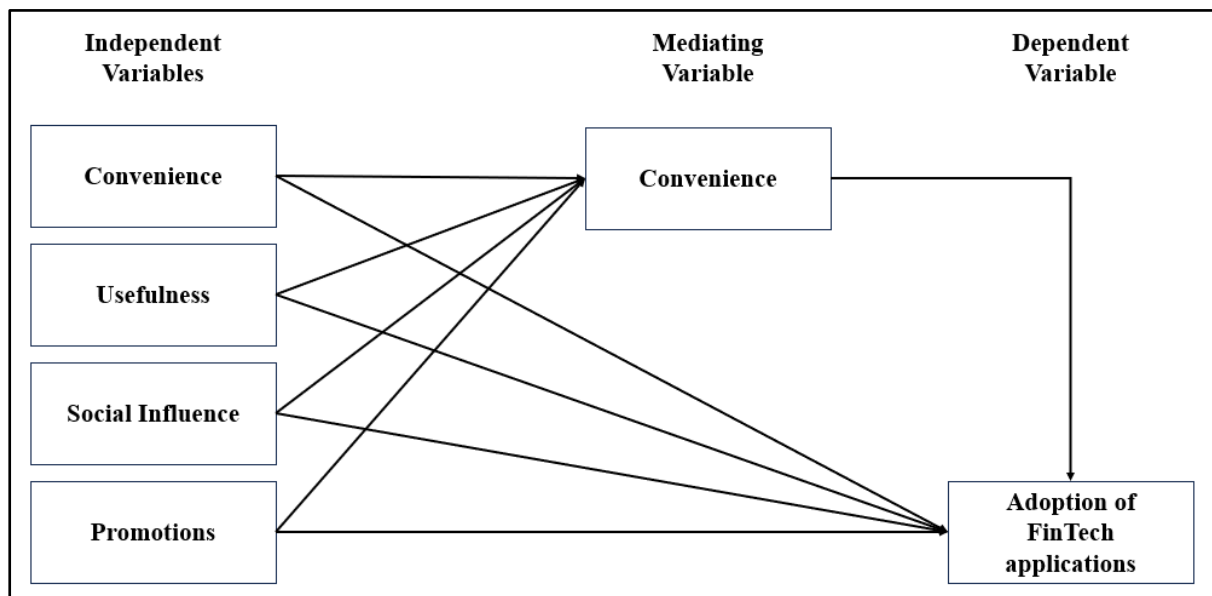
Despite recognising that the advantages of FinTech adoption outweigh its disadvantages from a consumer perspective, the public still lacks confidence and trust in using the technology due to the neglected issues of security and data protection (Kitagawa et al., 2020). The issues are further aggravated by the perceived lack of innovation post-M&A activities, as many studies have shown that the key innovation derives from start-ups or smaller organisations (Goo et al., 2020).

The increased FinTech adoption rate observed lately in the non-business environment is linked to the norm pressure of the pandemic, where the community is encouraged to embrace FinTech applications due to the enforcement of contactless payments for health security purposes in curbing the spread of the virus (Abdul-Rahim et al., 2022). This scenario is no stranger to Malaysia, but regulations for the development and use of FinTech are improving owing to the support provided by the government and international regulators (Shahzad et al., 2022).

Based on a recent study conducted by Shahzad et al. (2022) using a questionnaire to gauge attitudes toward adopting FinTech services in Malaysia, the results indicated that trust, perceived ease of use, and customer innovation play significant roles in influencing technology adoption. In another research study, Alam et al. (2019) argue that FinTech applications (e.g.,

e-wallets) have substantial potential in Malaysia. They agree that many variables within the TAM model, such as accessibility, perceived usefulness, and convenience, are critical in enhancing FinTech adoption. However, they note that the lack of "trust" in its infrastructure and promotions, as well as social influence, impedes public adoption of the application.

This leads to the purpose and novelty of this study: to investigate the perceived benefits based on the current literature and to position "trust" as a mediating factor in determining FinTech adoption among urban working professionals in Malaysia, measured through the intention to use. This conceptual research framework is reflected in Figure 2.12 below.



**Figure 2.12** Research Framework



## **2.6 Formulation of Hypotheses**

This section outlines the hypotheses developed to address the research questions presented in Section 1.8. The hypotheses are derived from the conceptual research framework illustrated in Figure 2.12, which examines the direct effects of convenience, usefulness, promotions, and social influence on intention to use FinTech applications, as well as the mediating role of trust.

### **2.6.1 Direct Effect Hypotheses**

The following hypotheses examine the direct relationships between the independent variables and intention to use FinTech applications:

- H1: Convenience can significantly impact intention to use FinTech among urban working professionals in Malaysia.
- H2: Usefulness can significantly impact intention to use FinTech among urban working professionals in Malaysia.
- H3: Social influence can significantly impact intention to use FinTech among urban working professionals in Malaysia.
- H4: Promotions can significantly impact intention to use FinTech among urban working professionals in Malaysia.

These hypotheses correspond to Research Questions 1 through 4, which investigate the individual effects of each independent variable on intention to use.

### **2.6.2 Mediation Hypotheses**

Research Question 5 explores the mediating role of trust in the relationships between the independent variables and intention to use FinTech applications. To provide a more detailed and nuanced examination of this mediation process, this research question is addressed through

four separate hypotheses, each testing the specific mediating effect of trust for a respective independent variable.

- H5: Convenience can significantly impact intention to use FinTech, mediated by trust, among urban working professionals in Malaysia.
- H6: Usefulness can significantly impact intention to use FinTech, mediated by trust, among urban working professionals in Malaysia.
- H7: Promotions can significantly impact intention to use FinTech, mediated by trust, among urban working professionals in Malaysia.
- H8: Social influence can significantly impact intention to use FinTech, mediated by trust, among urban working professionals in Malaysia.

This approach allows for the determination of whether trust mediates the relationships between each independent variable and intention to use FinTech applications individually.

## **2.7 Summary of Chapter**

This chapter provided an overview of the current sentiment surrounding FinTech in both business and non-business contexts, offering a comprehensive perspective on the opportunities and challenges associated with FinTech adoption, both globally and in Malaysia. It is evident that the TAM theory continues to serve as a foundational framework for evaluating the intended use of technologies, including FinTech, among various user groups. Central to TAM are the concepts of perceived usefulness and ease of use, which heavily influence individuals' acceptance of new technologies.

However, recent scholarly and practical discourse has increasingly highlighted the significance of "trust" as a pivotal factor in shaping attitudes and behaviours towards FinTech adoption. Against this backdrop, this study aims to augment the conventional TAM model with slight

modifications tailored to the unique context of urban working professionals in Malaysia. Specifically, the study will explore how trust acts as a mediating variable, influencing the intention to use FinTech services among this demographic group. By focusing on urban working professionals in Malaysia, this research seeks to provide valuable insights into the specific needs, preferences, and concerns of this target population regarding FinTech adoption. Through an integrated theoretical framework that combines elements of TAM with the mediating role of trust, this study endeavours to offer a comprehensive understanding of the factors driving FinTech usage intentions among urban professionals in Malaysia.

## CHAPTER 3

### 3.0 Research Methodology

#### 3.1 General Introduction

This chapter presents the methodological framework used to investigate factors influencing the adoption of FinTech applications among urban working professionals in Malaysia. The study adopts an extended TAM, incorporating trust as a mediating variable, to provide a comprehensive understanding of the adoption process. The research employs a quantitative approach, using a survey questionnaire and statistical analysis to explore this evolving area. As Hunter et al. (2019) suggest, such an approach is valuable for examining less understood phenomena, particularly in emerging fields like FinTech where limited research exists. The findings aim to enhance understanding of trust in promoting FinTech adoption and contribute to the existing literature.

The research philosophy of this study follows a positivist paradigm using a deductive approach. This involves formulating hypotheses based on existing theory, followed by applying various statistical methods to draw conclusions about whether the data support or reject these hypotheses (Pandey, 2019). The design of this research details the role of trust (as a mediating variable) between perceived benefits (comprising four independent variables) and technology acceptance of FinTech applications (as the dependent variable).

This chapter details the questionnaire development process, which includes adapting established measurement scales and conducting a rigorous expert panel review to ensure content validity and contextual relevance. A multi-phase pilot study, involving both pre- and post-refinement stages, was essential for refining the questionnaire, addressing reliability and multicollinearity issues, and ensuring its suitability for the main study.

The target population and sampling strategy are described, justifying the use of purposive sampling and the selection of LinkedIn as the primary data collection platform. The final data collection process is elaborated upon, emphasizing the use of a distinct sample to mitigate bias and the measures taken to ensure ethical considerations were adhered to.

Finally, the statistical techniques employed for data analysis are outlined. These include descriptive statistics, reliability assessment, normality testing, correlation analysis, regression analysis, confirmatory factor analysis (“CFA”), and structural equation modelling (“SEM”). These methods were selected to thoroughly examine the direct and mediating relationships between the constructs, providing robust support for the study’s hypotheses. This chapter aims to provide a clear and detailed explanation of the research methods, ensuring the findings are valid and reliable.

### **3.1.1 Saunders' Research Onion Summary**

Saunders’ Research Onion was used to guide the methodological choices in this research. This model provides a visual and systematic framework illustrating the layers of the research methodology.

This study adopts a positivist philosophy, aligning with the quantitative approach and the aim to establish objective relationships between variables. Positivism, as defined by Saunders et al. (2019), involves the pursuit of objective truth through empirical observation and statistical analysis. For further discussion of the sampling method and its limitations, see Section 3.2.3.

To test hypotheses derived from existing theories, specifically TAM and the mediating role of trust, a deductive research approach was employed using quantitative data. This approach, justified by Saunders et al. (2019), moves from general theories to specific observations, directly supporting the study’s aim to confirm or reject proposed relationships.

A survey strategy was chosen, using a structured questionnaire distributed via Google Forms. This method facilitates the collection of quantifiable data from a large sample, which is essential for statistical analysis and hypothesis testing. Surveys are well-suited for examining relationships between variables and are commonly used in quantitative research (Saunders et al., 2019).

The study employed a cross-sectional time horizon, collecting data over six months. While acknowledging that some changes may have occurred during this period, this approach is appropriate for examining relationships between variables within a defined timeframe and is commonly used in survey research (Saunders et al., 2019).

See Section 3.2.1 for details of the questionnaire design and validation. The collected data were analysed using SPSS and AMOS. Statistical techniques included descriptive statistics, reliability assessment (Cronbach's alpha), normality tests (skewness and kurtosis), Pearson correlation analysis, regression analysis, CFA, and SEM. These methods were selected to thoroughly examine the relationships between constructs and test the study's hypotheses.

## **3.2 Research Design and Methods**

### **3.2.1 Questionnaire Development and Validation**

A survey questionnaire was created using Google Forms to collect responses for this research. The questionnaire primarily consisted of closed-ended questions to ensure standardisation of datasets, which is essential for accurate data analysis (Desai & Reimers, 2019). Closed-ended questions provide more objective and uniform responses, thereby minimising uncertainties and ambiguities that could potentially affect the study's results (Bolton & Brace, 2022). This approach enhances consistency in data interpretation and facilitates meaningful comparisons among respondents.

A five-point Likert scale questionnaire was developed to measure respondents' level of agreement on various factors, including convenience, usefulness, social influence, promotions, trust, and intention to use (Taherdoost, 2019). The scale was structured as follows: 1) Strongly Disagree, 2) Disagree, 3) Neutral, 4) Agree, and 5) Strongly Agree. The questionnaire items were adapted from established studies to ensure theoretical consistency and alignment with prior research (Davis et al., 1989; Koenig-Lewis et al., 2015; Lu et al., 2005; Al-Sharafi et al., 2017). Adaptations were made to enhance contextual relevance for FinTech adoption among urban working professionals in Malaysia while preserving the original conceptual meaning.

The initial questionnaire, used in the first phase of the pilot study involving 50 respondents, contained 45 items structured into seven sections covering demographic information, convenience, perceived usefulness, social influence, promotions, trust, and intention to use FinTech applications. Questions within each section were adapted from previous literature, as detailed in Tables 3.1 and 3.2. The adoption of established measurement scales enhanced the validity and reliability of the questionnaire.

**Table 3.1** Questionnaire structure and references to earlier literature (initial 45-item questionnaire).

<b>Variables</b>	<b>No. of Questions</b>	<b>References</b>
Convenience	10	Davis et al. (1989)
Usefulness	10	Davis et al. (1989)
Social influence	8	Koenig-Lewis et al. (2015); Lu et al. (2005)
Promotions	6	Koenig-Lewis et al. (2015); Lu et al. (2005)
Trust	6	Al-Sharafi et al. (2017); Mosavi & Ghaedi (2012)
Intention to use FinTech	5	Lu et al. (2005); Putritama (2019)
<b>Total</b>	<b>45</b>	-



**Table 3.2** Survey questionnaire questions by section (initial 45-item questionnaire).

Section	Variable	Questions
A	Demographic	<ul style="list-style-type: none"> <li>• Gender</li> <li>• Age group</li> <li>• Race</li> <li>• Educational level</li> <li>• Employment status</li> <li>• Household income</li> </ul>
B	Convenience	<ol style="list-style-type: none"> <li>1. I find FinTech application not cumbersome to use.</li> <li>2. Learning to operate FinTech application is easy for me.</li> <li>3. Interacting with FinTech applications is not frustrating to me.</li> <li>4. I find it easy to get the FinTech application do what I want it to do.</li> <li>5. FinTech application is flexible for me to interact with.</li> <li>6. I can easily remember how to perform tasks using FinTech applications.</li> <li>7. Interacting with FinTech applications requires minimal effort from me.</li> <li>8. My interaction with FinTech application is clear and understandable.</li> <li>9. I find it takes less effort to become skilful at using FinTech applications.</li> <li>10. Overall, I find FinTech application convenient to use.</li> </ol>
C	Usefulness	<ol style="list-style-type: none"> <li>1. Using FinTech applications improves the quality of the tasks I do.</li> <li>2. Using FinTech applications gives me greater control over my tasks.</li> <li>3. FinTech applications enable me to accomplish tasks more quickly.</li> <li>4. FinTech applications support critical aspects of my tasks.</li> <li>5. Using FinTech applications increases my productivity.</li> <li>6. Using FinTech applications improves my job performance.</li> <li>7. Using FinTech applications allows me to accomplish more tasks than would otherwise be possible.</li> <li>8. FinTech applications enhance my effectiveness at my tasks.</li> <li>9. Using FinTech applications makes it easier to do my tasks.</li> <li>10. Overall, I find the FinTech applications useful in my tasks.</li> </ol>
D	Social influence	<ol style="list-style-type: none"> <li>1. People who are important to me are likely to recommend using FinTech applications.</li> <li>2. People who are important to me would probably suggest that I should use FinTech applications.</li> <li>3. People who are important to me expect me to use FinTech applications.</li> <li>4. People around me who use FinTech applications have more prestige than those who do not.</li> <li>5. People who use FinTech applications have a higher profile.</li> <li>6. Using FinTech applications is considered a status symbol among my friends.</li> <li>7. People who influence my behaviour think that I should use FinTech applications.</li> <li>8. My friend thinks that I should use FinTech applications.</li> </ol>
E	Promotions	<ol style="list-style-type: none"> <li>1. Using FinTech applications with promotions is rather pleasant.</li> <li>2. The FinTech application is rather enjoyable.</li> <li>3. If I heard about new FinTech applications, I'd look for ways to experiment with it.</li> <li>4. Among my peers, I am usually the first to explore new FinTech applications.</li> <li>5. I like to experiment with new FinTech applications.</li> <li>6. In general, I am not hesitant to try out new FinTech applications.</li> </ol>
F	Trust	<ol style="list-style-type: none"> <li>1. FinTech applications give me a feeling of trust.</li> <li>2. FinTech applications give a trustworthy impression.</li> <li>3. I have trust in FinTech applications.</li> <li>4. The service provider for FinTech applications can be relied upon to keep promises.</li> <li>5. The service provider for FinTech applications is trustworthy.</li> <li>6. I have full confidence in the service provider for FinTech applications.</li> </ol>
G	Intention to use	<ol style="list-style-type: none"> <li>1. Assuming I have access to a FinTech application, I intend to adopt it.</li> <li>2. Given that I have access to a FinTech application, I predict that I would adopt it.</li> <li>3. I would positively consider FinTech by choice.</li> <li>4. I prefer to use FinTech.</li> <li>5. I intend to continue to use FinTech.</li> </ol>

To ensure content validity, an expert panel review was conducted, comprising two academic researchers in digital finance and three industry professionals from one of the Big 4 consulting firms specialising in FinTech. The academic researchers held PhDs in information systems and had extensive publications on technology adoption, while the industry professionals possessed over 20 years of experience in FinTech consulting and implementation. The panel assessed whether the questionnaire items appropriately measured the intended constructs and provided feedback on wording clarity, relevance, cultural appropriateness, and suggested improvements. Their input led to refinements in phrasing to improve readability and comprehension.

Initial pilot testing with 50 respondents using the 45-item questionnaire revealed Cronbach's alpha values below the acceptable threshold ( $\alpha < 0.7$ ) for the Promotions and Trust constructs. Subsequent analysis of the extended pilot data ( $n=313$ ) identified significant multicollinearity issues. To address these concerns, the questionnaire was substantially revised-reducing items from 45 to 19 and refining item wording. This reduction was primarily driven by the need to eliminate redundant and irrelevant questions, particularly highly correlated 'convenience' items, as well as other questions contributing to multicollinearity. Wording refinements were also made to enhance clarity and reduce ambiguity, based on feedback from respondents and statistical analysis.

A post-refinement reliability test, conducted with the same 313 participants during the extended pilot study, demonstrated improved Cronbach's alpha values for all constructs, confirming enhanced internal consistency. These validation steps, including expert review and pre- and post-refinement pilot testing, affirm the suitability of the refined 19-item questionnaire for investigating FinTech adoption among urban working professionals in Malaysia.

### **3.2.2 Target Population**

The target population for this research comprised urban working professionals in Malaysia, over the age of 18, who have used or expressed interest in using at least one of the FinTech applications available in Malaysia. These FinTech applications include internet banking, mobile banking applications, contactless payment, e-wallets, and others (i.e., cryptocurrency). This specific demographic was chosen due to their likely familiarity and engagement with FinTech services, which makes them ideal for providing insightful data on factors influencing FinTech adoption.

### **3.2.3 Sample Size & Sampling Method**

This study employed purposive sampling, a non-probability sampling technique, to target urban working professionals in Malaysia who are likely to adopt FinTech applications. This approach was chosen due to its effectiveness in selecting respondents with relevant experience and knowledge of FinTech adoption (Etikan et al., 2016). Unlike random sampling, which may include individuals with little to no exposure to FinTech applications, purposive sampling ensures that the sample consists of individuals who can provide meaningful insights into the factors influencing FinTech adoption. While purposive sampling limits generalisability due to the absence of random selection, it enhances the relevance and depth of the responses gathered. The sample is thus representative of the intended study population, urban working professionals in Malaysia with exposure to FinTech, rather than the general Malaysian workforce (Creswell & Plano Clark, 2018; Saunders et al., 2019).

The primary distribution channel for the survey was LinkedIn, a professional networking platform with approximately 6.85 million registered users in Malaysia in 2023 (Statista, 2024). The researcher leveraged professional connections on LinkedIn comprising individuals from

diverse industries and backgrounds. This makes it an appropriate and accessible population for studying FinTech adoption. The use of LinkedIn also facilitated broader outreach and increased the likelihood of obtaining responses from individuals actively engaged in professional settings, thus enhancing the applicability of the sample to the study. However, it is acknowledged that reliance on LinkedIn may introduce digital literacy bias, as individuals who do not actively use the platform or who prefer alternative networking methods may have been underrepresented.

The determination of an appropriate sample size was guided by Krejcie & Morgan's (1970) sample size formula and further validated using G\*Power 3.1 software for structural equation modelling ("SEM") analysis. Given the study's target population of urban working professionals in Malaysia, the recommended sample size for a medium effect size ( $f^2 = 0.15$ ), a significance level of  $\alpha = 0.05$ , and a statistical power of 0.80 was approximately 150 to 200 respondents. However, since SEM requires a larger sample to achieve reliable model estimation, a target of at least 300 responses was established in alignment with past research on FinTech adoption (Memon et al., 2021). The minimum recommended sample size for SEM varies in the literature. Kline (2011) suggests that a sample of 200 is generally adequate for most SEM applications. However, more recent reviews, such as Memon et al. (2021), recommend a minimum of 300 respondents to ensure robust estimation, particularly for complex models or mediation analysis. In this study, a sample of 313 was obtained, exceeding both recommendations and ensuring sufficient power and reliability for the planned analyses.

### **3.2.4 Data Collection Method**

#### **3.2.4.1 Pilot Study Overview**

A pilot study was conducted in multiple phases to ensure the reliability and validity of the questionnaire. The primary objective of this pilot study was to refine the 45-item questionnaire, which was initially developed based on previous literature, and to ensure that it accurately measured the intended constructs. This process involved assessing the questionnaire's psychometric properties, including reliability, normality, linearity, correlation, and multicollinearity, before its use in the final data collection. The pilot study was structured into a first phase (initial), pre-refinement, and post-refinement phases, each designed to address specific aspects of the questionnaire's performance.

The first phase involved a small sample of 50 participants to evaluate preliminary reliability. Subsequent phases, with a larger sample of 313 participants, aimed to provide more robust reliability estimates and to thoroughly assess the questionnaire's psychometric properties. These phases also allowed for the identification and correction of any issues related to normality, linearity, correlation, and multicollinearity, ensuring that the final questionnaire was suitable for the main study.

#### **3.2.4.2 Initial Pilot Study (1st Phase)**

The first phase of the pilot study, involving 50 participants, was conducted to evaluate the preliminary reliability of the 45-item questionnaire using Cronbach's alpha. The results, as shown in Table 3.3, revealed that while several variables exhibited acceptable reliability (Cronbach's alpha > 0.7), the Promotions ( $\alpha = 0.687$ ) and Trust ( $\alpha = 0.626$ ) variables were marginally below the recommended threshold of 0.7 (Taber, 2018). These findings, along with

the need for more robust psychometric testing, led to the extension of the pilot study to include a larger sample size.

**Table 3.3** Reliability test of questionnaire during pilot study using Cronbach's alpha (first phase - 50 participants, 45-item questionnaire).

Variables	No. of items	Mean	Standard deviation	Cronbach's alpha
Convenience	10	34.96	5.904	0.796
Usefulness	10	34.78	5.567	0.769
Social Influence	8	28.16	4.497	0.739
Promotions	6	20.24	3.836	0.687
Trust	6	20.64	3.579	0.626
Intention to Use	5	17.46	3.500	0.723
Overall scale	45	156.24	17.954	0.883

### 3.2.4.3 Extended Pilot Study (2nd Phase, Pre-Refinement of Questionnaire)

Recognising the need for more robust reliability estimates and a thorough assessment of the questionnaire's psychometric properties with a larger sample size, the pilot study was extended to include an additional 263 participants, bringing the total pilot sample size to 313. This extended pre-refinement pilot study also used the original 45-item questionnaire. This sample size was chosen to align with the intended sample size for the final data collection (313 participants) to ensure a more reliable evaluation of the questionnaire's performance within the target population for the main study. This alignment was crucial for accurately assessing the questionnaire's effectiveness and informing necessary revisions before final data collection. However, it does not imply generalisability beyond the defined target population.

The Cronbach's alpha results for this extended pilot study (second phase, pre-refinement of questionnaire) are presented in Table 3.4. There was improved reliability across all variables compared to the initial phase.

**Table 3.4** Reliability test of questionnaire using Cronbach's alpha (second phase, pre-refinement pilot - 313 participants, 45-item questionnaire).

Variables	No. of items	Mean	Standard deviation	Cronbach's alpha
Convenience	10	34.62	6.023	0.811
Usefulness	10	34.76	5.982	0.805
Social Influence	8	27.47	4.956	0.775
Promotions	6	20.59	3.850	0.707
Trust	6	20.04	3.969	0.728
Intention to Use	5	17.28	3.423	0.712
Overall scale	45	157.76	19.728	0.905

The extended pre-refinement pilot study with 313 participants demonstrated improved Cronbach's alpha values across all variables compared to the initial 50-participant pilot. Key improvements included increases in Cronbach's alpha values for Convenience from 0.796 to 0.811, Usefulness from 0.769 to 0.805, Social Influence from 0.739 to 0.775, Promotions from 0.687 to 0.707, and Trust from 0.626 to 0.728. The overall scale also showed an increase from 0.883 to 0.905. However, the Intention to Use variable decreased slightly from 0.723 to 0.712 but remained acceptable.

Following the reliability analysis, the normality of the dataset was examined through skewness, kurtosis, and P-P plots. As indicated in Table 3.5, the skewness and kurtosis values for each variable were within acceptable limits (-1 to +1). This indicates that the data were normally distributed with minimal skewness.

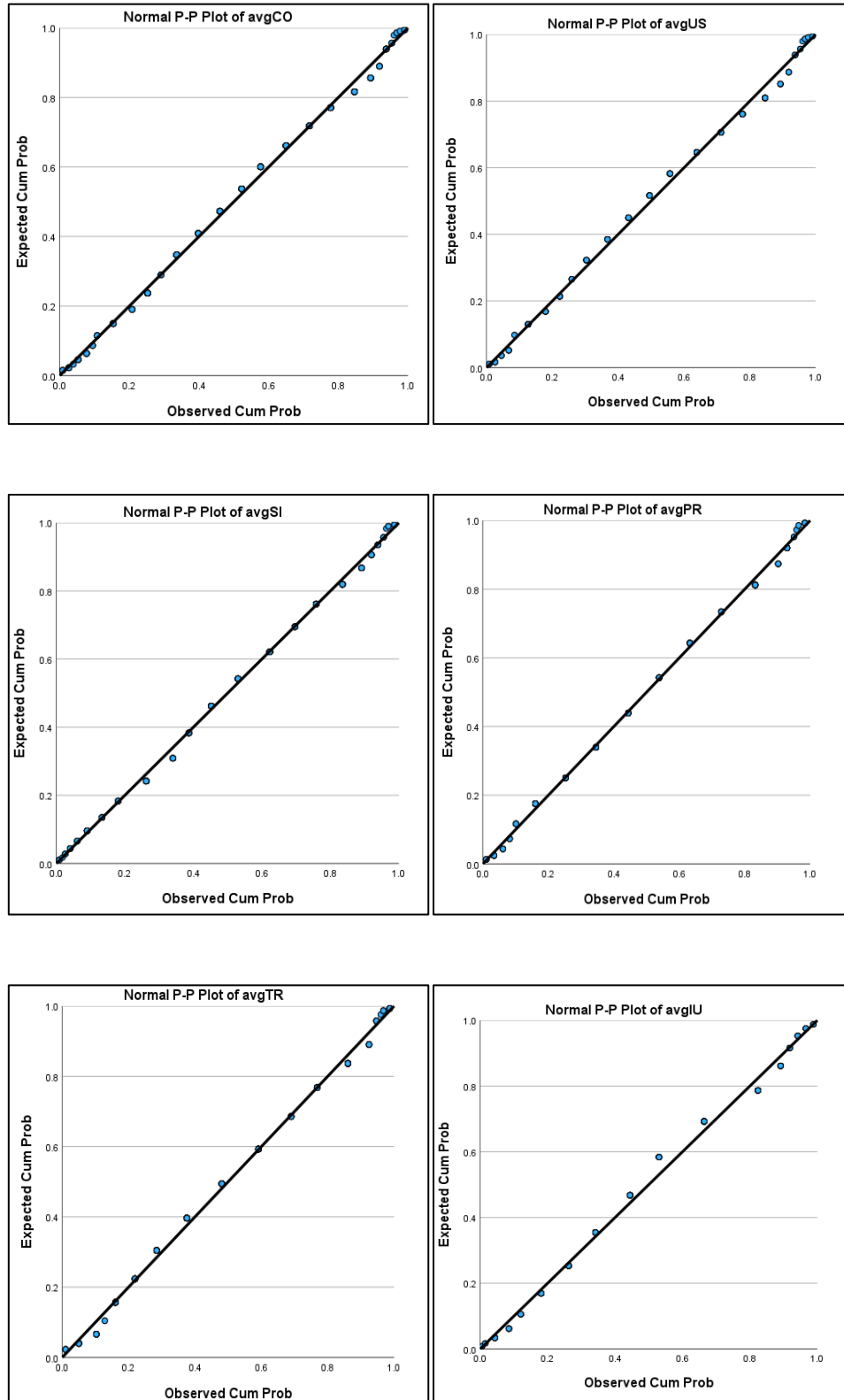
**Table 3.5** Skewness and kurtosis of the data (second phase, pre-refinement pilot - 313 participants, 45-item questionnaire).

	N	Mean	SD	SE	Skewness		Kurtosis	
					Value	SE	Value	SE
Convenience	10	3.46	0.602	0.034	0.050	0.138	-0.054	0.275
Usefulness	10	3.48	0.598	0.034	0.057	0.138	0.179	0.275
Social Influence	8	3.43	0.619	0.035	0.181	0.138	0.030	0.275
Promotions	6	3.43	0.642	0.036	0.094	0.138	0.078	0.275
Trust	6	3.34	0.661	0.037	0.102	0.138	-0.078	0.275
Intention to Use	5	3.46	0.685	0.039	-0.101	0.138	-0.237	0.275

Normal P-P plots were generated to evaluate the degree of agreement between theoretical and observed values for each dataset. The plots demonstrated that the data points for each predictor variable and outcome aligned closely along the distribution line, further supporting the normality of the datasets (Figure 3.1). This met the primary requirement for parametric testing, such as multiple regression (Mishra et al., 2019).

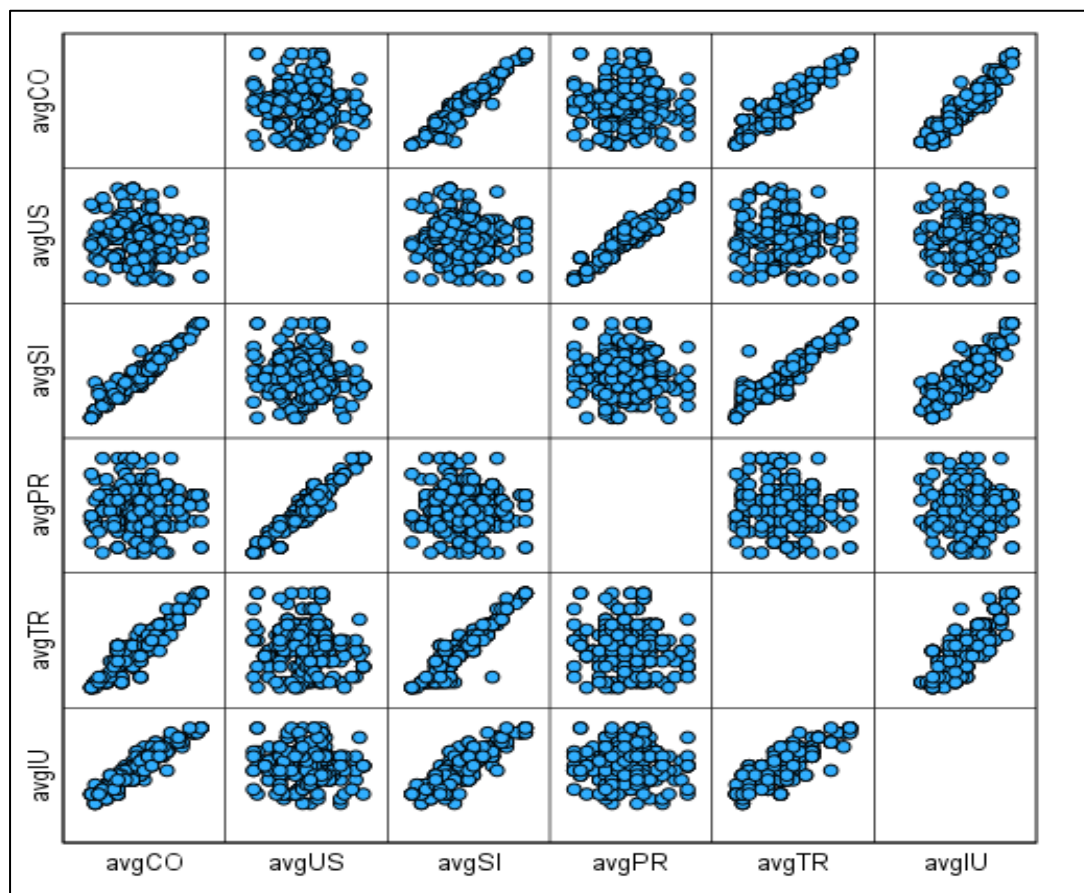


**Figure 3.1** Normal P-P plot for (A) convenience, (B) usefulness, (C) social influence, (D) promotions, (E) trust, and (F) intention to use.



Subsequently, a linearity test was performed using scatter plots to visually assess the relationship between the predictor variables and the outcome variable (Intention to Use) (Mishra et al., 2019). As depicted in Figure 3.2, the datasets for Convenience, Social Influence, and Trust exhibited a positive linear correlation with Intention to Use. However, Usefulness and Promotions displayed no discernible pattern, suggesting a potential lack of linear relationship with Intention to Use. This observation was further validated through Pearson correlation analysis the next section.

**Figure 3.2** Scatter plots of datasets.



The Pearson correlation analysis was then employed to measure the degree and direction of correlation between the variables in the extended pre-refinement pilot study (313 participants), confirming the linearity findings from the scatter plots.

For this analysis, the variables must be numerical, normally distributed without outliers, and exhibit a linear relationship (Ly et al., 2018). Based on the reliability, normality, and assumption tests conducted on the extended pre-refinement pilot data, these criteria were met. The coefficient value ranges from -1 to +1, with higher values indicating a stronger connection between variables. Positive correlation signifies changes in the same direction, while negative correlation indicates changes in opposite directions.

According to Table 3.6, based on the extended pre-refinement pilot data, Convenience, Social Influence, and Trust exhibited significant positive correlations with Intention to Use, with Pearson correlation values of 0.930, 0.876, and 0.846, respectively. This indicates that, compared to Usefulness and Promotions, these three variables have a greater influence on Intention to Use in the context of FinTech adoption within the extended pre-refinement pilot study. Interestingly, there was a significant positive correlation between Convenience and Social Influence, mediated by Trust. This suggests that Trust plays a pivotal role in advocating for Convenience or Social Influence. In contrast, the Promotions variable exhibited significant correlation only with Usefulness, showing no correlation with the other variables.

**Table 3.6** Pearson correlations of the datasets (second phase, pre-refinement pilot - 313 participants, 45-item questionnaire) (significant at the 0.01 level; 2 tailed).

Variables	Convenience	Usefulness	Social Influence	Promotions	Trust	Intention to Use
Convenience	1.000					
Usefulness	-0.050	1.000				
Social Influence	0.960**	-0.064	1.000			
Promotions	-0.037	0.950**	-0.062	1.000		
Trust	0.911**	-0.098	0.950**	-0.094	1.000	
Intention to Use	0.930**	-0.055	0.876**	-0.055	0.846**	1.000

Following the Pearson correlation analysis, which revealed significant correlations among several variables, a multicollinearity test was conducted in this second phase of the pre-refinement pilot study. This aims to verify that the predictor variables datasets are not highly correlated with each other before proceeding with multiple regression analysis. This step is crucial as multicollinearity can distort associated variance accuracy, leading to erroneous inferences when establishing a regression model. One method for this test involves examining the variance inflation factor (“VIF”) values, where a value of less than five is considered acceptable, along with a tolerance value of more than 0.1. These values serve as indicators of variable non-collinearity (Senaviratna & Cooray, 2019).

As shown in Table 3.7, the VIF and tolerance values for each variable did not meet the acceptable criteria, indicating multicollinearity among the variables. Consequently, further analysis such as regression or SEM would produce inconclusive results. To ensure non-collinear datasets, it was necessary to revise the questionnaire and conduct further testing, primarily reliability testing and multicollinearity testing, in the post-refinement phase of the extended pilot test.

**Table 3.7** Results of the multicollinearity test (second phase, pre-refinement pilot - 313 participants, 45-item questionnaire).

	Tolerance	VIF
Constant	-	-
Convenience	0.076	13.115
Usefulness	0.097	10.330
Social influence	0.044	22.510
Promotions	0.097	10.361
Trust	0.097	10.313

#### **3.2.4.4 Refinement of Questionnaire**

Based on the results of the second phase, pre-refinement pilot study, specifically the identified multicollinearity issues and the high correlations among certain variables, the 45-item questionnaire was refined. The primary objective of this refinement was to mitigate multicollinearity and enhance the reliability and validity of the measurement constructs. This was achieved by carefully reviewing the questionnaire items and identifying redundant or highly correlated questions. Items that measured similar constructs were either merged or removed to reduce redundancy and improve the distinctiveness of each variable. This process aimed to ensure that each item contributed uniquely to the measurement of its respective construct, thereby minimising multicollinearity. The revised structure of the questionnaire, which consisted of 19 items, is presented in Table 3.8. This reduction in items was intended to streamline the questionnaire and improve the clarity and focus of the measurement scales.

**Table 3.8** Refined survey questionnaire questions by section (19-item questionnaire).

Section	Variable	Questions
A	Demographic	<ul style="list-style-type: none"> <li>• Gender</li> <li>• Age group</li> <li>• Race</li> <li>• Educational level</li> <li>• Employment status</li> <li>• Household income</li> </ul>
B	Convenience	<ol style="list-style-type: none"> <li>1. Interacting with FinTech applications is not frustrating to me.</li> <li>2. Interacting with FinTech applications requires minimal effort from me.</li> </ol>
C	Usefulness	<ol style="list-style-type: none"> <li>1. FinTech applications enable me to accomplish tasks more quickly.</li> <li>2. FinTech applications support critical aspects of my tasks.</li> <li>3. Using FinTech applications allows me to accomplish more tasks than would otherwise be possible.</li> </ol>
D	Social influence	<ol style="list-style-type: none"> <li>1. People who are important to me would probably suggest that I should use FinTech applications.</li> <li>2. People who are important to me expect me to use FinTech applications.</li> <li>3. People around me who use FinTech applications have more prestige than those who do not.</li> <li>4. People within my social circle view FinTech applications as important.</li> <li>5. Using FinTech applications is considered a status symbol among my friends.</li> <li>6. People who influence my behaviour think that I should use FinTech applications.</li> </ol>
E	Promotions	<ol style="list-style-type: none"> <li>1. Using FinTech applications with promotions is rather pleasant.</li> <li>2. Among my peers, I am usually the first to explore new FinTech applications.</li> <li>3. I like to experiment with new FinTech applications.</li> </ol>
F	Trust	<ol style="list-style-type: none"> <li>1. FinTech applications give a trustworthy impression.</li> <li>2. I have full confidence in the service provider for FinTech applications.</li> </ol>
G	Intention to Use	<ol style="list-style-type: none"> <li>1. Given that I have access to a FinTech application, I predict that I would adopt it.</li> <li>2. I would positively consider FinTech as my choice.</li> <li>3. I prefer to use FinTech applications.</li> <li>4. I intend to continue to use FinTech applications.</li> </ol>

### 3.2.4.5 Extended Pilot Study (3rd Phase, Post-Refinement of Questionnaire)

Following the refinement of the questionnaire, a post-refinement pilot study was conducted using the revised 19-item questionnaire with the same sample size of 313 participants. This phase aimed to assess the impact of the questionnaire revisions on reliability and multicollinearity. The results of this post-refinement pilot study were crucial in validating the effectiveness of the refinements made to the questionnaire. While the second phase, pre-refinement pilot study involved a more comprehensive assessment of reliability, normality, linearity, correlation, and multicollinearity to identify potential issues, the third phase, post-refinement pilot study focused specifically on reliability and multicollinearity. This narrowed focus was due to the primary concerns identified in the second phase, which were addressed through the questionnaire revision.

The Cronbach's alpha results for the revised 19-item questionnaire, obtained from the third phase, post-refinement pilot study with 313 participants, are presented in Table 3.9. This assessment aimed to ensure that the refined questionnaire maintained acceptable reliability after the item reductions and wording changes.

**Table 3.9** Reliability test of refined questionnaire using Cronbach's alpha (third phase, post-refinement pilot - 313 participants, 19-item questionnaire).

Variables	No. of items	Mean	SD	Cronbach's alpha
Convenience	2	6.57	1.635	0.738
Usefulness	3	9.68	2.488	0.768
Social Influence	5	16.78	3.662	0.791
Promotions	3	9.73	2.477	0.718
Trust	2	6.42	1.668	0.708
Intention to Use	4	13.58	2.922	0.712
Overall scale	19	62.72	9.791	0.852

The Cronbach's alpha values presented in Table 3.9 indicate satisfactory reliability for the refined 19-item questionnaire. All constructs demonstrate Cronbach's alpha values above 0.7, which is generally considered an acceptable threshold for internal consistency in social science research (Hair et al., 2019). Social Influence exhibits the highest reliability ( $\alpha = 0.791$ ), followed closely by Usefulness ( $\alpha = 0.768$ ) and Convenience ( $\alpha = 0.738$ ). Promotions, Trust, and Intention to Use all show alpha values slightly above 0.7, indicating adequate reliability. The overall scale also demonstrates strong reliability, with a Cronbach's alpha of 0.852. These results confirm that the questionnaire refinements, including item reductions and wording changes, did not compromise the internal consistency of the constructs. Instead, they maintained or even improved the reliability of the measurements, ensuring that the questionnaire is suitable for assessing FinTech adoption among urban working professionals in Malaysia.

Subsequently, a multicollinearity test was conducted to ensure that the revised 19-item questionnaire exhibited reduced multicollinearity. The results, shown in Table 3.10, indicated that the VIF and tolerance values for each variable met the acceptable criteria, confirming a significant reduction in multicollinearity.

**Table 3.10** Results of the multicollinearity test (third phase, post-refinement pilot - 313 participants, 19-item questionnaire).

	Tolerance	VIF
Constant	-	-
Convenience	0.248	4.032
Usefulness	0.198	5.051
Social influence	0.328	3.049
Promotions	0.193	5.181
Trust	0.189	5.291



This confirmed that the questionnaire refinements effectively addressed the multicollinearity issues identified in the pre-refinement phase. While some VIF values are slightly above 5, they are deemed acceptable for this study. This is supported by research indicating that in complex social science models, slight deviations from this threshold can be tolerated, especially when the model is theoretically sound (Hair et al., 2019). With the refined 19-item questionnaire demonstrating satisfactory reliability and minimal multicollinearity, it was deemed suitable for the final data collection in the main study.

#### **3.2.4.6 Pilot Study Summary**

The pilot study, conducted in three distinct phases, was crucial for refining and validating the 45-item questionnaire used in the main study. First, the initial phase (n=50) identified preliminary reliability issues, specifically with the Promotions and Trust constructs. Therefore, further investigation was necessary. Second, the pre-refinement phase (n=313) involved a comprehensive assessment of reliability, normality, linearity, correlation, and multicollinearity. This phase revealed significant multicollinearity and correlation issues, leading to required questionnaire revisions. These revisions were made in consultation with industry experts and academics, ensuring both practical relevance and theoretical rigour. Third, the post-refinement phase (n=313) confirmed that the revised 19-item questionnaire exhibited satisfactory reliability and minimal multicollinearity. This validated the effectiveness of the refinements. Consequently, the findings ensured that the questionnaire was psychometrically sound and suitable for the final data collection, enhancing the validity and reliability of the study's results.

### **3.2.4.7 Final Data Collection**

The final data collection for the main study was conducted online between September 2023 and March 2024. The refined 19-item questionnaire, as validated in the pilot study, was disseminated to approximately 1,700 potential participants via LinkedIn messages, professional groups, and public posts. To enhance the response rate and minimise non-response bias, follow-up reminders were sent every two weeks. By the end of the data collection period, 313 complete responses were obtained. Once this target was reached, further recruitment efforts ceased.

The final dataset was collected from a separate group of 313 participants, distinct from those involved in the extended pilot studies (pre- and post-refinement). This ensures that the results obtained were not influenced by potential biases or learning effects from the pilot study participants. Throughout the survey period, participants were assured of the voluntary nature of the study and the confidentiality of their responses. This encouraged them to provide candid and unbiased answers. The final sample size of 313 responses, obtained from the refined 19-item questionnaire, exceeded the recommended threshold (Memon et al., 2021), ensuring sufficient statistical power and applicability within the defined population. Given the methodological rigour applied in the sampling design and implementation, the collected data is considered appropriate for analysis using SEM and supports the study's overall objectives.

### **3.2.5 Ethical Issues and Accessibility**

In conducting this research, the researcher adhered to UWTSD's Research Ethics & Integrity Code of Practice and related policies and guidelines to uphold integrity and validity. This included preventing disputes related to research integrity, such as lack of participants' consent, data fabrication, and falsification (Bos, 2020). Ethical approval for this study was obtained

from the UWTSD Research Ethics Committee before data collection commenced. To ensure informed participation, potential respondents were provided with a clear overview of the research study before accessing the questionnaire and were free to engage or opt out at any time (Josephson & Smale, 2021). Informed consent was obtained through an explicit agreement before participation. Participants were assured that their responses would remain confidential and be used solely for academic purposes.

As the research was conducted in Malaysia, compliance with the Personal Data Protection Act (“PDPA”), 2010 was ensured, particularly in handling sensitive personal information. No personally identifiable information, such as names or dates of birth, was collected to maintain participant anonymity (Hunter et al., 2018). Furthermore, all data were securely stored in Google Drive and are only accessible to the researcher with password protection to ensure privacy and confidentiality (Oh, 2024). Data retention and deletion will be carried out in accordance with PDPA, with all data scheduled for deletion upon completion of the study.

To further minimise the risk of data loss, leakage, or unethical use by third parties, no hardcopy records of research-related materials were created. The questionnaire did not contain any sensitive questions to promote voluntary participation. Participants were not obligated to answer the survey and could withdraw at any time. Contact information for UWTSD’s appointed Lead Supervisor/Director of Studies (Prof. Dr. Ilham Sentosa) was also provided to participants in case of any ethical issues unresolved by the researcher. The online questionnaire was designed to be accessible across various devices and platforms to ensure inclusivity.

### **3.2.6 Data Analysis**

The data analysis approach followed the conceptual framework outlined in Chapter 2. The selection of variables and analysis techniques were aligned with the theoretical foundation of TAM and its extensions, particularly to assess the mediating role of trust in influencing the intention to adopt FinTech applications. Each statistical method was chosen to test the hypotheses derived from this framework.

Data analysis was conducted using two statistical tools: SPSS and AMOS. SPSS was employed for reliability testing, Pearson correlation, and regression analysis to assess the effects of different factors (i.e., Convenience, Usefulness, Social Influence, Promotions, and Trust) on the adoption of FinTech applications among urban working professionals in Malaysia. AMOS was used for CFA and SEM to examine the relationships between constructs. SEM is particularly advantageous for simultaneously estimating multiple independent variables, thus complementing SPSS results (Memon et al., 2021). All of these tests were conducted on the final data collection (n=313), which used the refined 19-item questionnaire, and was conducted independently of the pilot studies.

#### **3.2.6.1 Demographic Analysis**

Descriptive statistics were employed to summarise the key characteristics of the respondents, including their age, gender, ethnicity, employment history, and household income (Mishra et al., 2019). This analysis provided insights into the demographic distribution and ensures the representativeness of the final data collection sample.

### **3.2.6.2 Reliability Assessment**

Cronbach's alpha was used to assess the internal consistency of the data from the final 19-item questionnaire. A reliability coefficient (alpha) above 0.70 was considered acceptable, while values above 0.80 indicate strong reliability (Taber, 2018).

### **3.2.6.3 Normality Test (Skewness and Kurtosis)**

The normality of the dataset was examined using skewness and kurtosis values. For a dataset to be considered normally distributed, skewness values should fall between -1.0 and 1.0, while kurtosis values should range from -1.5 to 1.5 (Mishra et al., 2019). If the data did not meet normality assumptions, non-parametric techniques were considered as an alternative to parametric methods.

### **3.2.6.4 Pearson Correlation Analysis**

The Pearson correlation analysis was conducted to examine the degree and direction of the correlation between variables. This analysis helped verify the linearity assumption, ensuring that variables had a measurable and significant relationship (Ly et al., 2018).

### **3.2.6.5 Regression Analysis**

Multiple linear regression ("MLR") analysis was performed to identify the independent variables that significantly influenced the dependent variable (intention to use FinTech applications). This preliminary analysis helped determine the strength and significance of relationships between factors affecting FinTech adoption (Brook & Arnold, 2018). However, regression analysis only examines direct effects and does not account for mediation or interaction effects. Therefore, SEM was later applied to provide a more comprehensive understanding of both direct and indirect relationships, as well as overall model fit.

Multicollinearity was assessed using VIF values to ensure the validity of the regression model. A VIF value below 10 indicates no severe multicollinearity issues (Hair et al., 2010).

### **3.2.6.6 Confirmatory Factor Analysis**

Before conducting SEM, CFA was performed to validate the latent variables. The CFA specifically assessed construct reliability and convergent validity. Convergent validity was determined using factor loadings and average variance extracted, while construct reliability was assessed to ensure internal consistency. Discriminant validity and overall model fit were also examined separately to confirm that constructs were distinct and the measurement model was adequate.

### **3.2.6.7 Structural Equation Modelling**

Once validation processes were completed and the data met parametric analysis requirements, structural models were developed using SPSS Amos. The SEM path analysis examined both direct effects and mediated influences among constructs. Model fit was evaluated using multiple fit indices to assess the adequacy of the model. These indices provided a robust framework for evaluating the relationships between constructs, ensuring a comprehensive assessment of the factors influencing adoption of FinTech applications among urban working professionals in Malaysia.

Given the hypothesised mediating role of trust in the relationship between influencing factors (e.g., Convenience, Usefulness, Social Influence, and Promotions) and the Intention to Adopt FinTech applications, SEM was selected as the most appropriate analysis technique. SEM allows for the simultaneous estimation of direct and indirect relationships between constructs, making it ideal for assessing mediation effects within the proposed conceptual model (Hair et al., 2010; Memon et al., 2021).

## **CHAPTER 4**

### **4.0 Findings and Discussions**

#### **4.1 General Introduction**

This chapter presents the findings and discussion of the study on FinTech adoption among urban working professionals in Malaysia. The results are organised according to the research objectives outlined in Chapter 1 and analysed using the methods described in Chapter 3. Both descriptive and inferential statistics are reported, and the discussion integrates relevant theories, including TAM and the mediating role of trust, as well as previous research. The chapter begins with respondent demographics and descriptive statistics, followed by measurement model assessment and regression analysis. Each subsequent section addresses a specific research objective, integrating findings with theoretical and empirical insights.

#### **4.2 Context and Rationale**

In Malaysia, although FinTech adoption is expected to increase (BNM, 2016; BNM, 2022), many customers still find it difficult to trust these applications, even though they are typically built using cutting-edge technologies (Meyliana & Fernando, 2019). This lack of trust is largely due to recurring incidents of fraud, identity theft, and data breaches. To instil confidence, a trend observed globally by Meyliana & Fernando (2019) is the backing or funding of FinTech applications by reputable organisations, a trend also evident in Malaysia. The Central Bank of Malaysia's push for digital transformation aligns with a projected compound annual growth rate ("CAGR") of over 15% in e-payments per capita (BNM, 2016; BNM, 2022).

While the Malaysian government has made substantial investments in promoting FinTech and addressing security concerns to enhance accessibility, the acceptance rate of FinTech in this

region may lag behind neighbouring nations. This disconnect may arise from persistent public concerns regarding data security and the perceived complexity of FinTech applications, despite governmental assurances. The public may still perceive the risks of FinTech use to outweigh the benefits (Tun-Pin et al., 2019). Lyons et al. (2022) highlight the importance of increasing public knowledge about FinTech adoption to build trust and confidence in service providers.

Addressing these challenges, the primary objective of this investigation is to explore the variables influencing FinTech adoption among urban working professionals in Malaysia, with a specific focus on the mediating role of trust. This study draws upon the TAM theory, initially proposed by Davis (1989), to assess the effects of FinTech adoption among urban working professionals in Malaysia, with trust as a mediating factor.

#### **4.3 Demographic Profile and Descriptive Analysis**

A total of 313 respondents from diverse backgrounds completed the survey questionnaire using the purposive sampling approach. To ascertain whether the respondents accurately represent the target population, demographic data on six variables (gender, age group, race, educational level, employment status, and household income) were collected. Table 4.1 provides a summary of the demographic information.



**Table 4.1** Demographic data of participants.

Demographic factors	Frequency	Percentage
<b>Gender</b>		
Male	153	48.9%
Female	160	51.1%
<b>Total</b>	<b>313</b>	<b>100.0%</b>
<b>Age group</b>		
18 – 25	44	14.1%
26 – 33	121	38.7%
34 – 41	65	20.8%
42 – 49	74	23.6%
50 and above	9	2.9%
<b>Total</b>	<b>313</b>	<b>100.0%</b>
<b>Race</b>		
Malay	121	38.7%
Chinese	101	32.3%
Indian	52	16.6%
Others	39	12.6%
<b>Total</b>	<b>313</b>	<b>100.0%</b>
<b>Educational level</b>		
Primary school	0	0.0%
Secondary school	0	0.0%
Diploma	0	0.0%
Degree	288	92.0%
Master	15	4.8%
Doctorate	10	3.2%
<b>Total</b>	<b>313</b>	<b>100.0%</b>
<b>Employment status</b>		
Self-employed	30	9.6%
Employed full-time	236	76.4%
Employed part-time	33	10.5%
Unemployed	14	4.5%
<b>Total</b>	<b>313</b>	<b>100.0%</b>
<b>Household income</b>		
Less than RM4,000	25	8.0%
RM4,000-RM7,000	67	21.4%
RM7,000-RM10,000	162	51.8%
More than RM10,000	59	18.8%
<b>Total</b>	<b>313</b>	<b>100.0%</b>

Among the 313 respondents, 48.9% were male ( $n = 153$ ), and 51.1% were female ( $n = 160$ ). This near-equal gender distribution ensures that the study captures the perspectives of both male and female urban working professionals. With regards to age group distribution, 38.7% ( $n = 121$ ) fell between 26 and 33 years old, followed by 23.6% ( $n = 74$ ) aged between 42 and 49, 20.8% ( $n = 65$ ) aged between 34 and 41, 14.1% ( $n = 44$ ) aged between 18 and 25, and 2.9% ( $n = 9$ ) aged 50 and above. The concentration of respondents in the 26-33 age group suggests that this demographic, often early adopters of technology, is crucial in understanding FinTech adoption trends, within the sample. Malays constituted the largest ethnic group in the study at 38.7% ( $n = 121$ ), followed by Chinese (32.3%;  $n = 101$ ), Indians (16.6%;  $n = 52$ ), and Others (12.6%;  $n = 39$ ). The racial make-up of the sample is relatively close to the general population of Malaysia, where approximately 69% of the population is Malay, 23% Chinese, 7% Indian, and 1% other (DOSM, 2023b). This indicates that the sample is fairly representative of the Malaysian population.

In terms of educational attainment, 92.0% ( $n = 288$ ) held bachelor's degrees, while 4.8% ( $n = 15$ ) held master's degrees, and 3.2% ( $n = 10$ ) held doctorates. The majority of respondents (76.4%,  $n = 236$ ) were employed full-time, with 10.5% ( $n = 33$ ) employed part-time, 9.6% ( $n = 30$ ) self-employed, and 4.5% ( $n = 14$ ) unemployed.

A significant portion of the participants (51.8%,  $n = 162$ ) reported earning between RM7,000 and RM10,000. This was followed by 21.4% ( $n = 67$ ) who earned between RM4,000 and RM7,000, while 18.8% ( $n = 59$ ) had incomes exceeding RM10,000. The smallest group, comprising 8.0% ( $n = 25$ ), earned less than RM4,000.

In terms of the variables, the dataset for Convenience had a mean of 3.44, with a variance of 0.382 and a standard deviation (SD) of 0.618. The dataset for Usefulness had a mean of 3.48, with a variance of 0.359 and an SD of 0.599. Similarly, both Social Influence and Promotions

had a mean of 3.43, with variances of 0.384 (SD 0.619) and 0.412 (SD 0.642), respectively. In contrast, Trust had the lowest mean of 3.34, with a variance of 0.449 and an SD of 0.670. Lastly, the dependent variable of Intention to Use had a mean of 3.46, with a variance of 0.469 and an SD of 0.685. The consistent range of 3.0 across all variables indicates substantial variation in responses and suggests no significant skewness (see Table 4.2).

**Table 4.2** Descriptive analysis of independent, mediating and dependent variables.

	Mean	Variance	SD	SE	Min	Max	Range
Convenience	3.44	0.382	0.618	0.035	2.0	5.0	3.0
Usefulness	3.48	0.359	0.599	0.034	2.0	5.0	3.0
Social Influence	3.43	0.384	0.619	0.035	2.0	5.0	3.0
Promotions	3.43	0.412	0.642	0.036	2.0	5.0	3.0
Trust	3.34	0.449	0.670	0.038	2.0	5.0	3.0
Intention to Use	3.46	0.469	0.685	0.039	2.0	5.0	3.0

The mean scores for all variables were relatively close, with trust having the lowest mean (3.34), suggesting respondents were less confident in the trustworthiness of FinTech applications compared to other factors. This highlights the importance of addressing trust to enhance adoption. The consistent range of 3.0 across all variables indicates a similar level of variability in responses, reflecting a diverse range of opinions among participants.

Having outlined the demographic characteristics and descriptive statistics of the sample, the following section examines the reliability and validity of the measurement instruments used in this study.

## 4.4 Measurement Model Assessment

### 4.4.1 Reliability Assessment

Following refinements to the questionnaire based on the extended pilot study addressing multicollinearity and redundancy, the reliability of the main study data was assessed using Cronbach's alpha, a measure of internal consistency. Cronbach's alpha values exceeding 0.7 indicate acceptable reliability (Taber, 2018). As shown in Table 4.3, all constructs demonstrated values above this threshold, with the overall scale achieving an alpha of 0.848, indicating excellent reliability. These results confirm that the refined questionnaire provides reliable measurements of the intended constructs, supporting the robustness of subsequent analyses of FinTech adoption among urban working professionals in Malaysia.

**Table 4.3** Reliability Test of Questionnaire Using Cronbach's Alpha (main study).

Variables	No. of items	Mean	SD	Cronbach's Alpha
Convenience	2	6.61	1.629	0.733
Usefulness	3	9.65	2.476	0.763
Social Influence	5	16.75	3.648	0.788
Promotions	3	9.71	2.483	0.711
Trust	2	6.43	1.680	0.702
Intention to Use	4	13.60	2.941	0.704
Overall scale	19	62.76	9.781	0.848

#### 4.4.2 Normality Test (Skewness and Kurtosis)

After questionnaire refinement, data normality was reassessed using skewness and kurtosis to confirm suitability for parametric tests. As shown in Table 4.4, the skewness values for all variables ranged from -0.228 to -0.030, and the kurtosis values ranged from -0.555 to 0.136, all within the acceptable range of -1 to +1 (Mishra et al., 2019). This indicates that the data for each variable are approximately normally distributed, with no significant deviations from symmetry or peakedness. For example, Trust, with 2 items, displayed a skewness of -0.088 and a kurtosis of -0.510, indicating a relatively symmetrical and slightly platykurtic distribution. Social influence, with 5 items, exhibited a skewness of -0.214, and a kurtosis of -0.119, also exhibiting approximate normal distribution. Meeting normality assumptions supports the use of parametric analyses such as SEM, which is robust to minor deviations (Kline, 2016; Hair et al., 2019).

**Table 4.4** Skewness and Kurtosis of the Data (main study).

	N	Mean	SD	SE	Skewness		Kurtosis	
					Value	SE	Value	SE
Convenience	2	3.31	0.815	0.046	-0.152	0.138	-0.475	0.275
Usefulness	3	3.22	0.828	0.047	-0.228	0.138	0.136	0.275
Social Influence	5	3.35	0.730	0.041	-0.214	0.138	-0.119	0.275
Promotions	3	3.24	0.828	0.047	-0.030	0.138	-0.555	0.275
Trust	2	3.22	0.840	0.047	-0.088	0.138	-0.510	0.275
Intention to Use	4	3.40	0.736	0.042	-0.139	0.138	-0.158	0.275

#### 4.4.3 Pearson Correlation Analysis

This section measures the degree of linear association between the variables using the Pearson correlation test. These coefficient values can range between -1 and +1, where a higher absolute value indicates a stronger linear relationship. A positive correlation reflects changes in the same direction of the variables, while a negative correlation reflects changes in opposite directions.

The results of the Pearson correlation test for the main study data, as shown in Table 4.5, indicate several significant correlations. Notably, Convenience ( $r = 0.607$ ,  $p < 0.01$ ), Social Influence ( $r = 0.691$ ,  $p < 0.01$ ), and Trust ( $r = 0.670$ ,  $p < 0.01$ ) all exhibit strong positive correlations with Intention to Use. Furthermore, a very strong correlation exists between Trust and Convenience ( $r=0.867$ ,  $p<0.01$ ). The very strong correlation between Trust and Convenience ( $r = 0.867$ ) suggests a close relationship between these constructs, which may warrant further investigation. Usefulness and Promotions show very low correlations with Intention to Use, indicating limited linear association.

**Table 4.5** Pearson correlations of the datasets (significant at the 0.01 level; 2 tailed).

Variables	Convenience	Usefulness	Social Influence	Promotions	Trust	Intention to Use
Convenience	1.000					
Usefulness	-0.057	1.000				
Social Influence	0.757**	-0.081	1.000			
Promotions	-0.090	0.898**	-0.093	1.000		
Trust	0.867**	-0.080	0.814**	-0.124*	1.000	
Intention to Use	0.607**	-0.030	0.691**	-0.023	0.670**	1.000

#### 4.4.4 Multicollinearity Test

Following the Pearson correlation analysis, a multicollinearity test was conducted to ensure that the predictor variables were not highly correlated before proceeding with multiple regression and SEM analysis. This step is crucial, as multicollinearity can inflate variance and lead to unstable parameter estimates in regression models. The analysis was conducted using VIF and tolerance values. VIF values below 5 and tolerance values above 0.1 indicate the absence of substantial multicollinearity (Senaviratna & Cooray, 2019).

As shown in Table 4.6, all VIF and Tolerance values for the main study data fall within the acceptable ranges, unlike the results from the pre-refinement pilot study reported in Chapter 3. Therefore, the data exhibits no significant multicollinearity, meeting the assumption for both regression and SEM analyses.

**Table 4.6** Results of the multicollinearity test (main study).

	Tolerance	VIF
Constant	-	-
Convenience	0.241	4.153
Usefulness	0.191	5.235
Social Influence	0.323	3.092
Promotions	0.189	5.281
Trust	0.187	5.333

Having established the reliability and validity of the measurement model, the following section presents the results of the multiple regression analysis examining the predictors of intention to use FinTech applications.

## 4.5 Regression Analysis

Multiple regression analysis was conducted to examine the predictive relationship between Convenience, Usefulness, Social Influence, Promotions, and Trust (predictor variables) and Intention to Use FinTech applications (outcome variable).

### 4.5.1 Model Fit and Assumptions

The overall model demonstrated a strong relationship between the predictors and the outcome variable, as indicated by a multiple R of 0.723. The R-squared value of 0.523 indicates that 52.3% of the variance in Intention to Use is explained by these predictors. The adjusted R-squared value of 0.515 accounts for model complexity and confirms the model's strong predictive power.

To assess the independence of residuals, the Durbin-Watson statistic was examined. A value close to 2.0 suggests minimal autocorrelation, while values below 1.5 indicate positive autocorrelation and values above 2.5 indicate negative autocorrelation. In this study, the Durbin-Watson statistic was 1.780 (Table 4.7), falling within the acceptable range of 1.5–2.5 (Field, 2018). This suggests that residuals are independent, and there is no significant autocorrelation.

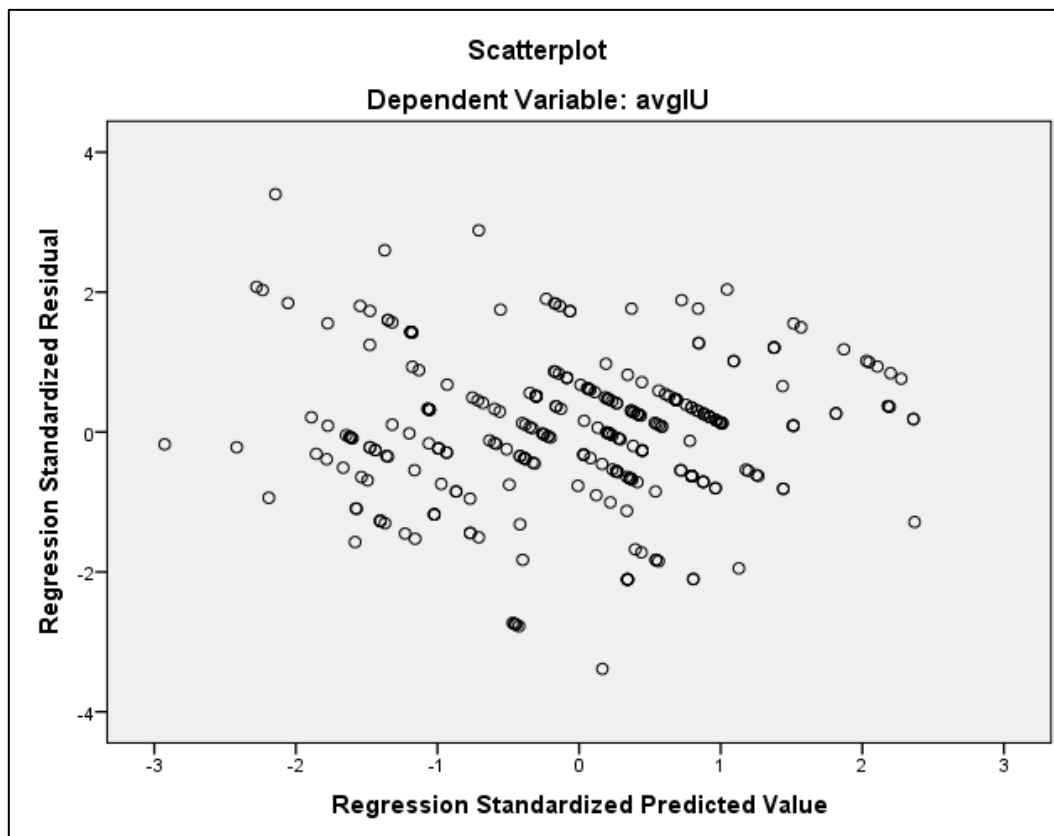
**Table 4.7** Statistics for regression analysis (main study).

Model	R	R square	Adjusted R square	Estimate	Durbin-Watson
1	0.723	0.523	0.515	0.513	1.780



To assess homoscedasticity, a scatterplot of standardised residuals vs. predicted values was examined (Figure 4.1). The random dispersion of points suggests no heteroscedasticity, supporting the assumption of equal variance across residuals.

**Figure 4.1** Scatterplot of standardised residuals vs. predicted values for homoscedasticity analysis (main study).



Furthermore, an analysis of variance (“ANOVA”) was used to assess the overall significance of the regression model. Table 4.8 indicates that the model is statistically significant ( $p < 0.05$ ), supporting the validity of the regression results.

**Table 4.8** ANOVA results for regression analysis (main study).

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	88.399	5	17.680	67.263	<0.001
Residual	80.693	307	0.263		
Total	169.092	312			

#### 4.5.2 Regression Coefficients

Following the confirmation of homoscedasticity, the regression model was analysed to determine the predictive relationships between the independent variables (Convenience, Usefulness, Social Influence, Promotions, and Trust) and Intention to Use FinTech applications. Table 4.9 presents the unstandardised (B) and standardised (Beta) coefficients, t-values, and significance levels for each predictor.

The analysis revealed significant positive associations between Usefulness ( $B = 0.186$ ,  $Beta = 0.209$ ,  $t = 2.325$ ,  $p = 0.021$ ), Social Influence ( $B = 0.447$ ,  $Beta = 0.443$ ,  $t = 6.386$ ,  $p < 0.001$ ), and Trust ( $B = 0.261$ ,  $Beta = 0.298$ ,  $t = 3.263$ ,  $p = 0.001$ ) and Intention to Use. Convenience ( $B = 0.012$ ,  $Beta = 0.013$ ,  $t = 0.164$ ,  $p = 0.874$ ) and Promotions ( $B = -0.117$ ,  $Beta = -0.132$ ,  $t = -1.444$ ,  $p = 0.147$ ) did not demonstrate significant predictive relationships.

The regression model can be represented as follows:

$$Intention\ to\ Use = 0.803 + 0.012(CO) + 0.186(US) + 0.447(SI) - 0.117(PO) + 0.261(TR) + \varepsilon$$

where:

CO = Convenience  
 US = Usefulness  
 SI = Social Influence  
 PO = Promotions  
 TR = Trust  
 $\varepsilon$  = Error term

**Table 4.9** Regression coefficients (main study).

	Unstandardised coefficients		Standardised coefficients	t	Sig.
	B	SE	Beta		
Constant	0.803	0.190	-	4.232	<0.001
Convenience	0.012	0.073	0.013	0.164	0.874
Usefulness	0.186	0.080	0.209	2.325	0.021
Social Influence	0.447	0.070	0.443	6.386	<0.001
Promotions	-0.117	0.081	-0.132	-1.444	0.147
Trust	0.261	0.080	0.298	3.263	0.001

### 4.5.3 Discussion of Regression Findings

The multiple regression analysis revealed significant predictors of intention to use FinTech applications among urban working professionals in Malaysia. Usefulness, social influence, and trust demonstrated significant positive relationships with intention to use.

The significant positive relationship between usefulness and intention to use aligns with TAM (Davis, 1989), which states that perceived usefulness is a key determinant of technology acceptance. The findings support this theory, suggesting that when urban working professionals perceive FinTech applications as useful, they are more likely to intend to use them. Multiple contexts across different studies (Almashhadani et al., 2023 in Jordan; Wu & Peng, 2024 in China; Noonpakdee, 2020 in Thailand; Meyliana & Fernando, 2019 and Ali et al., 2021 in general consumer research) consistently demonstrate that perceived usefulness is a significant driver of FinTech adoption. This includes the influence of practical features like real-time monitoring and efficient transactions, as well as the suitability of FinTech tools for workplace applications.

However, while the regression analysis in this study revealed that usefulness did have a significant direct impact on intention to use FinTech applications ( $B = 0.186$ ,  $\text{Beta} = 0.209$ ,  $t = 2.715$ ,  $p = 0.021$ ), the impact was relatively low. One potential explanation for this discrepancy, when compared to other studies, lies in the cultural context of Malaysia. Given the collectivist nature of Malaysian society (Urus et al., 2022), individuals may prioritise social acceptance and trust over individual task efficiency. For example, studies on technology adoption in other collectivist cultures have shown that social influence often outweighs perceived usefulness (Kurniasari et al., 2021; Kurniasari et al., 2022; Hamza et al., 2025).

Furthermore, the urban working professionals in Malaysia, who formed the sample for this study, are likely to be digitally literate and already familiar with the basic functionalities of FinTech applications. In this context, the perceived usefulness of these applications may be taken for granted, leading to a ceiling effect. This is supported by findings that indicate that when a technology is very common, usefulness becomes less of a predictor of usage (Marikyan & Papagiannidis, 2024). Moreover, TAM may not fully capture the complexities of FinTech adoption in emerging markets like Malaysia, where trust and security concerns are paramount. In such contexts, users may prioritise trust-related factors over usefulness (Marikyan & Papagiannidis, 2024). This finding offers a unique perspective on FinTech adoption in Malaysia, suggesting that cultural and contextual factors can significantly influence user behaviour. It highlights the need to extend the TAM to incorporate these factors when studying technology adoption in emerging markets. In summary, the relatively low impact of usefulness, is likely due to cultural, and contextual factors, and a limitation in the TAM model.

Social influence also emerged as a strong predictor of intention to use, suggesting that the opinions and recommendations of peers, colleagues, and family members significantly influence intention to use FinTech applications. This finding is consistent with UTAUT (Venkatesh et al., 2003), which highlights the role of social influence in shaping technology acceptance. Tun-Pin et al. (2019) investigated the factors influencing the intention to adopt FinTech in Malaysia using the UTAUT model and found a significant and positive relationship between social influence and the intention to adopt FinTech. Many studies generally support a positive relationship between social influence and FinTech adoption (Irimia-Diéguez et al., 2023; Hassan et al., 2022). However, Bajunaied et al. (2023) found no significant impact in Saudi Arabia, highlighting the potential influence of cultural context on this relationship.

Trust was also found to be a significant predictor, indicating that urban working professionals who trust FinTech applications are more likely to intend to use them. This aligns with research that has highlighted the importance of trust in online transactions and technology adoption (e.g., Nangin et al., 2020; Ali et al., 2021; Ryu & Ko, 2020; Tang, 2019; Wiczorek & Meyer, 2019; Zhao et al., 2024; Arli et al., 2020; Cojoianu et al., 2021; Leong et al., 2020; Ventre & Kobe, 2020; Ryu & Ko, 2020; Kowalski et al., 2021; Dawood, 2021; Kiew et al., 2022; Indiani et al., 2024; Chawla et al., 2023; Amnas et al., 2024; Roh et al., 2023; Bajunaied et al., 2023; Zakariyah et al., 2023; Jafri et al., 2024). Factors influencing trust include perceived benefits, perceived risks, security, privacy, service quality, regulatory compliance, ease of use, and brand image. Trust mitigates uncertainty and is essential for building strong user-provider relationships, particularly in high-risk digital environments like FinTech.

However, convenience and promotions did not significantly predict intention to use. This is inconsistent with some studies that have found a positive relationship between these factors and technology adoption. Research from diverse geographical contexts demonstrates the significant impact of both convenience and promotions on FinTech adoption (Amnas et al., 2023; Ahiabenu, 2022; Ali et al., 2021; Sheng, 2021; Tun-Pin et al., 2019). Similarly, promotional strategies, including the use of coupons, discounts, and rewards, have been found to be effective in driving FinTech adoption across various markets, particularly during periods of increased digital financial activity (Kiew et al., 2022; Meidawati et al., 2022; Jenweeranon, 2020).

It should also be noted that other studies suggest a more nuanced role for both convenience and promotions. While research across various regions indicates their significant impact on FinTech adoption (Amnas et al., 2023; Ahiabenu, 2022; Ali et al., 2021; Sheng, 2021; Tun-Pin et al., 2019; Kiew et al., 2022; Meidawati et al., 2022; Jenweeranon, 2020), Windasari et al.

(2022) found that while promotions are important, they are just one of several factors influencing digital banking adoption, and should be complemented by user-friendly interfaces and customer feedback. Similarly, Nguyen & Nguyen (2022) suggest that promotions may not directly impact intention to use mobile wallets but may influence factors like social influence, as consumers are more likely to recommend mobile wallets to others when enticing promotional campaigns are in place.

These discrepancies suggest that the effectiveness of convenience and promotions in driving FinTech adoption may vary depending on the context and the specific FinTech service. In the context of urban working professionals in Malaysia, factors such as usefulness and trust may be more influential than convenience and promotional offers. It is possible that the urban professionals sampled, find the existing FinTech applications to be already convenient enough, and are less influenced by promotional offers, when compared to other demographics. It is also possible that other factors were more heavily weighted. Further research may be required to explore the specific role of convenience and promotions in FinTech adoption among this demographic.

The high R-squared value (0.523) indicates that the model explained a substantial portion of the variance in intention to use, suggesting that the included predictors are relevant and important. The Durbin-Watson statistic and residual scatterplot indicated that the assumptions of independence of residuals and homoscedasticity were met, supporting the validity of the regression results. In conclusion, the regression analysis provides valuable insights into the direct factors influencing intention to use FinTech applications among urban working professionals in Malaysia. The findings highlight the importance of usefulness, social influence, and trust, while suggesting that convenience and promotions may be less influential in this direct relationship context.

## **4.6 Confirmatory Factor Analysis**

CFA was conducted to assess the measurement model, including convergent and discriminant validity, and construct reliability. The results of these assessments are presented in Tables 4.10, 4.11, and 4.12.

### **4.6.1 Convergent Validity and Construct Reliability**

Table 4.10 presents the convergent validity and construct reliability of the variables. The composite reliability (“CR”) values for all constructs exceeded the recommended threshold of 0.6, indicating adequate internal consistency: Convenience (CO) = 0.813, Usefulness (US) = 0.777, Social Influence (SI) = 0.887, Promotions (PR) = 0.840, Trust (TR) = 0.736, and Intention to Use (IU) = 0.777.

Furthermore, the average variance extracted (“AVE”) values for all constructs were above the recommended threshold of 0.5, confirming convergent validity. This indicates that the items of each construct adequately represent the underlying latent variable.



**Table 4.10** Convergent validity and construct reliability (main study).

<b>Construct</b>	<b>Sub-Construct</b>	<b>Factor Loading</b>	<b>CR (Above 0.6)</b>	<b>AVE (Above 0.5)</b>
Convenience	CO1	0.828	0.813	0.685
	CO2	0.827		
Usefulness	US1	0.668	0.777	0.539
	US2	0.761		
	US3	0.769		
Social Influence	SI1	0.799	0.887	0.571
	SI2	0.675		
	SI3	0.832		
	SI4	0.690		
	SI5	0.852		
	SI6	0.660		
Promotions	PR1	0.796	0.840	0.636
	PR2	0.827		
	PR3	0.768		
Trust	TR1	0.693	0.736	0.584
	TR2	0.829		
Intention to Use	IU1	0.551	0.777	0.627
	IU2	0.691		
	IU3	0.813		
	IU4	0.662		

#### 4.6.2 Discriminant Validity

Discriminant validity was assessed using the heterotrait-monotrait (“HTMT”) ratio and the Fornell-Larcker criterion. Table 4.11 presents the HTMT ratios, all of which are below the recommended threshold of 0.9, indicating adequate discriminant validity.

**Table 4.11** Discriminant validity: HTMT ratios (main study).

Variables	Convenience	Usefulness	Social Influence	Promotions	Trust	Intention to Use
Convenience	-					
Usefulness	0.060	-				
Social Influence	0.862	0.105	-			
Promotions	0.129	0.862	0.131	-		
Trust	0.849	0.113	0.892	0.178	-	
Intention to Use	0.814	0.044	0.885	0.002	0.868	-

Furthermore, Table 4.12 shows that the square roots of the AVE values for each construct are higher than the correlations between pairs of constructs, further supporting discriminant validity.

**Table 4.12** Discriminant validity: square root of AVE and correlations (main study).

Variables	Convenience	Usefulness	Social Influence	Promotions	Trust	Intention to Use
Convenience	0.828					
Usefulness	0.033	0.734				
Social Influence	0.433	0.050	0.756			
Promotions	0.065	0.419	0.058	0.798		
Trust	0.479	0.061	0.432	0.088	0.762	
Intention to Use	0.381	0.019	0.354	0.001	0.391	0.792

With both convergent and discriminant validity established for the measurement model, the next section presents the results of SEM, examining the direct and mediated effects among the study variables.

## 4.7 Structural Equation Modelling

SEM was conducted to examine the relationships between Convenience, Usefulness, Social Influence, Promotions, and Trust in influencing the Intention to Use FinTech applications. The analysis was performed in two stages. First, without a mediating factor, and subsequently, with Trust introduced as a mediator.

The model explains 55.9% of the variance in intention to use FinTech applications without Trust as a mediator, increasing to 60.4% when Trust is included, indicating that incorporating Trust strengthens the model's explanatory power. While these  $R^2$  values do not correspond directly to traditional model fit indices, they demonstrate the enhanced explanatory capability of the model when Trust is included as a mediator.

As shown in Table 4.13, the path coefficient estimates reveal that Convenience ( $p = 0.006$ ) and Social Influence ( $p < 0.001$ ) significantly influence intention to use FinTech applications, supporting hypotheses H1 and H3. However, Usefulness ( $p = 0.073$ ) and Promotions ( $p = 0.133$ ) did not show significant direct effects, thereby not supporting H2 and H4. These results were evaluated using the standard  $p < 0.05$  threshold for statistical significance, a commonly accepted benchmark in SEM studies (Hair et al., 2019).

Interestingly, when Trust was introduced as a mediator, all studied variables (Convenience, Usefulness, Social Influence, and Promotions) exhibited a significant impact on the intention to use FinTech applications, supporting hypotheses H5 to H8. This suggests that trust plays a critical mediating role in strengthening the relationships between these independent variables and users' decisions to adopt FinTech applications.

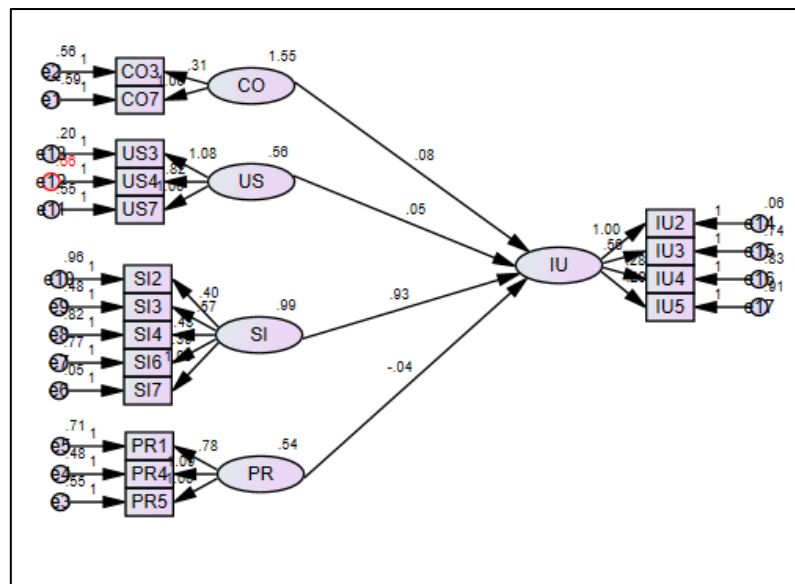
Figures 4.2 and 4.3 illustrate the relationships between the variables, both without and with trust as a mediator, providing a visual representation of the findings. The results highlight the importance of trust, alongside convenience and social influence, in shaping users' intentions to use FinTech applications.

**Table 4.13** Unstandardised path coefficients and significance (main study).

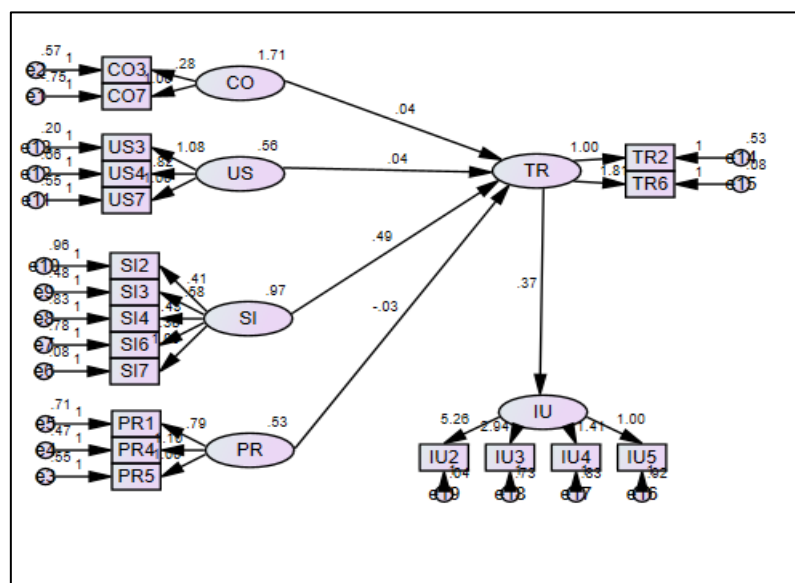
Construct	Path	Construct	Estimate	S.E.	C.R.	P	Hypotheses
CO	→	IU	0.085	0.031	2.732	0.006	Significant
US	→	IU	0.046	0.026	1.790	0.073	Not-significant
SI	→	IU	0.928	0.023	40.355	<0.001	Significant
PR	→	IU	0.042	0.028	1.503	0.133	Not-significant
CO	→	TR	0.039	0.015	2.634	0.008	Significant
US	→	TR	0.037	0.013	2.884	0.004	Significant
SI	→	TR	0.485	0.043	11.321	<0.001	Significant
PR	→	TR	0.032	0.014	2.320	0.020	Significant
TR	→	IU	0.373	0.118	3.152	0.002	Significant

Note: The critical ratio (“CR”) for the path from SI to IU is approximately 40.35. While this value is unusually high compared to typical SEM outputs, it accurately reflects the very strong and statistically precise effect of Social Influence in the model. Such a large CR can occur due to the combination of a large sample size and a very small standard error, indicating high confidence in this parameter estimate.

**Figure 4.2** SEM of constructs without mediating factor (main study).



**Figure 4.3** SEM of constructs with mediating factor (main study).



The findings from the SEM analysis provide a comprehensive understanding of the relationships between the variables, particularly the mediating role of Trust. These results are further synthesised and discussed in the following section, which provides an overall interpretation of the research findings.

## **4.8 Findings and Discussions**

This section presents the analysis and interpretation of the research findings, structured according to the research objectives. The discussion links empirical results to established theories such as TAM, UTAUT, and prior FinTech adoption studies. It also provides a comprehensive understanding of factors influencing FinTech adoption among urban working professionals in Malaysia.

### **4.8.1 The Impact of Convenience in FinTech Adoption**

The first objective examined the effect of Convenience on the intention to use FinTech applications. Both the correlation and regression analyses showed that Convenience is a significant positive predictor of intention to use FinTech among urban working professionals in Malaysia, supporting hypothesis H1. This finding is consistent with previous research (Amnas et al., 2023), which identified convenience as a key driver of technology adoption.

Furthermore, the SEM analysis revealed that Convenience also significantly influences intention to use FinTech when mediated by Trust (supporting H5). This aligns with extended TAM frameworks that incorporate trust as a mediator (Marikyan & Papagiannidis, 2024). These results suggest that while convenience is important on its own, its effect is further enhanced when users also trust the technology and service providers.

This highlights the importance for FinTech providers to focus on delivering reliable, seamless, and user-friendly experiences, as well as fostering trust through transparent communication and robust security features.

#### **4.8.2 The Impact of Usefulness on Adoption Intention**

The second objective focused on Usefulness as a determinant of FinTech adoption among urban working professionals in Malaysia. Regression results did not find a significant direct effect of Usefulness on Intention to Use, thus hypothesis H2 was not supported in a direct context. This finding diverges from the core proposition of TAM (Davis, 1989), which identifies perceived usefulness is a primary driver of technology acceptance.

Previous research, such as Almashhadani et al. (2023) and Wu & Peng (2024), has consistently found Usefulness to be a strong predictor of FinTech adoption in various cultural contexts. The lack of a significant direct effect in this study may be explained by several factors. First, urban working professionals in Malaysia may already expect a high baseline level of usefulness from FinTech applications, making it less of a differentiator. Second, other variables such as Trust and Social Influence may play a more prominent role in this demographic, overshadowing the direct impact of Usefulness. Third, a “ceiling effect” may be present, where perceived usefulness is uniformly high and thus does not explain variation in adoption intention.

However, the SEM analysis revealed that Usefulness significantly influences Intention to Use FinTech when mediated by Trust (supporting H6). This highlights the critical role of trust in reinforcing the perceived benefits of FinTech services. Users may recognise the utility of these platforms, but their adoption decisions are ultimately strengthened when they trust the platform’s security, reliability, and service quality.

This result contributes to the literature by showing that, in the Malaysian urban professional context, the predictive power of perceived usefulness may be diminished unless trust is also present. This challenges the universality of TAM and offers new insights for both researchers and practitioners.

### **4.8.3 The Impact of Social Influence and FinTech Adoption**

Social Influence emerged as a significant positive predictor of intention to use FinTech in both regression and SEM analyses, supporting hypotheses H3 and H8. This aligns with the UTAUT model (Venkatesh et al., 2003), which identifies Social Influence as a key factor in technology adoption, particularly in collectivist cultures.

Studies such as Tun-Pin et al. (2019) corroborate these findings in the Malaysian context, whereas Bajunaied et al. (2023) found cultural differences in Saudi Arabia that attenuated social influence effects. The mediation by Trust further amplifies Social Influence's impact. This indicates that peer recommendations and social validation build trust, which in turn drives adoption.

FinTech providers should leverage social proof, influencer endorsements, and community engagement to enhance trust and adoption.

### **4.8.4 The Impact of Promotions on Adoption Intention**

Promotions did not have a significant direct effect on intention to use FinTech among urban working professionals in Malaysia. This is consistent with recent findings by Lim et al. (2023) and Rahman et al. (2022), who reported that promotional offers and activities were not significant predictors of mobile payment or e-wallet adoption in Malaysia. Instead, trust, perceived usefulness, and security concerns were found to be more influential factors.

Several factors may account for this result. First, urban professionals may be less influenced by short-term incentives and more motivated by long-term factors such as trust, convenience, and peer influence. Second, the saturation of promotional offers in the Malaysian FinTech market may have reduced their effectiveness, leading users to view them as standard rather



than exceptional. Third, higher income levels among the sample may mean that financial incentives are less persuasive compared to other adoption drivers. However, the SEM analysis showed that Promotions can indirectly influence Intention to Use FinTech when mediated by trust. This suggests that promotional activities may be more effective when they enhance users' trust in the platform, for example, by signalling legitimacy or reliability.

This finding contributes to the literature by highlighting the limited direct impact of promotions in this demographic and underscores the importance of trust as a mediating factor in FinTech adoption.

#### **4.8.5 The Mediating Role of Trust in FinTech Adoption**

A key finding of this study is the critical mediating role of Trust in the relationships between all predictor variables (Convenience, Usefulness, Promotions, and Social Influence) and the Intention to Use FinTech applications, supporting hypotheses H5 through H8. While these factors influence adoption intention, their impact is significantly strengthened when users place trust in the FinTech platforms.

Trust mitigates perceived risks and uncertainties inherent in digital financial services, such as concerns about security, privacy, and reliability. Given the intangible nature of FinTech products and the sensitive financial information involved, users often face concerns related to security, privacy, and reliability. Trust alleviates these concerns by fostering confidence in the FinTech platform's ability to protect user data, deliver promised services, and act in the consumer's best interest (Nangin et al., 2020; Ali et al., 2021; Ryu & Ko, 2020). This is especially important in emerging markets like Malaysia, where regulatory frameworks and consumer protection are still developing and digital literacy varies.

From a theoretical standpoint, this finding reinforces the growing consensus in technology adoption literature that trust is a foundational construct that complements established models such as TAM. While TAM emphasises perceived usefulness and ease of use, the integration of Trust addresses the socio-technical complexities and risk dimensions unique to FinTech adoption. This extended TAM framework better captures user decision-making processes in contexts marked by high uncertainty and perceived vulnerability.

Practically, FinTech firms must recognise that building and maintaining trust is not ancillary but central to user acquisition and retention. Strategies to foster trust include implementing robust cyber security measures, ensuring transparent and accessible privacy policies, obtaining relevant certifications, and providing consistent, high quality customer service. Furthermore, leveraging social proof such as positive user reviews and endorsements can enhance perceived trustworthiness. FinTech companies should also engage in proactive communication to educate users about security features and data protection practices, thereby reducing anxiety and enhancing perceived control.

Regulators and policymakers also play a vital role in creating an environment that supports trust through clear guidelines, consumer protection laws, and oversight mechanisms. Collaborative efforts between industry players and regulators can help establish standards that reassure users and encourage broader FinTech adoption. In summary, the mediating role of trust demonstrates its importance as a critical enabler that bridges perceived benefits and social influences with actual adoption intentions. For both researchers and practitioners, this highlights the necessity of integrating trust-centric strategies and frameworks when studying or promoting FinTech adoption, especially in emerging economies.

#### 4.8.6 Summary of Hypothesis Testing

Table 4.14 summarises the support for each hypothesis based on regression and SEM analyses, reflecting the direct and mediated effects observed.

**Table 4.14** Summary of results and hypotheses.

No.	Hypotheses	Results
1	H1: Convenience significantly impacts intention to use FinTech among urban working professionals in Malaysia.	Supported
2	H2: Usefulness significantly impacts intention to use FinTech among urban working professionals in Malaysia.	Not supported (direct), Supported (mediated by Trust)
3	H3: Social Influence significantly impacts intention to use FinTech among urban working professionals in Malaysia.	Supported
4	H4: Promotions significantly impact intention to use FinTech among urban working professionals in Malaysia.	Not supported (direct), Supported (mediated by Trust)
5	H5: Convenience significantly impacts intention to use FinTech, mediated by Trust, among urban working professionals in Malaysia.	Supported
6	H6: Usefulness significantly impacts intention to use FinTech, mediated by Trust, among urban working professionals in Malaysia.	Supported
7	H7: Promotions significantly impact intention to use FinTech, mediated by Trust, among urban working professionals in Malaysia.	Supported
8	H8: Social Influence significantly impacts intention to use FinTech, mediated by Trust, among urban working professionals in Malaysia.	Supported

The findings confirm Trust as a key mediator in the adoption of FinTech services among urban working professionals in Malaysia. While Convenience and Social Influence exert direct effects on users' intention to adopt FinTech, Usefulness and Promotions primarily impact adoption indirectly by building trust. This distinction highlights that users may recognise the practical benefits and social pressures associated with FinTech use, but their ultimate decision to adopt is strongly contingent on the level of trust they place in the technology and FinTech service providers.

Given these insights, FinTech companies should prioritise building and maintaining Trust through transparent communication, robust security measures, and consistent service quality. Enhancing convenience remains important, as it directly influences adoption, but without Trust, even the most user-friendly platforms may struggle to gain sustained acceptance. Similarly, leveraging social influence through peer recommendations, endorsements, and community engagement can effectively encourage adoption by reinforcing Trust within users' social networks.

Furthermore, contextual and demographic factors shape perceptions of convenience and promotional effectiveness. Urban professionals in Malaysia may respond differently to promotions and convenience than other groups, reflecting variations in financial literacy, income, and cultural attitudes. Therefore, FinTech marketing strategies should be tailored to these nuances to resonate with target segments. Combining trust-building, user experience improvements, and socially informed marketing is essential for promoting FinTech adoption in diverse and evolving markets.

## CHAPTER 5

### 5.0 Conclusions, Recommendations and Suggestions for Future Research

#### 5.1 Overall Conclusions and Implications

The findings of this study unequivocally highlight the critical mediating role of trust in driving FinTech adoption among urban working professionals in Malaysia. While Convenience and Social Influence demonstrated direct positive effects on adoption intention (addressing ROs 1 and 4), the influence of Usefulness and Promotions was contingent upon the presence of Trust (addressing ROs 2, 3, and 5). This highlights the importance of building and maintaining user trust by addressing security and operational reliability concerns.

The financial services industry has been transformed by the introduction of technology-powered FinTech applications, which have significantly impacted how businesses manage accounts, process payments, and secure financing (Murinde et al., 2022). FinTech has made it feasible to close the gap between 'banked' and 'unbanked' consumers, particularly among low-income households and underprivileged groups. This advancement supports the financial inclusion agenda by facilitating access to finance through microfinance and crowdfunding, thereby increasing economic opportunities (Hasan et al., 2022; Le et al., 2019).

Despite these compelling benefits, real-world implementation remains challenging. Consumers are often reluctant to adopt FinTech due to various concerns, including security risks and operational reliability, which have contributed to low adoption rates (Abdul-Rahim et al., 2022). Although customers recognise advantages such as cost savings, rapid and seamless transactions, economic efficiency, and convenience, they remain cautious because of the risks associated with these technology-driven services (Kamali et al., 2021).

FinTech inevitably involves cyber-related risks, including compromised data privacy and security, financial losses from fraud and scams, unclear legal and regulatory frameworks, and operational risks linked to service providers. Many of these vulnerabilities stem from inadequate data governance and management, leading to public trust issues (Albarrak & Alokley, 2021).

The findings of this study confirm the critical role of trust in driving FinTech adoption among urban working professionals in Malaysia. The analysis revealed that while convenience and social influence independently have significant effects on FinTech adoption, usefulness and promotions do not show significant impacts without trust acting as a mediator. However, when trust is introduced as a mediating factor, all variables-including convenience, usefulness, social influence, and promotions-demonstrate a significant influence on adoption. This highlights trust's critical role in promoting adoption beyond the perceived benefits of the other factors.

Pearson correlation tests confirmed significant positive relationships between convenience, social influence, and trust with the intention to use FinTech. Multicollinearity tests indicated that the predictor variables were not highly correlated, supporting the validity of multiple regression and SEM analyses. Regression results further showed that while usefulness and promotions alone did not significantly impact adoption intention, all variables, including trust, exerted significant effects when trust mediated their influence. This affirms the importance of trust in mitigating concerns related to security and operational reliability, thereby enhancing overall FinTech adoption.

In conclusion, trust emerges as a crucial mediator that can substantially increase FinTech adoption among urban working professionals in Malaysia. Efforts to improve adoption should prioritise building and maintaining trust by addressing security and privacy concerns and ensuring the operational reliability of FinTech services. By doing so, FinTech providers can

better leverage the inherent benefits of convenience, usefulness, social influence, and promotions, driving higher adoption rates and contributing to greater financial inclusion.

The financial services industry has undergone significant transformation with the emergence of FinTech applications, revolutionising how businesses manage accounts, process payments, and secure financing. FinTech plays a pivotal role in bridging the gap between 'banked' and 'unbanked' populations, advancing financial inclusion through accessible microfinance and crowdfunding services. Its primary value in emerging markets like Malaysia lies in offering more affordable and convenient customer experiences. Despite these advantages, adoption rates among urban working professionals remain relatively low, largely due to persistent security concerns and operational uncertainties.

Trust has emerged as a critical mediating factor driving FinTech adoption among urban working professionals in Malaysia. This study confirms that while factors such as convenience and social influence significantly impact adoption, usefulness and promotions do not exhibit significant effects without trust. However, when trust acts as a mediator, all factors—convenience, usefulness, social influence, and promotions—show a significant influence on FinTech adoption. This underscores trust's pivotal role in mitigating concerns about security risks and operational reliability, thereby encouraging higher adoption rates. These findings align with Rahman et al. (2024), who reported that lower trust in mobile wallets discourages continued use.

This study also highlights the importance of a user-friendly interface, clear instructions, and overall positive user experience in influencing engagement with FinTech applications. These factors contribute to perceived convenience, which is crucial for adoption. The protection of personal data and robust security measures are paramount for building trust and encouraging FinTech adoption. Strong correlations were found between internal motivations for using

FinTech applications and the perceived security of these services, consistent with findings from Abdul-Rahim et al. (2022).

Demographic factors such as age and gender also play significant roles in FinTech adoption. Younger generations, including Millennials and Gen Z, who are generally more tech-savvy, tend to adopt new technologies more readily (Osmani et al., 2020). However, these younger users may be less vulnerable to financial losses from cyber-attacks due to limited financial resources. Gender differences in risk aversion further influence adoption, with men typically exhibiting lower risk aversion compared to women (Murinde et al., 2022; Najaf et al., 2021).

Because rational consumers tend to avoid products or services that result in negative experiences, FinTech providers must proactively address risks associated with their offerings (Dawood et al., 2021). Further research is needed to explore consumers' potential overestimation of risks and its implications for FinTech adoption. Additionally, studies consistently demonstrate that users' perceptions of risk significantly impact their intent to use FinTech, regardless of acceptance or rejection (Vergara & Agudo, 2021). Future research should investigate the mediating and moderating effects of demographic factors such as gender, age, and educational attainment on FinTech adoption to deepen understanding of how these variables interact and influence consumer behaviour across different segments.

The implications of this study for financial business decision-making, particularly within commercial procedures involving financial institutions, are noteworthy. Understanding the critical factors influencing FinTech adoption can help refine strategies for promoting financial innovations like e-wallets and other digital financial services (Hasan et al., 2022). Ensuring data protection and addressing perceived risks are crucial for sustaining and enhancing FinTech ecosystems.



However, it is important to acknowledge that the findings of this study should be interpreted within the context of urban working professionals in Malaysia. While the findings are robust for the sampled group, the use of purposive sampling and focus on urban working professionals means that the results may not fully represent the broader Malaysian population, including rural or less digitally engaged groups. Nevertheless, these insights provide a valuable benchmark for understanding FinTech adoption in Malaysia's urban context and can inform targeted strategies for similar demographic segments. Future research should seek to include a wider range of participants to enhance generalisability and capture the diversity of FinTech adoption across Malaysia.

In conclusion, trust is a crucial mediator that can significantly enhance the adoption of FinTech among urban working professionals in Malaysia. Efforts to improve FinTech adoption should focus on building and maintaining trust, addressing security and privacy concerns, and ensuring the operational reliability of FinTech services (Rahman et al., 2024). By doing so, FinTech providers can better leverage the inherent benefits of convenience, usefulness, social influence, and promotions, thereby driving higher adoption rates and contributing to greater financial inclusion.

The findings highlight the need for ongoing investment in digital literacy and cyber security awareness, especially among younger and less experienced users who may underestimate cyber risks. Regulatory frameworks must keep pace with technological advances to foster trust and protect users, as concerns over data privacy and operational risks remain major barriers to adoption. Policymakers should continue to support FinTech innovation while ensuring robust consumer protection, as trust in institutions and clear legal governance are essential for sustainable growth in Malaysia's FinTech sector.

## 5.2 Recommendations

Based on the findings of this study and aligned with the research objectives, the following detailed recommendations are proposed to enhance FinTech adoption among urban working professionals in Malaysia:

### **Recommendation 1: Enhance Convenience to Boost Adoption**

Addressing RO1, which aimed to determine the relationship between Convenience and Intention to Use FinTech applications among urban working professionals in Malaysia, the findings of this study indicate a significant positive relationship. Therefore, it is recommended that FinTech providers prioritise improving platform convenience by simplifying user interfaces, streamlining transaction processes, and ensuring seamless integration with users' existing financial tools.

Convenience has a direct positive impact on adoption intention, making usability and accessibility critical (Tapanainen, 2020; Ahiabenu, 2022). Leveraging large datasets and novel analytics can help tailor services efficiently, especially in emerging markets where financial systems are less developed and more receptive to innovation (Goldstein et al., 2019; Kong & Loubere, 2021). Addressing cyber security vulnerabilities is essential to sustain trust and adoption. FinTech providers must invest in robust security measures, safeguard customer data, and offer prompt support to mitigate security issues, maintaining user confidence and reducing abandonment due to perceived instability (Mohd et al., 2024; Rahman et al., 2024).

## **Recommendation 2: Communicate Practical Usefulness to Build Trust**

In relation to RO2, which sought to determine the relationship between Usefulness and Intention to Use FinTech applications among urban working professionals in Malaysia, the study revealed an indirect positive effect mediated by Trust. To leverage the potential of usefulness and build the crucial trust identified in RO5, FinTech companies should clearly communicate the practical benefits of their services such as cost savings, time efficiency, and improved financial management to build user confidence (Singh et al., 2020; Ali et al., 2021). Demonstrating real-world value helps users appreciate how FinTech enhances their financial activities, supporting trust development (Meyliana & Fernando, 2019). Highlighting automation and streamlining features that simplify financial tasks can increase efficiency and convenience (Lin et al., 2020). Transparent messaging about usefulness not only attracts users but also strengthens the trust necessary for sustained adoption.

## **Recommendation 3: Design Promotions That Reinforce Trust**

Concerning RO3, which aimed to determine the relationship between Promotions and Intention to Use FinTech applications among urban working professionals in Malaysia, the findings indicated an indirect positive effect through the mediation of Trust (as highlighted in RO5). Therefore, promotional campaigns should be designed not only to attract users but also to reinforce trust by highlighting security features, data protection policies, and reliable service delivery (Nangin et al., 2020; Hamzah et al., 2022). While promotions alone may not directly drive adoption, when combined with trust-building messages, they become powerful motivators (Jenweeranon, 2020). FinTech companies should ensure promotional offers do not compromise security or user experience and that incentives are accompanied by clear communication about the platform's commitment to safeguarding users' interests.

#### **Recommendation 4: Leverage Social Influence Through Community Engagement**

Addressing RO4, which sought to determine the relationship between Social Influence and Intention to Use FinTech applications among urban working professionals in Malaysia, our analysis confirms a significant positive effect. To capitalise on this, FinTech providers should actively engage social networks, peer endorsements, and influencer partnerships to strengthen social influence, which has a direct positive effect on adoption (Xie et al., 2021; Hassan et al., 2022). Creating communities around FinTech services encourages positive word-of-mouth and peer recommendations, especially among urban working professionals (Chan et al., 2022). Providers can facilitate forums, social media groups, and referral programs to empower users to share positive experiences. Recognising social influence allows FinTech firms to tap into existing social dynamics to expand their user base effectively.

#### **Recommendation 5: Prioritise Trust-Building Measures Across the Ecosystem**

Underpinning the findings related to RO5, which aimed to determine whether Trust mediates the relationship between Convenience, Usefulness, Promotions, Social Influence, and Intention to Use FinTech applications among urban working professionals in Malaysia, it is paramount that FinTech providers and regulators invest heavily in trust-building strategies. These include robust cyber security protocols, transparent privacy policies, and responsive customer support (Leong et al., 2020; Cojoianu et al., 2021; Ryu & Ko, 2020).

Compliance with regulatory frameworks is essential to protect users and enhance confidence in FinTech services (Mohd et al., 2024). In Malaysia, the Cyber Security Act 2024 and Data Sharing Act 2025 have recently come into effect to strengthen cyber security, data protection and governance. Regulators should establish comprehensive frameworks that include legally binding customer contracts, clear guidelines for third-party engagements, compensation

mechanisms for data breaches, and streamlined transaction processes. Awareness campaigns are crucial to educate users about the benefits of FinTech while addressing security and privacy concerns (Cornelli et al., 2023). By implementing a secure, transparent, and user-centric environment, stakeholders can alleviate fears of fraud and operational risks, thereby encouraging sustained adoption and contributing to greater financial inclusion.

### **5.3 Limitations and Suggestions for Future Study**

#### **5.3.1 Limitations of the Study**

This study, while providing valuable insights into FinTech adoption among urban working professionals in Malaysia, has several limitations that should be acknowledged. The use of purposive sampling and a cross-sectional design limits the generalisability of the findings beyond the specific demographic studied. The sample size of 313 respondents in this study meets and exceeds commonly accepted methodological standards for quantitative research, ensuring statistical power and reliability in the findings (Hair et al., 2019). This robust sample allows for confident interpretation of the relationships among key variables, particularly given the focus on urban working professionals-a segment highly relevant to Malaysia's FinTech landscape.

The focus on urban working professionals means that perspectives from rural populations or other demographic groups remain unexplored. Additionally, the study primarily examines trust as a mediating factor, potentially overlooking other important influences on adoption and long-term usage. These methodological constraints suggest that the results should be interpreted with caution and highlight the need for broader, longitudinal research to validate and extend these findings.

Perceived risk, defined as users' negative effects and ambiguity regarding FinTech services, significantly impacts user behaviour. Sharing prior technology expertise can reduce uncertainty for new adopters. Perceived risk affects the adoption of technology services (Suryono et al., 2020). Marketers and FinTech service providers must understand these risks before implementation. E-commerce risks deter customers, reducing activity (Shahzad et al., 2022).

Despite the similarities in risks between FinTech and e-commerce, perceived risk is a major factor negatively impacting FinTech adoption due to security and financial concerns. Environmental and behavioural uncertainties categorise risk in FinTech (Shahzad et al., 2022). Behavioural uncertainty relates to the service provider's honesty, while online environmental uncertainty involves transaction completion uncertainties. Understanding technology usage and control can decrease users' trust and desire to use FinTech services (Ryu & Ko, 2020).

Confidence in FinTech applications is influenced by environmental and behavioural variables. Reducing uncertainty in these areas can decrease user anxiety and boost adoption trust. FinTech requires users to open accounts, posing risks such as internet issues, personal security, unauthorised transactions, and document concerns (Ventre & Kolbe, 2020). Studies show a negative correlation between perceived risk and trust. This study anticipates that perceived risk negatively impacts FinTech adoption (Vasquez & San-Jose, 2022). Future studies should address this limitation or use a larger sample size.

### **5.3.2 Interdisciplinary Challenges in FinTech Research**

FinTech research inherently requires interdisciplinary collaboration due to the convergence of finance and technology. Understanding technological underpinnings such as blockchain demands expertise from computer science and data science fields (Szopinski et al., 2022). For example, blockchain's impact on financial markets is best understood through insights from

computer science literature (Miraz et al., 2019). Similarly, addressing legal complexities surrounding data privacy, anti-discrimination laws, and large borrower datasets necessitates collaboration with legal scholars (Miraz et al., 2019; Pimentel & Boulianne, 2020). Such interdisciplinary approaches are crucial for comprehensively understanding FinTech adoption and its broader implications.

While FinTech introduces innovative tools and new information sources, many economic issues it raises are not entirely new. This new information will continue to transform the financial sector (Pimentel & Boulianne, 2020). However, substantial research already exists regarding information asymmetry and its effects on financial market efficiency and welfare. Future research should build upon this existing knowledge base instead of reinventing the wheel (Wamba & Queiroz, 2020). The disruptive nature of FinTech has parallels to past disruptions caused by disintermediation and shadow banking. Lessons from past disruptions and existing work should inform analysis of anticipated FinTech trends (Wamba & Queiroz, 2020).

### **5.3.3 Scope and Contextual Limitations**

The decline in public confidence towards central banks and traditional financial institutions has significantly catalysed FinTech growth. Meyliana & Fernando (2019) linked the surge in FinTech adoption to the 2008 financial crisis, while Beirne et al. (2022) noted similar trends following the COVID-19 pandemic. These patterns suggest a recurring increase in FinTech adoption in response to major economic disruptions. Meyliana & Fernando (2019) attributed the rise of cryptocurrencies, built on blockchain technology, to waning public trust in traditional financial institutions. Blockchain's decentralisation principle offers an alternative system for transactions and payments, bypassing financial intermediaries and central banks (Nangin et al., 2020).

Current research on FinTech adoption among urban Malaysian professionals provides valuable insights into user behaviour but has a limited scope regarding FinTech's broader societal impact. Meyliana & Fernando (2019) also emphasise the need for research to encompass a wider range of stakeholders. Beyond user adoption, FinTech's influence extends to investors and their risk profiles in the evolving financial landscape. The competition between traditional banks and FinTech lenders in credit provision necessitates examining the impact on financial inclusion, credit availability, and overall liquidity (Meyliana & Fernando, 2019). A crucial question remains: does FinTech truly democratise access to financial services, particularly for the underbanked? Realising FinTech's potential for well-being requires a deeper understanding of its multifaceted effects. Szopinski et al. (2022) suggest that data-driven modelling can provide crucial insights into FinTech's impact on credit provision, liquidity, and financial health across demographics.

The current research primarily examines trust as a mediating factor. While valuable, this perspective might overlook a potentially more disruptive future for traditional financial institutions. The rapid evolution of FinTech raises the possibility that banks could lose their competitive edge if they fail to adapt. On the other hand, traditional strengths like deposit safety and access to secure assets might still offer advantages (Chorzempa, 2021). According to Faour & Al-Sowaidi (2023), banks are already embracing FinTech by acquiring new technologies or developing their own, leading to a more technologically advanced financial landscape with a reshuffled, but not entirely replaced, industry structure. Future research could explore how trust interacts with factors such as perceived safety and brand loyalty in a potentially more competitive environment.

This research also overlooks the user perspective and factors influencing long-term adoption beyond initial convenience. Kabengele & Hahn (2021) highlight that effective FinTech



services require more than technological advancement; they must offer tangible economic rewards and a user-friendly interface. FinTech's success hinges on demonstrably improving users' financial well-being. Building trust is equally crucial. Khalid & Kunhibava (2020) emphasise the importance of robust privacy policies, strong security controls, and a well-established reputation for integrity. Research could benefit from exploring how FinTech companies address user concerns about data privacy and security, particularly compared to established financial institutions. Investigating how FinTech companies cultivate trust through brand reputation and ethical business practices can provide valuable insights into user behaviour and long-term adoption patterns.

Khalid & Kunhibava (2020) further emphasise user benefits in fostering trust. FinTech service providers must offer substantial advantages to attract and retain users, such as mobility, accessibility, reduced costs, and improved security. For instance, FinTech services that allow users to manage finances conveniently anytime and anywhere can significantly enhance user experience. Lower transaction fees or higher interest rates on savings can incentivise users to switch from traditional institutions. Robust security features and data privacy policies can alleviate user concerns about using FinTech services. Meyliana & Fernando (2019) highlight the role of perceived advantages in driving user adoption. The ability to easily move money fosters trust and a positive perception of the technology. By focusing solely on adoption rates within a specific demographic, current research may miss the importance of user needs and the benefits that drive long-term adoption. Future research exploring how FinTech services address these needs and build trust through tangible advantages can provide valuable insights into user behaviour and sustainable FinTech growth.

In addition, accessibility and ease of use are primary advantages for FinTech consumers. FinTech service providers bridge the gap between sellers and buyers, saving time and money,

which builds mutual trust. Businesses benefit from the FinTech model, especially for financial transactions. Accessibility, enabling financial gains, is a significant advantage (Murinde et al., 2022). FinTech service providers ensure secure transactions and safe customer information. The user-friendliness and compatibility with customers' lifestyles are crucial. Convenience, such as one-touch payments, is a perceived benefit, increasing the desire to use various IT-based applications (Nangin et al., 2020).

### **5.3.4 Directions for Future Research**

Future studies should build on the existing knowledge base regarding information asymmetry, financial market disruptions, and trust dynamics rather than reinventing these concepts (Wamba & Queiroz, 2020). Research could explore how trust interacts with other factors such as perceived safety, brand loyalty, and competitive pressures in a rapidly evolving FinTech landscape where traditional banks may lose or reshape their market positions (Chorzempa, 2021; Faour & Al-Sowaidi, 2023).

Further investigation into long-term adoption factors beyond initial convenience is needed. This includes examining how FinTech companies address user concerns about data privacy, security, and ethical business practices to build sustained trust (Khalid & Kunhibava, 2020). Research focusing on tangible user benefits-such as mobility, accessibility, cost reduction, and improved security-and their role in fostering trust and loyalty would provide valuable insights into sustainable FinTech growth (Meyliana & Fernando, 2019).

Future research should also consider demographic influences on risk perception and adoption, particularly among younger generations who may exhibit different tolerance levels due to less exposure to financial risks. Expanding studies to rural populations and other underrepresented groups will also enhance understanding of FinTech's inclusive potential (Murinde et al., 2022).

The current research on FinTech adoption among Malaysian professionals provides valuable data, but to truly understand the long-term drivers of FinTech use, a richer understanding of the user landscape is needed. One limitation of this study is its focus on a single demographic. Factors like age, income level, and technological literacy likely influence how people adopt FinTech. Expanding future research to include diverse populations can reveal these variations. For instance, how do rural communities or those with limited technological experience interact with FinTech services? Exploring these user groups can highlight potential barriers and opportunities for FinTech to reach underserved populations.

Furthermore, this study does not fully consider the global context of FinTech adoption. Infrastructure, regulations, and cultural preferences all play a significant role in how different regions embrace FinTech. Including data from established FinTech markets like Singapore, the United States, China, and the United Kingdom alongside Malaysia would allow researchers to see how these variations impact user behaviour. By conducting comparative analyses, researchers can identify best practices and potential challenges in different contexts, fostering a more comprehensive understanding of FinTech's global reach.

Finally, this study used a limited number of variables with trust as a mediating factor, suggesting future research incorporate additional parameters for FinTech adoption. Furthermore, the study only observed urban working professionals in Malaysia who are interested in FinTech adoption. Future studies may narrow the sample size by targeting traditional and window bank consumers to gather more information about FinTech adoption in the banking industry or increase the sample size for better statistical conclusions. The model approach was restricted to few variables, but other variables' usage patterns may interest future researchers.

In conclusion, while the current study offers a great starting point, a richer user landscape that considers diverse demographics and global contexts is crucial for a more nuanced understanding of FinTech adoption. Looking at the bigger picture can help us better understand the social and economic forces that influence how FinTech affects people's lives around the world.

## REFERENCES

- Abdul-Rahim, R., Bohari, S. A., Aman, A. & Awang, Z. (2022). Benefit-risk perceptions of fintech adoption for sustainability from bank consumers' perspective: The moderating role of fear of COVID-19. *Sustainability*, 14(14), p. 8357.
- Ahiabenu, K. (2022). A comparative study of the design frameworks of the Ghanaian and Nigerian Central Banks' Digital Currencies (CBDC). *FinTech*, 1(3), pp. 235-249.
- Ahmad, A. H., Green, C. & Jiang, F. (2020). Mobile money, financial inclusion and development: A review with reference to African experience. *Journal of Economic Surveys*, 34(4), pp. 753-792.
- Ahmed, W., Hizam, S. M., Sentosa, I., Ali, J. & Ali, T. (2020). Structural equation modelling for acceptance of cloud computing. *2019 International Conference on Advances in the Emerging Computing Technologies (AECT)*, pp. 1-6. IEEE.
- Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, 50(2), pp. 179-211.
- Akcam, B. K. (2023). The impact of technology on the Starbucks experience. *Journal of Information Technology Teaching Cases*, 13(1), 104-110.
- Alam, N., Gupta, L., & Zameni, A. (2019). *Fintech and Islamic finance: digitalization, development and disruption. (1st ed.)*. Palgrave Macmillan.
- Alam, S. T. (2024). The convergence of artificial intelligence, blockchain, and fintech in energy, oil, and gas trading: Increasing efficiency, transparency, and automation. *World Journal of Advanced Research and Reviews*, 22(2), pp. 2064–2073.
- Albarrak, M. S. & Alokley, S. A. (2021). FinTech: Ecosystem, opportunities and challenges in Saudi Arabia. *Journal of Risk and Financial Management*, 14(10), p. 460.
- Aldboush, H. H. H. & Ferdous, M. (2023). Building trust in Fintech: An analysis of ethical and privacy considerations in the intersection of big data, AI, and customer trust. *International Journal of Financial Studies*, 11(3), p. 90.

Alexander, K. (2021). Financial inclusion and banking regulation: The role of proportionality. *Law and Contemporary Problems*, 84(1), pp. 129-152.

Ali, M., Raza, S. A., Khamis, B., Puah, C. H. & Amin, H. (2021). How perceived risk, benefit and trust determine user Fintech adoption: a new dimension for Islamic finance. *Foresight*, 23(4), pp. 403-420.

Almashhadani, I. S., Abuhashesh, M., Bany Mohammad, A., Masa'deh, R., & Al-Khasawneh, M. (2023). Exploring the determinants of FinTech adoption and intention to use in Jordan: The impact of COVID-19. *Cogent Social Sciences*, 9(2), pp. 1-18.

Al-Okaily, M., Al Natour, A. R., Shishan, F., Al-Dmour, A., Alghazzawi, R. & Alsharairi, M. (2021). Sustainable FinTech innovation orientation: A moderated model. *Sustainability*, 13(24), p. 13591.

Al-Okaily, M., Lutfi, A., Alsaad, A., Taamneh, A. & Alsyouf, A. (2020). The determinants of digital payment systems' acceptance under cultural orientation differences: the case of uncertainty avoidance. *Technology in Society*, 63, p. 101367.

Al-Sharafi, M. A., Abdullah Arshah, R., Herzallah, F. & Alajmi, Q. (2017). The Effect of Perceived Ease of Use and Usefulness on Customers Intention to Use Online Banking Services: The Mediating Role of Perceived Trust. *International Journal of Innovative Computing*, 7(1).

Alwi, S., Alpandi, R. M., Salleh, M. N. M. & Najihah, I. (2019). An empirical study on the customers' satisfaction on fintech mobile payment services in Malaysia. *International Journal of Advanced Science and Technology*, 28(16), pp. 390-400.

Amnas, M. B., Selvam, M. & Parayitam, S. (2024). FinTech and financial inclusion: Exploring the mediating role of digital financial literacy and the moderating influence of perceived regulatory support. *Journal of Risk and Financial Management*, 17(3), p. 108.

Anifa, M., Ramakrishnan, S., Joghee, S., Kabiraj, S. & Bishnoi, M. M. (2022). Fintech innovations in the financial service industry. *Journal of Risk and Financial Management*, 15(7), p. 287.

Arli, D., van Esch, P., Bakpayev, M. & Laurence, A. (2020). Do consumers really trust cryptocurrencies?. *Marketing Intelligence & Planning*, 39(1), pp. 74-90.

Arner, D. W., Barberis, J. & Buckley, R. P. (2015). The evolution of Fintech: A new post-crisis paradigm. *Georgetown Journal of International Law*, 47, p. 1271.

Arner, D. W., Buckley, R. P., Zetsche, D. A. & Veidt, R. (2020). Sustainability, FinTech and financial inclusion. *European Business Organisation Law Review*, 21(1), pp.7-35.

Ashta, A. (2021). Fintech–technology in finance: Strategic risks and challenges. *Innovation Economics, Engineering and Management Handbook 2: Special Themes*, pp. 137-143.

Avarmaa, M., Torkkeli, L., Laidroo, L. & Koroleva, E. (2022). The interplay of entrepreneurial ecosystem actors and conditions in FinTech ecosystems: An empirical analysis. *Journal of Entrepreneurship, Management, and Innovation*, 18(4), pp. 79-113.

Baber, H. (2020). FinTech, crowdfunding and customer retention in Islamic banks. *Vision*, 24(3), pp. 260-268.

Babin, R., and Smith, D. (2022). Open banking and regulation: Please advise the government. *Journal of Information Technology Teaching Cases*, 12(2), 108-114.  
<https://doi.org/10.1177/20438869221082316>

Bains, P. & Wu, C. (2023). Institutional Arrangements for Fintech Regulation: Supervisory Monitoring. *Fintech Notes 2023*, 004, A001.

Bajunaied, K., Hussin, N., and Kamarudin, S. (2023). Behavioural intention to adopt FinTech services: An extension of unified theory of acceptance and use of technology. *Journal of Open Innovation: Technology, Market, and Complexity*, 9(1), 100010.

Bajwa, I. A., Ur Rehman, S., Iqbal, A., Anwer, Z., Ashiq, M., & Khan, M. A. (2022). Past, present and future of FinTech research: A bibliometric analysis. *Sage Open*, 12(4).

Barefoot, J. A. (2020). Digital technology risks for finance: dangers embedded in fintech and regtech. *Mossavar-Rahmani Center for Business & Government (M-RCBG) Associate Working Paper No, 151*.

Barroso, M. & Laborda, J. (2022). Digital transformation and the emergence of the FinTech sector: Systematic literature review. *Digital Business*, 2(2), 100028.

BCG (2023). Reimagining the Future of Finance. *Global Fintech Report 2023*. Boston Consulting Group.

Beirne, J., Villafuerte, J. and Zhang, B. (2022). *Fintech and COVID-19: Impacts, challenges, and policy priorities for Asia*. Manila, Philippines: Asian Development Bank Institute.

Ben-David, I., Johnson, M. J. & Stulz, R. M. (2021). *Why Did Small Business Fintech Lending Dry Up During March 2020?* (No. w29205). National Bureau of Economic Research.

Berkmen, P., Beaton, M. K., Gershenson, M. D., del Granado, M. J. A., Ishi, K., Kim, M., Kopp, E. & Rousset, M. M. V. (2019). *Fintech in Latin America and the Caribbean: Stocktaking*. International Monetary Fund.

Bhattacharjee, I., Srivastava, N., Mishra, A., & Adhav, S. (2024). The Rise of FinTech: Disrupting Traditional Financial Services. *Educational Administration Theory and Practice Journal*, 30(4), pp. 89-97.

Bhuiyan, A. B., Ali, M. J., Zulkifli, N. & Kumarasamy, M. M. (2020). Industry 4.0: challenges, opportunities, and strategic solutions for Bangladesh. *International Journal of Business and Management Future*, 4(2), pp. 41-56.

Biancone, P. P., Secinaro, S. & Kamal, M. (2019). Crowdfunding and Fintech: Business model sharia compliant. *European Journal of Islamic Finance*, 12, pp. 1-10.

BNM (2016). Malaysia experience in financial inclusion: Unlocking shared benefits for all through inclusive finance. *Bank Negara Malaysia*.

BNM (2022). Financial Sector Blueprint 2022-2026. *Bank Negara Malaysia*.

BNM (2023). Annual Report 2023. *Bank Negara Malaysia*.

BNM (2024a). Financial Technology Regulatory Sandbox Framework. *Bank Negara Malaysia*.



BNM (2024b). Policy Document on Digital Insurance and Takaful Operators. *Bank Negara Malaysia*.

Bolton, K., & Brace, I. (2022). *Questionnaire Design: How to Plan, Structure and Write Survey Material for Effective Market Research (5th ed.)*. Kogan Page.

Bos, J. (2020). *Research ethics for students in the social sciences* (p. 287). Springer Nature.

Boukherouaa, E. B., AlAjmi, K., Deodoro, J., Farias, A., and Ravikumar, R. (2021). Powering the Digital Economy: Opportunities and Risks of Artificial Intelligence in Finance. *International Monetary Fund Departmental Papers*, 2021(024), 34.

Brahma, M., Tripathi, S. S. & Sahay, A. (2020). Developing curriculum for industry 4.0: Digital workplaces. *Higher Education, Skills and Work-Based Learning*, 11(1), pp. 144-163.

Breidbach, C. F., Keating, B. W. & Lim, C. (2020). FinTech: research directions to explore the digital transformation of financial service systems. *Journal of Service Theory and Practice*, 30(1), pp. 79-102.

Brook, R. J., & Arnold, G. C. (2018). *Applied regression analysis and experimental design*. CRC Press.

Burke, J. J. (2021). Impact of FinTech: A prediction. In *Financial Services in the Twenty-First Century* (pp. 199-212). Palgrave Macmillan, Cham.

Campbell, T., Knox, M. W., Rowlands, J., Cui, Z. Y. A. & DeJesus, L. (2021). Leadership in FinTech: Authentic leaders as enablers of innovation and competitiveness in financial technology firms. In *Fostering Innovation and Competitiveness with FinTech, RegTech, and SupTech* (pp. 250-270). IGI Global.

Chan, R., Troshani, I., Hill, S. R. and Hoffmann, A. (2022). Towards an understanding of consumers' FinTech adoption: The case of open banking. *International Journal of Bank Marketing*, 40(4), pp. 886-917.

Chaudhry, S. M., Ahmed, R., Huynh, T. L. D. & Benjasak, C. (2022). Tail risk and systemic risk of finance and technology (FinTech) firms. *Technological Forecasting and Social Change*, 174, p. 121191.

Chauhan, R., Chirputkar, A. & Pathak, P. (2022), March. Blockchain and IoT in developing Fintech ecosystem – assistance to insurance industry. In *2022 International Conference on Decision Aid Sciences and Applications (DASA)* (pp. 431-437). IEEE.

Chawla, U., Mohnot, R., Singh, H. V. & Banerjee, A. (2023). The mediating effect of perceived trust in the adoption of cutting-edge financial technology among digital natives in the post-COVID-19 era. *Economies*, 11(12), 286

Chemmanur, T. J., Imerman, M. B., Rajaiya, H. & Yu, Q. (2020). Recent developments in the FinTech industry. *Journal of Financial Management, Markets and Institutions*, 8(01), p. 2040002.

Chen, M. A., Wu, Q. & Yang, B. (2019). How valuable is FinTech innovation?. *The Review of Financial Studies*, 32(5), pp. 2062-2106.

Chen, X., You, X. & Chang, V. (2021). FinTech and commercial banks' performance in China: A leap forward or survival of the fittest?. *Technological Forecasting and Social Change*, 166, p. 120645.

Chen, Y. & Bellavitis, C. (2020). Blockchain disruption and decentralized finance: The rise of decentralized business models. *Journal of Business Venturing Insights*, 13, Article e00151.

Chiu, J. & Koepl, T. V. (2019). Blockchain-based settlement for asset trading. *The Review of Financial Studies*, 32(5), pp. 1716-1753.

Chorzempa, M. (2021). China, the United States, and central bank digital currencies: how important is it to be first?. *China Economic Journal*, 14(1), pp. 102-115.

Christensen, C. M. & Raynor, M. E. (2003). *The innovator's solution: Creating and sustaining successful growth*. Harvard Business Review Press.

Christensen, C. M. (1997). *The innovator's dilemma: When new technologies cause great firms to fail*. Harvard Business Review Press.

Coco, A., Dias, T., & Van Benthem, T. (2022). Illegal: The SolarWinds Hack under International Law. *European Journal of International Law*, 33(4), pp. 1275-1286.

Cojoianu, T. F., Clark, G. L., Hoepner, A. G., Pažitka, V. & Wójcik, D. (2021). Fin vs. tech: are trust and knowledge creation key ingredients in fintech start-up emergence and financing?. *Small Business Economics*, 57(4), pp. 1715-1731.

Cornelli, G., Frost, J., Gambacorta, L., Rau, P. R., Wardrop, R. & Ziegler, T. (2023). Fintech and big tech credit: Drivers of the growth of digital lending. *Journal of Banking & Finance*, 148, p. 106742.

Creswell, J. W. & Plano Clark, V. L. (2018). *Designing and conducting mixed methods research* (3rd ed.). Sage publications.

Croux, C., Jagtiani, J., Korivi, T. & Vulcanovic, M. (2020). Important factors determining Fintech loan default: Evidence from a LendingClub consumer platform. *Journal of Economic Behavior & Organization*, 173, pp. 270-296.

Croxson, K., Frost, J., Gambacorta, L. & Valletti, T. (2022). Platform-based business models and financial inclusion. *BIS Papers*.

D'Acunto, F. & Rossi, A. G. (2021). Robo-advising. In *The Palgrave Handbook of Technological Finance* (pp. 725-749). Palgrave Macmillan, Cham.

Das, S. R. (2019). The future of FinTech. *Financial Management*, 48(4), pp. 981-1007.

Davis, F. D. & Venkatesh, V. (1996). A critical assessment of potential measurement biases in the technology acceptance model: Three experiments. *International journal of human-computer studies*, 45(1), pp. 19-45.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*, pp. 319-340.

Davis, F. D. (1993). User acceptance of information technology: System characteristics, user perceptions and behavioral impacts. *International journal of man-machine studies*, 38(3), pp. 475-487.

Davis, F. D., Bagozzi, R. P. & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management science*, 35(8), pp. 982-1003.

Dawood, H. M., Liew, C. Y. & Lau, T. C. (2021). Mobile perceived trust mediation on the intention and adoption of FinTech innovations using mobile technology: A systematic literature review. *F1000Research*, 10, p. 1252.

Desai, S. C. & Reimers, S. (2019). Comparing the use of open and closed questions for Web-based measures of the continued-influence effect. *Behavior Research Methods*, 51(3), pp. 1426-1440.

Dhiaf, M. M., Khakan, N., Atayah, O. F., Marashdeh, H. & El Khoury, R. (2022). The role of FinTech for manufacturing efficiency and financial performance: in the era of industry 4.0. *Journal of Decision Systems*, pp. 1-22.

Di Maggio, M., Ratnadiwakara, D. & Carmichael, D. (2022). *Invisible primes: Fintech lending with alternative data* (No. w29840). National Bureau of Economic Research.

Digital 2023: Malaysia. Datareportal [online]. Available at: <https://datareportal.com/reports/digital-2023-malaysia> [Accessed 4 May 2023].

Dömötör, B., Illés, F., & Ölvedi, T. (2023). Peer-to-peer lending: Legal loan sharking or altruistic investment? Analyzing platform investments from a credit risk perspective. *Journal of International Financial Markets, Institutions and Money*, 86, 101801.

DOSM (2023a). Malaysia Digital Economy 2023. *Department of Statistics, Malaysia (DOSM)*.

DOSM (2023b). Kawasanku. OpenDOSM. *Department of Statistics, Malaysia*.

Duran, R. E. & Griffin, P. (2020). Smart contracts: will Fintech be the catalyst for the next global financial crisis?. *Journal of Financial Regulation and Compliance*, 29(1), pp. 104-122.

Edelman, D. C. & Abraham, M. (2022). Customer Experience in the Age of AI. *Harvard Business Review*.

Elrick, J. & Thies, C. F. (2018). The social responsibility of business: Milton Friedman reconsidered. *Journal of Markets & Morality*, 21(2), p. 297307.

Etikan, I., Musa, S. A., & Alkassim, R. S. (2016). Comparison of convenience sampling and purposive sampling. *American Journal of Theoretical and Applied Statistics*, 5(1), pp. 1-4.

Faour, A. & Al-Sowaidi, A. S. S. S. (2023). Fintech revolution: How established banks are embracing innovation to stay competitive. *Journal of Business and Management Studies*, 5(5), 166-172.

Fenwick, M., Uytsel, S. V. & Ying, B. (2020). Regulating Fintech in Asia: An introduction. In *Regulating FinTech in Asia* (pp. 1-10). Springer, Singapore.

Feyen, E., Frost, J., Gambacorta, L., Natarajan, H., & Saal, M. (2021). *Fintech and the digital transformation of financial services: Implications for market structure and public policy* (BIS Papers No. 117). The Bank for International Settlements and the World Bank Group. Retrieved from <https://www.bis.org/publ/bppdf/bispap117.pdf>.

Field, A. (2018). *Discovering statistics using IBM SPSS statistics*. Sage Publications.

FinTech News Malaysia (2022). FinTech Malaysia companies and FinTech Malaysia startups. <https://fintechnews.sg/fintech-companies-in-malaysia-fintech-startups/>.

Fintech News Malaysia (2023). Malaysia Digital ID: Is It the Key to Shaping a Digitised Society? Retrieved from <https://fintechnews.my/41129/regtech-fintech-regulation-malaysia/is-malaysias-national-digital-id-the-key-to-shaping-a-digitised-society/>.

Fishbein, M. & Ajzen, I. (1975). *Belief, attitude, intention, and behavior: An introduction to theory and research*. Reading, Mass; Don Mills, Ontario: Addison-Wesley Pub. Co.

FMT (2024). The challenges and potential of Malaysia's fintech industry. *Free Malaysia Today*.

FSB (2019). FinTech and Market Structure in Financial Services. *Financial Stability Board, Basel, Switzerland*. <https://www.fsb.org/wp-content/uploads/P140219.pdf>.

Fuster, A., Plosser, M., Schnabl, P. & Vickery, J. (2019). The role of technology in mortgage lending. *The Review of Financial Studies*, 32(5), pp. 1854-1899.

Galvin, J., Han, F., Hynes, S., Qu, J., Rajgopal, K. & Shek, A. (2018). Synergy and disruption: Ten trends shaping fintech. *McKinsey Report*.

Gambe, R. L., & Estopace, E. (2022). Malaysia's fintech industry slow to capitalize on Islamic finance growth. *S&P Global Market Intelligence*.

Garanina, T., Ranta, M. & Dumay, J. (2022). Blockchain in accounting research: current trends and emerging topics. *Accounting, Auditing & Accountability Journal*, 35(7), pp. 1507-1533.

Gerrans, P., Baur, D. G. & Lavagna-Slater, S. (2022). Fintech and responsibility: Buy-now-pay-later arrangements. *Australian Journal of Management*, 47(3), pp. 474-502.

Giglio, F. (2021). Fintech: A literature review. *European Research Studies Journal*, 24(2B), pp. 600-627.

Goldstein, I., Jiang, W. & Karolyi, G. A. (2019). To FinTech and beyond. *The Review of Financial Studies*, 32(5), pp. 1647-1661.

Gomber, P., Kauffman, R. J., Parker, C. & Weber, B. W. (2018). On the fintech revolution: Interpreting the forces of innovation, disruption, and transformation in financial services. *Journal of Management Information Systems*, 35(1), pp. 220-265.

Goodhue, D. L. & Thompson, R. L. (1995). Task-technology fit and individual performance. *MIS quarterly*, pp. 213-236.

Government of Malaysia (n.d.). *Penjana*. Malaysia Government Portal. <https://www.malaysia.gov.my/portal/content/31148>.

Griffin, J. M. & Shams, A. (2020). Is Bitcoin really untethered?. *The Journal of Finance*, 75(4), pp. 1913-1964.

Guttman-Kenney, B., Firth, C. & Gathergood, J. (2023). Buy now, pay later (BNPL) on your credit card. *Journal of Behavioral and Experimental Finance*, 37, 100788.

Hair, J. F., Black, W. C., Babin, B. J. & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage Learning.

Hamid, N. A., Suria, K., Jasni, N. S., & Salleh, K. A. M. (2024). Fintech in Malaysia: Navigating challenges and shaping a digital future. *Accounting and Finance Research*, 13(1), 42.

- Hamza, S. M., Aysan, A. F. & Kayani, U. N. (2025). Cultural catalysts of FinTech: Baring long-term orientation and indulgent cultures in OECD countries. *Economics*, 19(1), 20250137.
- Hamzah, M. F., Razak, T. M. T. A., Yahaya, C. K. H. C. K., Shamsuddin, Z. & Zahrin, S. N. A. (2022). Adoption factors of fintech products & services in Islamic banking industry in Malaysia: A literature review. *Journal of Positive School Psychology*, 6(3), pp. 8883-8893.
- Hasan, M. M., Yajuan, L. & Khan, S. (2022). Promoting China's inclusive finance through digital financial services. *Global Business Review*, 23(4), pp. 984-1006.
- Hassan, M. S., Islam, M. A., Sobhani, F. A., Nasir, H., Mahmud, I. & Zahra, F. T. (2022). Drivers influencing the adoption intention towards mobile fintech services: A study on the emerging Bangladesh market. *Information*, 13(7), p. 349.
- Hodson, D. (2021). The politics of FinTech: Technology, regulation, and disruption in UK and German retail banking. *Public Administration*, 99(4), pp.859-872.
- Hoque, M. Z., Chowdhury, N. J., Hossain, A. A., & Tabassum, T. (2024). Social and facilitating influences in fintech user intention and the fintech gender gap. *Heliyon*, 10(1), e23457.
- Huang, G. & Ren, Y. (2020). Linking technological functions of fitness mobile apps with continuance usage among Chinese users: Moderating role of exercise self-efficacy. *Computers in Human Behavior*, 103, pp. 151-160.
- Hunter, D., McCallum, J. & Howes, D. (2019). Defining exploratory-descriptive qualitative (EDQ) research and considering its application to healthcare. *Journal of Nursing and Health Care*, 4(1), pp. 1-7.
- Hunter, R. F., Gough, A., O'Kane, N., McKeown, G., Fitzpatrick, A., Walker, T., McKlinley, M., Lee, M. & Kee, F. (2018). Ethical issues in social media research for public health. *American Journal of Public Health*, 108(3), pp. 343-348.
- Imerman, M. B. & Fabozzi, F.J. (2020). Cashing in on innovation: A taxonomy of FinTech. *Journal of Asset Management*, 21(3), pp. 167-177.
- IMF (2020). Malaysia: A flourishing fintech ecosystem. *International Monetary Fund News*.

Indiani, N. L. P., Amerta, I. M. S., & Sentosa, I. (2024). Exploring the moderation effect of consumers' demography in the online purchase behaviour. *Cogent Business & Management*, 11(1), 2393742.

Irimia-Diéguez, A., Velicia-Martín, F. & Aguayo-Camacho, M. (2023). Predicting fintech innovation adoption: the mediator role of social norms and attitudes. *Financial Innovation*, 9(36), pp. 1-23.

Jafri, J. A., Amin, S. I. M., Rahman, A. A., & Nor, S. M. (2024). A systematic literature review of the role of trust and security on Fintech adoption in banking. *Heliyon*, 10(1), e22980.

Jamhor, R., Fisal, S., & Rafdi, N. J. (2021). Issues and challenges of financial technology (FinTech) in the Malaysian financial market. In *Proceeding of the 8th International Conference on Management and Muamalah 2021 (Icomm 2021)*.

Javed, A. R., Shahzad, F., ur Rehman, S., Zikria, Y.B., Razzak, I., Jalil, Z. & Xu, G. (2022). Future smart cities requirements, emerging technologies, applications, challenges, and future aspects. *Cities*, 129, p. 103794.

Jenweeranon, P. (2020). Thai regulatory approaches to technology-driven innovation in financial services. *Regulating FinTech in Asia*, pp. 97-114.

Johnson, K., Pasquale, F. & Chapman, J. (2019). Artificial intelligence, machine learning, and bias in finance: Toward responsible innovation. *Fordham Law Review*, 88, p. 499.

Josephson, A. & Smale, M. (2021). What do you mean by “informed consent”? Ethics in economic development research. *Applied Economic Perspectives and Policy*, 43(4), pp. 1305-1329.

Kabengele, C. & Hahn, R. (2021). Institutional and firm-level factors for mobile money adoption in emerging markets - a configurational analysis. *Technological Forecasting and Social Change*, 171, p. 120934.

Kamali Saraji, M., Streimikiene, D. & Kyriakopoulos, G. L. (2021). Fermatean fuzzy CRITIC-COPRAS method for evaluating the challenges to industry 4.0 adoption for a sustainable digital transformation. *Sustainability*, 13(17), p. 9577.



Khalid, M. & Kunhibava, S. (2020). Fintech regulatory sandboxes in Australia and Malaysia: A legal analysis. *IIUM Law Journal*, 28(1), pp. 1-35.

Khan, H. H., Khan, S. & Ghafoor, A. (2023). Fintech adoption, the regulatory environment and bank stability: An empirical investigation from GCC economies. *Borsa Istanbul Review*, 23(6), pp. 1263-1281.

Kiew, J. P., Toh, E. T. L., Ngian, E. T., & Law, S. H. C. (2022). Perceived trust, convenience and promotion for the adoption of e-wallet. *International Journal of Academic Research in Business and Social Sciences*, 12(9), pp. 374 – 385.

Kitagawa, T., Masuda, Y. & Umezawa, M. (2020). Impact of technology development costs on licensing form in a differentiated Cournot duopoly. *International Journal of Economic Theory*, 16(2), pp.153-166.

Kline, R. B. (2016). *Principles and practice of structural equation modelling*. Guilford Publications.

Koenig-Lewis, N., Marquet, M., Palmer, A., & Zhao, A. L. (2015). Enjoyment and social influence: Predicting mobile payment adoption. *The Service Industries Journal*, 35(10), pp. 537-554.

Kong, S. T. & Loubere, N. (2021). Digitally down to the countryside: Fintech and rural development in China. *The Journal of Development Studies*, 57(10), pp.1739-1754.

Kowalski, M., Lee, Z. W. & Chan, T. K. (2021). Blockchain technology and trust relationships in trade finance. *Technological Forecasting and Social Change*, 166, p.120641.

KPMG (2023). *Harnessing the power of Embedded Finance*. Retrieved from: <https://assets.kpmg.com/content/dam/kpmg/ie/pdf/2023/05/ie-embedded-finance.pdf>.

Krejcie, R. V. and Morgan, D. W. (1970). Determining Sample Size for Research Activities. *Educational and Psychological Measurement*, 30, pp. 607-610.

Kumar, S., Kumar, B., Nagesh, Y. and Christian, F. (2022). Application of blockchain technology as a support tool in economic & financial development. *Manager-The British Journal of Administrative Management*, ISSN, pp. 1746-1278.

- Kumar, S., Lim, W. M., Sivarajah, U. and Kaur, J. (2023). Artificial intelligence and blockchain integration in business: trends from a bibliometric-content analysis. *Information Systems Frontiers*, 25, pp. 871-896.
- Kumari, A., & Nagarjan, C. (2022). The impact of FinTech and blockchain technologies on banking and financial services. *Technology Innovation Management Review*, 12(1/2), pp. 12-23.
- Kurniasari, F., Gunardi, A., Putri, F. & Firmansyah, A. (2021). The role of financial technology to increase financial inclusion in Indonesia. *International Journal of Data and Network Science*, 5(3), pp. 391-400.
- Kurniasari, F., Urus, S. T., Utomo, P., Abd Hamid, N., Jimmy, S. Y. & Othman, I. W. (2022). Determinant factors of adoption of fintech payment services in Indonesia using the UTAUT approach. *Asian-Pacific Management Accounting Journal*, 17(1), pp. 97-125.
- Larsson, B., Rolandsson, B., Ilsøe, A., Larsen, T. P., Lehr, A., & Masso, J. (2024). Digital disruption diversified - FinTechs and the emergence of a cooperative market ecosystem. *Socio-Economic Review*, 22(2), pp. 655–675.
- Lashitew, A. A., van Tulder, R. & Liasse, Y. (2019). Mobile phones for financial inclusion: What explains the diffusion of mobile money innovations? *Research Policy*, 48(5), pp. 1201-1215.
- Le, T. T., Dang, N. D. L., Nguyen, T. D. T., Vu, T. S. & Tran, M. D. (2019). Determinants of financial inclusion: comparative study of Asian countries. *Asian Economic and Financial Review*, 9(10), pp. 1107-1123.
- Leong, L. Y., Hew, T. S., Ooi, K. B. & Dwivedi, Y. K. (2020). Predicting trust in online advertising with an SEM-artificial neural network approach. *Expert Systems with Applications*, 162, p. 113849.
- Lim, K. T., Teoh, A. P. & Wong, S. F. (2023). Factors influencing the adoption of mobile payment services in Malaysia: The moderating role of trust. *Journal of Asian Business and Economic Studies*, 30(1), pp. 1-15.

Lim, S. H., Kim, D. J., Hur, Y. & Park, K. (2019). An empirical study of the impacts of perceived security and knowledge on continuous intention to use mobile fintech payment services. *International Journal of Human–Computer Interaction*, 35(10), pp. 886-898.

Lin, W. R., Lin, C. Y. & Ding, Y. H. (2020). Factors affecting the behavioral intention to adopt mobile payment: An empirical study in Taiwan. *Mathematics*, 8(10), p.1851.

Liu, C. (2021). FinTech and its disruption to financial institutions. In *Research Anthology on Blockchain Technology in Business, Healthcare, Education, and Government*, pp. 1679-1699. IGI Global.

Lu, J., Yao, J., & Yu, C-S. (2005). Personal innovativeness, social influences and adoption of wireless internet services via mobile technology. *The Journal of Strategic Information Systems*, 14(3), pp. 245-268.

Lutfiani, N., Apriani, D., Nabila, E. A. & Juniar, H. L. (2022). Academic certificate fraud detection system framework using blockchain technology. *Blockchain Frontier Technology*, 1(2), pp. 55-64.

Ly, A., Marsman, M., & Wagenmakers, E. J. (2018). Analytic posteriors for Pearson's correlation coefficient. *Statistica Neerlandica*, 72(1), pp. 4-13.

Lyons, A. C., Kass-Hanna, J. & Fava, A. (2022). Fintech development and savings, borrowing, and remittances: A comparative study of emerging economies. *Emerging Markets Review*, 51, p. 100842.

Malali, A. B. & Gopalakrishnan, S. (2020). Application of artificial intelligence and its powered technologies in the Indian banking and financial industry: An overview. *IOSR Journal of Humanities and Social Science*, 25(4), pp. 55-60.

Marikyan, D., & Papagiannidis, S. (2024). *Technology acceptance model: A review*. In S. Papagiannidis (Ed), TheoryHub Book.

Mathew, V. & Soliman, M. (2021). Does digital content marketing affect tourism consumer behavior? An extension of technology acceptance model. *Journal of Consumer Behaviour*, 20(1), pp. 61-75.

Mawadi, C. P., Sitanggang, N. V., Olfabri, O. & Saidah, D. (2023). The role of trust as a mediating factor in the influence of reverse logistics on customer satisfaction at Shopee Indonesia. *Journal of Business and Management*, 9(1), 1-10.

McKinsey & Company (2021). Buy Now, Pay Later: Five Business Models to Compete. Retrieved from <https://www.mckinsey.com/industries/financial-services/our-insights/buy-now-pay-later-five-business-models-to-compete>.

Meidawati, N., Yunitasari, F., & Puspita, O. D. (2022). Effect of promotion, perceived usefulness, and perceived ease of use on interest in adopting e-wallet (Ovo and Dana). *International Journal of Research in Business and Social Science*, 11(8), pp. 191-201. DOI: 10.20525/ijrbs.v11i8.2060.

Memon, M. A., Ramayah, T., Cheah, J. H., Ting, H., Chuah, F. & Cham, T. H. (2021). PLS-SEM statistical programs: A review. *Journal of Applied Structural Equation Modeling*, 5(1), pp. 1-14.

Meyliana, M. & Fernando, E. (2019). The influence of perceived risk and trust in adoption of fintech services in Indonesia. *CommIT (Communication and Information Technology) Journal*, 13(1), pp. 31-37.

Miraz, M. H., Hye, A. M. & Habib, M. M. (2019). The impact of Blockchain-Bitcoin in Malaysian markets. *International Journal of Supply Chain Management*, 8(5), p. 136.

Mishra, P., Pandey, C. M., Singh, U., Gupta, A., Sahu, C. & Keshri, A. (2019). Descriptive statistics and normality tests for statistical data. *Annals of Cardiac Anaesthesia*, 22(1), p. 67.

MOF (2023). *Budget 2024 Highlights*. Ministry of Finance, Malaysia.

Mohamed, H. & Ali, H. (2022). *Blockchain, Fintech, and Islamic finance: Building the future in the new Islamic digital economy*. Walter de Gruyter GmbH & Co KG.

Mohd, N., Razali, M., & Ab Manan, S. K. (2024). Navigating obstacles encountered by Fintech startups: An in-depth systematic literature review. *Management and Accounting Review*, 23(1), pp. 1-13.

- Mohsin, M. I. A., Ahmad, R. and Chan, W. M. (2022). Exploring Digitalisation of Malaysian Banking and Fintech Companies' Services from the Customer's Perspective. *International Journal of Management and Applied Research*, 9(2), pp. 140-160.
- Mosavi, S. A., & Ghaedi, M. (2012). A survey on the relationship between trust, customer loyalty, commitment and repurchase intention. *African Journal of Business Management*, 6, pp. 10089-10098.
- Mosteanu, N. R. & Faccia, A. (2021). Fintech frontiers in quantum computing, fractals, and blockchain distributed ledger: Paradigm shifts and open innovation. *Journal of Open Innovation: Technology, Market, and Complexity*, 7(1), p. 19.
- Murinde, V., Rizopoulos, E. & Zachariadis, M. (2022). The impact of the FinTech revolution on the future of banking: Opportunities and risks. *International Review of Financial Analysis*, 81, p. 102103.
- Najaf, K., Mostafiz, M. I. & Najaf, R. (2021). Fintech firms and banks sustainability: Why cyber security risk matters? *International Journal of Financial Engineering*, 8(02), p. 2150019.
- Nangin, M. A., Barus, I. R. G. & Wahyoedi, S. (2020). The effects of perceived ease of use, security, and promotion on trust and its implications on fintech adoption. *Journal of Consumer Sciences*, 5(2), pp. 124-138.
- Natile, S. (2020). Digital finance inclusion and the mobile money "social" enterprise. *Historical Social Research/Historische Sozialforschung*, 45(3), pp.74-94.
- Nguyen, D. B. & Vaubourg, A-G. (2021). Financial intermediation, trade agreements and international trade. *The World Economy*, 44(3), pp. 788-817.
- Nguyen, O. T. K., & Nguyen, H. T. (2022). Impacts of promotional benefit on actual use behaviour of mobile wallet: Evidence from Vietnam. *International Journal of eBusiness and eGovernment Studies*, 14(3), pp. 530-559.

Noonpakdee, W. (2020). The adoption of artificial intelligence for financial investment service. In *2020 22nd International Conference on Advanced Communication Technology (ICACT)* (pp. 396-400). IEEE.

Noor, U., Anwar, Z., Amjad, T. & Choo, K. K. R. (2019). A machine learning-based FinTech cyber threat attribution framework using high-level indicators of compromise. *Future Generation Computer Systems*, 96, pp. 227-242.

OECD (2021). *Artificial Intelligence, Machine Learning and Big Data in Finance: Opportunities, Challenges, and Implications for Policy Makers*. Retrieved from <https://www.oecd.org/finance/artificial-intelligence-machine-learning-big-data-in-finance.htm>.

Oh, K. E. (2024). A comprehensive investigation of researchers' shared file management practices in cloud storage. *Human-Computer Interaction*, 1–20.

Osmani, M., El-Haddadeh, R., Hindi, N., Janssen, M. & Weerakkody, V. (2020). Blockchain for next generation services in banking and finance: Cost, benefit, risk and opportunity analysis. *Journal of Enterprise Information Management*, 34(3), pp. 884-899.

Ozili, P. K. (2022). Embedded finance: assessing the benefits, use case, challenges and interest over time. *Journal of Internet and Digital Economics*, 2(2), pp. 108-123.

Pandey, J. (2019). Deductive approach to content analysis. In *Qualitative techniques for workplace data analysis* (pp. 145-169). IGI Global.

Papadimitri, P., Tasiou, M., Tsagkarakis, M. P., & Pasiouras, F. (2021). FinTech and financial intermediation. In *The Palgrave Handbook of FinTech and Blockchain* (pp. 347-374). Palgrave Macmillan.

Parasuraman, A. (2000). Technology readiness index (TRI): A multiple-item scale to measure readiness to embrace new technologies. *Journal of Service Research*, 2(4), 307-320.

Philippon, T. (2016). *The fintech opportunity* (No. w22476). National Bureau of Economic Research.

Pimentel, E. & Boulianne, E. (2020). Blockchain in accounting research and practice: Current trends and future opportunities. *Accounting Perspectives*, 19(4), pp. 325-361.

Poornima, M. K. (2022). Use of robo-advisors by fintech companies to facilitate mutual fund investments. *Journal of Positive School Psychology*, 6(3), pp. 10006-10012.

Popelo, O., Dubyna, M. & Kholiavko, N. (2021). World experience in the introduction of modern innovation and information technologies in the functioning of financial institutions. *Baltic Journal of Economic Studies*, 7(2), pp. 188-199.

Putritama, A. (2019). The Mobile Payment Fintech Continuance Usage Intention in Indonesia. *Journul Economia*, 15(2), pp. 243–258.

PwC (2022). *Our Take: Financial Services Regulatory Update*. PwC US.

PwC (2023). *FinTech innovation in Singapore: Sustaining growth in uncertain times*. PwC Singapore.

PwC (2023a). Leading in the new reality. *PwC 26<sup>th</sup> Annual Global CEO Survey*. PwC Asia Pacific.

Rabbani, M. R., Abdulla, Y., Basahr, A., Khan, S. & Moh'd Ali, M. A. (2020). Embracing of Fintech in Islamic Finance in the post COVID era. In *2020 International Conference on Decision Aid Sciences and Application (DASA)*, pp. 1230-1234. IEEE.

Rahman, M. S., Ismail, I. & Nor, M. N. M. (2022). Determinants of e-wallet adoption among working adults in Malaysia. *Journal of Financial Services Marketing*, 27(2), pp. 123-135.

Rahman, S. U., Nguyen-Viet, B., Nguyen, Y. T. H. & Kamran, S. (2024). Promoting fintech: driving developing country consumers' mobile wallet use through gamification and trust. *International Journal of Bank Marketing*, 42(5), pp. 841-869.

Research and Markets (2022). Insights on the Open Banking Global Market to 2031. *Financial Services, Distribution Channel and Region*. Retrieved from <https://www.globenewswire.com/en/news-release/2022/10/28/2543585/28124/en/Insights-on-the-Open-Banking-Global-Market-to-2031-by-Financial-Services-Distribution-Channel-and-Region.html>.

- Robiady, N. D., Windasari, N. A. & Nita, A. (2021). Customer engagement in online social crowdfunding: The influence of storytelling technique on donation performance. *International journal of research in marketing*, 38(2), pp. 492-500.
- Rogers, E. M. (1995). Lessons for guidelines from the diffusion of innovations. *The Joint Commission Journal on Quality Improvement*, 21(7), pp. 324-328.
- Roh, T., Park, B. I., & Xiao, S. (2023). Adoption of AI-enabled robo-advisors in FinTech: Simultaneous employment of UTAUT and the theory of reasoned action. *Journal of Electronic Commerce Research*, 24(1), 29-55.
- Rossi, A. G. & Utkus, S. P. (2020). Who benefits from robo-advising? Evidence from machine learning. *Evidence from Machine Learning* (March 10, 2020).
- Ryu, H. S. and Ko, K. S. (2020). Sustainable development of Fintech: Focused on uncertainty and perceived quality issues. *Sustainability*, 12(18), p. 7669.
- Salampasis, D. & Mention, A. L. (2018). FinTech: Harnessing innovation for financial inclusion. In *Handbook of Blockchain, Digital Finance, and Inclusion*, 2, pp. 451-461. Academic Press.
- Sampat, B., Mogaji, E. & Nguyen, P. N. (2024). The dark side of FinTech in financial services: a qualitative enquiry into FinTech developers' perspective. *International Journal of Bank Marketing*, 42(1), pp. 38-65.
- Saunders, M., Lewis, P. & Thornhill, A. (2019). *Research methods for business students* (8th ed.). Pearson Education Limited.
- SC (2023). Annual Report 2023. *Securities Commission Malaysia*.
- Senaviratna, N. A. M. R. & Cooray, T. M. J. A. (2019). Diagnosing multicollinearity of logistic regression model. *Asian Journal of Probability and Statistics*, 5(2), pp. 1-9.
- Shahzad, A., Zahrullail, N., Akbar, A., Mohelska, H. & Hussain, A. (2022). COVID-19's impact on Fintech adoption: Behavioural intention to use the financial portal. *Journal of Risk and Financial Management*, 15(10), p. 428.



Sharin, F. H., Hernandez, M. S., & Sentosa, I. (2023). Future trends of blockchain technology in the technological fields. *2023 3rd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE)*, pp. 1307-1313.

Sheng, T. (2021). The effect of fintech on banks' credit provision to SMEs: Evidence from China. *Finance Research Letters*, 39, p. 101558.

Sieber, S. (2021). Open Banking: What does it mean for the US? Retrieved from: <https://www.forbes.com/sites/scarlettsieber/2021/03/03/open-banking-what-does-it-mean-for-the-us/?sh=180aa28db52a>.

Singh, S., Sahni, M. M. & Kovid, R. K. (2020). What drives FinTech adoption? A multi-method evaluation using an adapted technology acceptance model. *Management Decision*, 58(8), pp. 1675-1697.

Solanki, R. & Sujee, S. L. (2022). Fintech: A disruptive innovation of the 21st century, or is it? *Global Business and Management Research: An International Journal*, 14(2s), p. 76.

Soni, G., Kumar, S., Mahto, R. V., Mangla, S. K., Mittal, M. L. and Lim, W. M. (2022). A decision-making framework for Industry 4.0 technology implementation: The case of FinTech and sustainable supply chain finance for SMEs. *Technological Forecasting and Social Change*, 180, p. 121686.

Statista (2024). *Share of LinkedIn users in Malaysia as of January 2023, by age group*. Retrieved from <https://www.statista.com/statistics/1114266/malaysia-share-of-linkedin-users-by-age/>.

Suryono, R. R., Budi, I. & Purwandari, B. (2020). Challenges and trends of financial technology (Fintech): A systematic literature review. *Information*, 11(12), p. 590.

Suseendran, G., Chandrasekaran, E., Akila, D. & Sasi Kumar, A. (2020). Banking and FinTech (financial technology) embraced with IoT device. In *Data management, Analytics and Innovation* (pp. 197-211). Springer, Singapore.

Szopinski, D., Massa, L., John, T., Kundisch, D. & Tucci, C. L. (2022). Modeling business models: A cross-disciplinary analysis of business model modeling languages and directions for future research. *Communications of the Association for Information Systems*, 51(1), p. 39.

Taber, K. S. (2018). The use of Cronbach's alpha when developing and reporting research instruments in science education. *Research in science education*, 48(6), pp. 1273-1296.

Taherdoost, H. (2019). What is the best response scale for survey and questionnaire design; review of different lengths of rating scale/attitude scale/Likert scale. *Hamed Taherdoost*, pp. 1-10.

Tan, G. K. S. (2022). Buy what you want, today! Platform ecologies of 'buy now, pay later'services in Singapore. *Transactions of the Institute of British Geographers*, 47(4), pp. 912-926.

Tang, H. (2019). Peer-to-peer lenders versus banks: Substitutes or complements?. *The Review of Financial Studies*, 32(5), pp. 1900-1938.

Tapanainen, T. (2020). Toward fintech adoption framework for developing countries-A literature review based on the stakeholder perspective. *Journal of Information Technology Applications and Management*, 27(5), pp. 1-22.

Taylor, S. & Todd, P. A. (1995). Understanding information technology usage: A test of competing models. *Information systems research*, 6(2), pp. 144-176.

Teoh, M. T. T., & Yap, A. K. H. (2021). The Adoption of FinTech during COVID-19 Pandemic in Malaysia. *Malaysia Digital Economy Corporation (MDEC)*.

Thakor, A. V. (2020). Fintech and banking: What do we know? *Journal of Financial Intermediation*, 41, p. 100833.

Treu, J. (2022). The FinTech sensation - what is it about? *Journal of International Business and Management*, 5(1), pp. 1-19.

Tsikriktsis, N. (2004). A technology readiness-based taxonomy of customers: A replication and extension. *Journal of Service Research*, 7(1), pp. 42-52.

- Tun-Pin, C., Keng-Soon, W. C., Yen-San, Y., Pui-Yee, C., Hong-Leong, J. T. and Shwu-Shing, N. (2019). An adoption of fintech service in Malaysia. *South East Asia Journal of Contemporary Business*, 18(5), pp. 134-147.
- Urus, S. T., & Mohamed, I. S. (2021). A flourishing fintech ecosystem: Conceptualisation and governing issues in Malaysia. *Business and Economic Research*, 11(3), p. 106.
- Urus, S. T., Othman, I. W., Nazri, S. N. F. S. M. & Kurniasari, F. (2022). Fintech payment services among fresh graduates: The UTAUT model perspective. *International Journal of Academic Research in Business and Social Sciences*, 12(3), pp. 850–869.
- Vallee, B. & Zeng, Y. (2019). Marketplace lending: A new banking paradigm? *The Review of Financial Studies*, 32(5), pp. 1939-1982.
- Vasquez, O. & San-Jose, L. (2022). Ethics and trust on Fintech platforms from an emerging markets perspective. In *Handbook of Banking and Finance in Emerging Markets* (pp. 479-491). Edward Elgar Publishing.
- Venkatesh, V. & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision sciences*, 39(2), pp. 273-315.
- Venkatesh, V. & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management science*, 46(2), pp. 186-204.
- Venkatesh, V., Morris, M. G., Davis, G. B. & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS quarterly*, pp. 425-478.
- Ventre, I. & Kolbe, D. (2020). The impact of perceived usefulness of online reviews, trust and perceived risk on online purchase intention in emerging markets: A Mexican perspective. *Journal of International Consumer Marketing*, 32(4), pp. 287-299.
- Vergara, C. C. & Agudo, L. F. (2021). Fintech and sustainability: Do they affect each other? *Sustainability*. 13(13), p. 7012.
- Wamba, S. F. & Queiroz, M. M. (2020). Blockchain in the operations and supply chain management: Benefits, challenges and future research opportunities. *International Journal of Information Management*, 52, p. 102064.

Wang, Y., Xiuping, S. & Zhang, Q. (2021). Can FinTech improve the efficiency of commercial banks? An analysis based on big data. *Research in International Business and Finance*, 55, p. 101338.

Wang, Z. N., Guan, Z. Z., Hou, F. F., Li, B. Y. & Zhou, W. Y. (2019). What determines customers' continuance intention of Fintech? Evidence from YuEbao. *Industrial Management & Data Systems*, 119(8), pp. 1625–1637.

Wiczorek, R. & Meyer, J. (2019). Effects of trust, self-confidence, and feedback on the use of decision automation. *Frontiers in Psychology*, 10, p. 519.

Windasari, N. A., Kusumawati, N., Larasati, N., & Amelia, R. P. (2022). Digital-only banking experience: Insights from gen Y and gen Z. *Journal of Innovation & Knowledge*, 7(2), 100170. DOI: 10.1016/j.jik.2022.100170.

WIPO (2024). WIPO-administered Treaties. *World Intellectual Property Organization*.

World Bank (2019). *Global Financial Inclusion and Consumer Protection Survey – 2019 Report*. World Bank, Washington, DC.

Worrell, D. (2020). Economic Progress in Central America and the Caribbean in the Past 30 Years.

Wu, G. & Peng, Q. (2024). Bridging the digital divide: unravelling the determinants of FinTech adoption in rural communities. *SAGE Open*, 14(1).

Xiao, H. (2021). The impact of cross-border mergers and acquisitions on competitors' innovation: evidence from Chinese firms. *Technology Analysis & Strategic Management*, pp. 1-14.

Xie, J., Ye, L., Huang, W. & Ye, M. (2021). Understanding FinTech platform adoption: impacts of perceived value and perceived risk. *Journal of Theoretical and Applied Electronic Commerce Research*, 16(5), pp. 1893-1911.

Zakariyah, H., Salaudeen, A. O., Othman, A. H. A. & Rosman, R. (2023). The determinants of financial technology adoption amongst Malaysian *waqf* institutions. *International Journal of Social Economics*, 50(9), 1302-1322.

Zarifis, A., & Cheng, X. (2024). The five emerging business models of FinTech for AI adoption, growth, and building trust. In A. Zarifis, D. Ktoridou, L. Efthymiou, & X. Cheng (Eds.), *Business Digital Transformation* (pp. 73-97). Palgrave Macmillan.

Zhao, H. & Liu, X. (2022). What makes consumers trust and adopt fintech? An empirical investigation in China. *Electronic Commerce Research*, 24(2), pp. 1-33.

Zhao, H., Khaliq, N., Li, C., Rehman, F. U. & Popp, J. (2024). Exploring trust determinants influencing the intention to use fintech via SEM approach: Evidence from Pakistan. *Heliyon*, 10(8), p. e29716.

Zhao, J., Li, X., Yu, C. H., Chen, S. and Lee, C. C. (2022). Riding the FinTech innovation wave: FinTech, patents and bank performance. *Journal of International Money and Finance*, 122, p. 102552.

Zhao, Y. (2023). The fintech revolution: Innovations reshaping the financial industry. *Highlights in Business, Economics and Management*, 15, pp. 123-128.

Ziouache, A. & Bouteraa, M. (2023). Descriptive approach of neo-banking system: conception, challenges and global practices. *International Journal of Business and Technology Management*, 5(2), pp. 194-204.

## APPENDICES

### Appendix 1: Design of the Survey Questionnaire

#### Part 1: Demographics

Gender: ☐ Male ☐ Female

Age group: ☐ 18 – 25 ☐ 26 – 33 ☐ 34 – 41 ☐ 42 – 49 ☐ 50 and above

Race: ☐ Malay ☐ Chinese ☐ Indian ☐ Others: \_\_\_\_\_

Education level: ☐ Primary school ☐ Secondary school ☐ Diploma ☐ Degree ☐ Master ☐ PhD

Employment status: ☐ Self-employed ☐ Employed full-time ☐ Employed part-time  
☐ Unemployed

Household income: ☐ Less than RM4,000 ☐ RM4,000 – RM7,000 ☐ RM7,000-RM10,000  
☐ More than RM10,000

## Part 2: Convenience

No.	Question	Factor	Likert Scale				
			1	2	3	4	5
1	I find FinTech application not cumbersome to use.	Convenience					
2	Learning to operate FinTech application is easy for me.	Convenience					
3	Interacting with FinTech applications is not frustrating to me.	Convenience					
4	I find it easy to get the FinTech application to do what I want it to do.	Convenience					
5	FinTech application is flexible for me to interact with.	Convenience					
6	I can easily remember how to perform tasks using FinTech applications.	Convenience					
7	Interacting with FinTech applications requires minimal effort from me.	Convenience					
8	My interaction with FinTech application is clear and understandable.	Convenience					
9	I find it takes less effort to become skilful at using FinTech applications.	Convenience					
10	Overall, I find FinTech application convenient to use.	Convenience					

### Part 3: Usefulness

No.	Question	Factor	Likert Scale				
			1	2	3	4	5
1	Using FinTech applications improves the quality of the tasks I do.	Usefulness					
2	Using FinTech applications gives me greater control over my tasks.	Usefulness					
3	FinTech applications enable me to accomplish tasks more quickly.	Usefulness					
4	FinTech applications support critical aspects of my tasks.	Usefulness					
5	Using FinTech applications increases my productivity.	Usefulness					
6	Using FinTech applications improves my job performance.	Usefulness					
7	Using FinTech applications allows me to accomplish more tasks than would otherwise be possible.	Usefulness					
8	FinTech applications enhance my effectiveness at my tasks.	Usefulness					
9	Using FinTech applications makes it easier to do my tasks.	Usefulness					
10	Overall, I find the FinTech applications useful in my tasks.	Usefulness					



#### Part 4: Social Influence

No.	Question	Factor	Likert Scale				
			1	2	3	4	5
1	People who are important to me are likely to recommend using FinTech applications.	Social influence					
2	People who are important to me would probably suggest that I should use FinTech applications.	Social influence					
3	People who are important to me expect me to use FinTech applications.	Social influence					
4	People around me who use FinTech applications have more prestige than those who do not.	Social influence					
5	People who use FinTech applications have a higher profile.	Social influence					
6	Using FinTech applications is considered a status symbol among my friends.	Social influence					
7	People who influence my behaviour think that I should use FinTech applications.	Social influence					
8	My friend thinks that I should use FinTech applications.	Social influence					

## Part 5: Promotions

No.	Question	Factor	Likert Scale				
			1	2	3	4	5
1	Using FinTech applications with promotions is rather pleasant.	Promotions					
2	The FinTech application is rather enjoyable.	Promotions					
3	If I heard about a new FinTech application, I'd look for ways to experiment with it.	Promotions					
4	Among my peers, I am usually the first to explore new FinTech applications.	Promotions					
5	I like to experiment with new FinTech applications.	Promotions					
6	In general, I am not hesitant to try out new FinTech applications.	Promotions					

## Part 6: Trust

No.	Question	Factor	Likert Scale				
			1	2	3	4	5
1	FinTech applications give me a feeling of trust.	Trust					
2	FinTech applications give a trustworthy impression.	Trust					
3	I have trust in FinTech applications.	Trust					
4	The service provider for FinTech applications can be relied upon to keep promises.	Trust					
5	The service provider for FinTech applications is trustworthy.	Trust					
6	I have full confidence in the service provider for FinTech applications.	Trust					

## Part 7: Intention to Use

No.	Question	Factor	Likert Scale				
			1	2	3	4	5
1	Assuming I have access to a FinTech application, I intend to adopt it.	Intention to use					
2	Given that I have access to a FinTech application, I predict that I would adopt it.	Intention to use					
3	I would positively consider FinTech in my choice set.	Intention to use					
4	I prefer to use FinTech.	Intention to use					
5	I intend to continue to use FinTech.	Intention to use					

## Appendix 2: Reliability of Questionnaire (Pilot Test)

### Convenience

#### Case Processing Summary

		N	%
Cases	Valid	50	100.0
	Excluded <sup>a</sup>	0	.0
	Total	50	100.0

a. Listwise deletion based on all variables in the procedure.

#### Reliability Statistics

Cronbach's Alpha	N of Items
.796	10

#### Item Statistics

	Mean	Std. Deviation	N
CO1	4.20	.700	50
CO2	3.44	1.110	50
CO3	3.18	.896	50
CO4	3.16	1.057	50
CO5	3.52	1.035	50
CO6	3.78	.954	50
CO7	3.16	1.076	50
CO8	3.34	1.099	50
CO9	3.78	.887	50
CO10	3.40	1.050	50

### Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
CO1	30.76	32.553	.227	.801
CO2	31.52	27.030	.572	.765
CO3	31.78	29.440	.474	.778
CO4	31.80	27.796	.533	.770
CO5	31.44	32.170	.138	.817
CO6	31.18	29.498	.429	.783
CO7	31.80	27.878	.512	.773
CO8	31.62	25.710	.712	.746
CO9	31.18	30.151	.402	.786
CO10	31.56	26.496	.671	.752

### Scale Statistics

Mean	Variance	Std. Deviation	N of Items
34.96	34.856	5.904	10

## Usefulness

### Case Processing Summary

		N	%
Cases	Valid	50	100.0
	Excluded <sup>a</sup>	0	.0
	Total	50	100.0

a. Listwise deletion based on all variables in the procedure.

### Reliability Statistics

Cronbach's Alpha	N of Items
.769	10

### Item Statistics

	Mean	Std. Deviation	N
US1	4.10	.735	50
US2	3.46	1.014	50
US3	3.28	.927	50
US4	3.08	1.007	50
US5	3.50	.974	50
US6	3.78	.975	50
US7	3.26	1.084	50
US8	3.40	1.107	50
US9	3.62	.901	50
US10	3.30	.995	50

### Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
US1	30.68	29.569	.110	.782
US2	31.32	24.059	.593	.727
US3	31.50	25.561	.488	.743
US4	31.70	24.337	.568	.731
US5	31.28	29.593	.042	.798
US6	31.00	25.714	.438	.749
US7	31.52	24.132	.533	.735
US8	31.38	23.220	.614	.722
US9	31.16	27.566	.276	.769
US10	31.48	23.724	.648	.719

### Scale Statistics

Mean	Variance	Std. Deviation	N of Items
34.78	30.991	5.567	10



## Social influence

### Case Processing Summary

		N	%
Cases	Valid	50	100.0
	Excluded <sup>a</sup>	0	.0
	Total	50	100.0

a. Listwise deletion based on all variables in the procedure.

### Reliability Statistics

Cronbach's Alpha	N of Items
.739	8

### Item Statistics

	Mean	Std. Deviation	N
SI1	4.20	.700	50
SI2	3.44	1.110	50
SI3	3.26	.777	50
SI4	3.24	.960	50
SI5	3.52	1.035	50
SI6	3.84	.866	50
SI7	3.26	.986	50
SI8	3.40	1.050	50

### Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
SI1	23.96	18.366	.227	.744
SI2	24.72	14.573	.521	.694
SI3	24.90	16.541	.486	.706
SI4	24.92	15.585	.490	.701
SI5	24.64	17.460	.195	.761
SI6	24.32	16.753	.383	.722
SI7	24.90	15.398	.497	.699
SI8	24.76	13.778	.685	.655

### Scale Statistics

Mean	Variance	Std. Deviation	N of Items
28.16	20.219	4.497	8

## Promotions

### Case Processing Summary

		N	%
Cases	Valid	50	100.0
	Excluded <sup>a</sup>	0	.0
	Total	50	100.0

a. Listwise deletion based on all variables in the procedure.

### Reliability Statistics

Cronbach's Alpha	N of Items
.687	6

### Item Statistics

	Mean	Std. Deviation	N
PR1	3.44	1.110	50
PR2	3.18	.896	50
PR3	3.16	1.057	50
RP4	3.52	1.035	50
PR5	3.78	.954	50
PR6	3.16	1.076	50

### Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
PR1	16.80	10.327	.443	.638
PR2	17.06	10.180	.653	.576
PR3	17.08	9.953	.547	.600
RP4	16.72	14.696	-.132	.806
PR5	16.46	10.621	.512	.617
PR6	17.08	9.381	.634	.566

### Scale Statistics

Mean	Variance	Std. Deviation	N of Items
20.24	14.717	3.836	6

## Trust

### Case Processing Summary

		N	%
Cases	Valid	50	100.0
	Excluded <sup>a</sup>	0	.0
	Total	50	100.0

a. Listwise deletion based on all variables in the procedure.

### Reliability Statistics

Cronbach's Alpha	N of Items
.626	6

### Item Statistics

	Mean	Std. Deviation	N
TR1	3.08	1.007	50
TR2	3.50	.974	50
TR3	3.78	.975	50
TR4	3.26	1.084	50
TR5	3.40	1.107	50
TR6	3.62	.901	50

### Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
TR1	17.56	8.986	.465	.539
TR2	17.14	11.470	.059	.686
TR3	16.86	9.837	.330	.592
TR4	17.38	8.281	.537	.503
TR5	17.24	8.104	.552	.494
TR6	17.02	10.673	.224	.628

### Scale Statistics

Mean	Variance	Std. Deviation	N of Items
20.64	12.807	3.579	6

## Intention to Use

### Case Processing Summary

		N	%
Cases	Valid	50	100.0
	Excluded <sup>a</sup>	0	.0
	Total	50	100.0

a. Listwise deletion based on all variables in the procedure.

### Reliability Statistics

Cronbach's Alpha	N of Items
.723	5

### Item Statistics

	Mean	Std. Deviation	N
IU1	3.78	.954	50
IU2	3.16	1.076	50
IU3	3.34	1.099	50
IU4	3.78	.887	50
IU5	3.40	1.050	50

### Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
IU1	13.68	9.242	.362	.719
IU2	14.30	8.255	.459	.686
IU3	14.12	7.373	.615	.618
IU4	13.68	9.283	.404	.705
IU5	14.06	7.772	.577	.636

### Scale Statistics

Mean	Variance	Std. Deviation	N of Items
17.46	12.253	3.500	5

## Overall

### **Reliability Statistics**

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.883	.880	45

### **Scale Statistics**

Mean	Variance	Std. Deviation	N of Items
156.24	322.349	17.954	45

### Appendix 3: Reliability Testing (Cronbach's Alpha): Pre-Refinement

#### Convenience

**Case Processing Summary**

		N	%
Cases	Valid	313	100.0
	Excluded <sup>a</sup>	0	.0
	Total	313	100.0

a. Listwise deletion based on all variables in the procedure.

**Reliability Statistics**

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.811	.811	10

**Item Statistics**

	Mean	Std. Deviation	N
CO1	3.94	.966	313
CO2	3.39	1.060	313
CO3	3.27	.844	313
CO4	3.13	1.037	313
CO5	3.43	1.042	313
CO6	3.68	.980	313
CO7	3.34	.984	313
CO8	3.30	1.037	313
CO9	3.67	.956	313
CO10	3.45	.980	313

**Inter-Item Correlation Matrix**

	CO1	CO2	CO3	CO4	CO5	CO6	CO7	CO8	CO9	CO10
CO1	1.000	.260	.008	.180	.458	.272	.091	.353	.354	.204
CO2	.260	1.000	.432	.362	.106	.465	.340	.383	.225	.542
CO3	.008	.432	1.000	.405	.087	.330	.586	.326	.148	.240
CO4	.180	.362	.405	1.000	.087	.435	.321	.407	.192	.430
CO5	.458	.106	.087	.087	1.000	.021	.113	.452	.371	.238
CO6	.272	.465	.330	.435	.021	1.000	.364	.154	.217	.303
CO7	.091	.340	.586	.321	.113	.364	1.000	.443	.299	.192
CO8	.353	.383	.326	.407	.452	.154	.443	1.000	.446	.496
CO9	.354	.225	.148	.192	.371	.217	.299	.446	1.000	.345
CO10	.204	.542	.240	.430	.238	.303	.192	.496	.345	1.000

**Inter-Item Covariance Matrix**

	CO1	CO2	CO3	CO4	CO5	CO6	CO7	CO8	CO9	CO10
CO1	.933	.266	.006	.181	.461	.257	.087	.354	.327	.193
CO2	.266	1.123	.386	.397	.117	.483	.355	.421	.228	.563
CO3	.006	.386	.713	.355	.077	.273	.487	.286	.120	.199
CO4	.181	.397	.355	1.076	.094	.442	.327	.438	.191	.437
CO5	.461	.117	.077	.094	1.086	.021	.116	.489	.370	.243
CO6	.257	.483	.273	.442	.021	.961	.351	.156	.203	.291
CO7	.087	.355	.487	.327	.116	.351	.968	.452	.282	.186
CO8	.354	.421	.286	.438	.489	.156	.452	1.076	.442	.504
CO9	.327	.228	.120	.191	.370	.203	.282	.442	.914	.323
CO10	.193	.563	.199	.437	.243	.291	.186	.504	.323	.960

**Item-Total Statistics**

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
CO1	30.67	31.086	.396	.361	.804
CO2	31.23	28.727	.566	.475	.785
CO3	31.34	31.194	.464	.457	.797
CO4	31.49	29.481	.508	.384	.792
CO5	31.19	31.222	.341	.361	.811
CO6	30.93	30.364	.459	.404	.797
CO7	31.28	30.028	.490	.479	.794
CO8	31.32	28.121	.644	.547	.776
CO9	30.95	30.398	.472	.310	.796
CO10	31.16	29.445	.553	.465	.787

**Scale Statistics**

Mean	Variance	Std. Deviation	N of Items
34.62	36.282	6.023	10



## Usefulness

**Case Processing Summary**

		N	%
Cases	Valid	313	100.0
	Excluded <sup>a</sup>	0	.0
	Total	313	100.0

a. Listwise deletion based on all variables in the procedure.

**Reliability Statistics**

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.805	.804	10

**Item Statistics**

	Mean	Std. Deviation	N
US1	3.98	.928	313
US2	3.43	1.045	313
US3	3.29	.925	313
US4	3.16	1.021	313
US5	3.45	1.025	313
US6	3.73	.963	313
US7	3.20	1.054	313
US8	3.35	1.043	313
US9	3.70	.934	313
US10	3.47	.974	313

**Inter-Item Correlation Matrix**

	US1	US2	US3	US4	US5	US6	US7	US8	US9	US10
US1	1.000	.221	-.060	.152	.455	.226	.001	.316	.317	.196
US2	.221	1.000	.453	.361	.086	.439	.336	.364	.186	.536
US3	-.060	.453	1.000	.525	.009	.409	.622	.348	.107	.255
US4	.152	.361	.525	1.000	.070	.440	.426	.397	.171	.432
US5	.455	.086	.009	.070	1.000	.012	.110	.433	.371	.224
US6	.226	.439	.409	.440	.012	1.000	.360	.148	.169	.299
US7	.001	.336	.622	.426	.110	.360	1.000	.529	.226	.159
US8	.316	.364	.348	.397	.433	.148	.529	1.000	.403	.500
US9	.317	.186	.107	.171	.371	.169	.226	.403	1.000	.340
US10	.196	.536	.255	.432	.224	.299	.159	.500	.340	1.000

**Inter-Item Covariance Matrix**

	US1	US2	US3	US4	US5	US6	US7	US8	US9	US10
US1	.862	.215	-.051	.145	.433	.202	.001	.306	.275	.177
US2	.215	1.092	.438	.385	.092	.442	.371	.397	.182	.545
US3	-.051	.438	.856	.496	.008	.364	.606	.335	.093	.230
US4	.145	.385	.496	1.043	.073	.433	.458	.422	.163	.429
US5	.433	.092	.008	.073	1.050	.012	.119	.463	.355	.224
US6	.202	.442	.364	.433	.012	.928	.366	.149	.152	.280
US7	.001	.371	.606	.458	.119	.366	1.112	.582	.223	.163
US8	.306	.397	.335	.422	.463	.149	.582	1.088	.392	.507
US9	.275	.182	.093	.163	.355	.152	.223	.392	.872	.310
US10	.177	.545	.230	.429	.224	.280	.163	.507	.310	.949

**Item-Total Statistics**

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
US1	30.78	31.510	.327	.376	.804
US2	31.33	28.556	.549	.459	.780
US3	31.47	29.884	.498	.537	.786
US4	31.60	28.727	.549	.437	.780
US5	31.31	31.170	.311	.351	.807
US6	31.03	30.047	.455	.391	.791
US7	31.56	28.889	.510	.578	.785
US8	31.41	27.582	.649	.597	.768
US9	31.06	30.618	.415	.268	.795
US10	31.29	29.098	.546	.518	.781

**Scale Statistics**

Mean	Variance	Std. Deviation	N of Items
34.76	35.779	5.982	10

## Social influence

**Case Processing Summary**

		N	%
Cases	Valid	313	100.0
	Excluded <sup>a</sup>	0	.0
	Total	313	100.0

a. Listwise deletion based on all variables in the procedure.

**Reliability Statistics**

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.775	.776	8

**Item Statistics**

	Mean	Std. Deviation	N
SI1	3.95	.958	313
SI2	3.40	1.057	313
SI3	3.28	.901	313
SI4	3.17	1.007	313
SI5	3.44	1.036	313
SI6	3.69	.962	313
SI7	3.21	1.025	313
SI8	3.34	1.000	313

**Inter-Item Correlation Matrix**

	SI1	SI2	SI3	SI4	SI5	SI6	SI7	SI8
SI1	1.000	.252	-.005	.166	.457	.285	.067	.327
SI2	.252	1.000	.471	.348	.099	.473	.348	.377
SI3	-.005	.471	1.000	.476	.046	.396	.602	.365
SI4	.166	.348	.476	1.000	.090	.389	.405	.372
SI5	.457	.099	.046	.090	1.000	.032	.109	.436
SI6	.285	.473	.396	.389	.032	1.000	.394	.151
SI7	.067	.348	.602	.405	.109	.394	1.000	.519
SI8	.327	.377	.365	.372	.436	.151	.519	1.000

**Inter-Item Covariance Matrix**

	SI1	SI2	SI3	SI4	SI5	SI6	SI7	SI8
SI1	.917	.256	-.004	.160	.453	.262	.066	.313
SI2	.256	1.118	.449	.371	.108	.481	.378	.399
SI3	-.004	.449	.812	.432	.043	.343	.556	.328
SI4	.160	.371	.432	1.015	.094	.377	.419	.375
SI5	.453	.108	.043	.094	1.074	.032	.116	.452
SI6	.262	.481	.343	.377	.032	.925	.389	.145
SI7	.066	.378	.556	.419	.116	.389	1.052	.532
SI8	.313	.399	.328	.375	.452	.145	.532	.999

**Item-Total Statistics**

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
SI1	23.53	20.628	.346	.352	.771
SI2	24.08	18.558	.536	.385	.740
SI3	24.19	19.450	.541	.500	.741
SI4	24.30	19.089	.506	.323	.745
SI5	24.04	20.887	.274	.326	.785
SI6	23.78	19.576	.477	.403	.750
SI7	24.26	18.598	.555	.511	.736
SI8	24.14	18.471	.592	.506	.730

**Scale Statistics**

Mean	Variance	Std. Deviation	N of Items
27.47	24.558	4.956	8

## Promotions

### Case Processing Summary

		N	%
Cases	Valid	313	100.0
	Excluded <sup>a</sup>	0	.0
	Total	313	100.0

a. Listwise deletion based on all variables in the procedure.

### Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.707	.705	6

### Item Statistics

	Mean	Std. Deviation	N
PR1	3.16	1.021	313
PR2	3.45	1.025	313
PR3	3.73	.963	313
PR4	3.20	1.054	313
PR5	3.35	1.043	313
PR6	3.70	.934	313

**Inter-Item Correlation Matrix**

	PR1	PR2	PR3	PR4	PR5	PR6
PR1	1.000	.070	.440	.426	.397	.171
PR2	.070	1.000	.012	.110	.433	.371
PR3	.440	.012	1.000	.360	.148	.169
PR4	.426	.110	.360	1.000	.529	.226
PR5	.397	.433	.148	.529	1.000	.403
PR6	.171	.371	.169	.226	.403	1.000

**Inter-Item Covariance Matrix**

	PR1	PR2	PR3	PR4	PR5	PR6
PR1	1.043	.073	.433	.458	.422	.163
PR2	.073	1.050	.012	.119	.463	.355
PR3	.433	.012	.928	.366	.149	.152
PR4	.458	.119	.366	1.112	.582	.223
PR5	.422	.463	.149	.582	1.088	.392
PR6	.163	.355	.152	.223	.392	.872

**Item-Total Statistics**

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
PR1	17.43	10.676	.465	.329	.659
PR2	17.14	11.724	.292	.260	.712
PR3	16.86	11.666	.338	.258	.697
PR4	17.39	10.212	.519	.388	.640
PR5	17.24	9.715	.618	.491	.606
PR6	16.89	11.377	.408	.225	.676

**Scale Statistics**

Mean	Variance	Std. Deviation	N of Items
20.59	14.819	3.850	6

## Trust

### Case Processing Summary

		N	%
Cases	Valid	313	100.0
	Excluded <sup>a</sup>	0	.0
	Total	313	100.0

a. Listwise deletion based on all variables in the procedure.

### Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.728	.732	6

### Item Statistics

	Mean	Std. Deviation	N
TR1	3.39	1.060	313
TR2	3.23	.905	313
TR3	3.13	1.037	313
TR4	3.43	1.042	313
TR5	3.68	.980	313
TR6	3.17	1.065	313

**Inter-Item Correlation Matrix**

	TR1	TR2	TR3	TR4	TR5	TR6
TR1	1.000	.498	.362	.106	.465	.344
TR2	.498	1.000	.456	.051	.371	.561
TR3	.362	.456	1.000	.087	.435	.430
TR4	.106	.051	.087	1.000	.021	.122
TR5	.465	.371	.435	.021	1.000	.383
TR6	.344	.561	.430	.122	.383	1.000

**Inter-Item Covariance Matrix**

	TR1	TR2	TR3	TR4	TR5	TR6
TR1	1.123	.477	.397	.117	.483	.389
TR2	.477	.819	.428	.048	.329	.541
TR3	.397	.428	1.076	.094	.442	.475
TR4	.117	.048	.094	1.086	.021	.135
TR5	.483	.329	.442	.021	.961	.400
TR6	.389	.541	.475	.135	.400	1.135

**Item-Total Statistics**

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
TR1	16.65	10.903	.532	.348	.668
TR2	16.81	11.286	.600	.448	.654
TR3	16.90	11.004	.534	.317	.668
TR4	16.60	13.836	.107	.028	.788
TR5	16.35	11.440	.505	.323	.678
TR6	16.87	10.738	.556	.377	.661

**Scale Statistics**

Mean	Variance	Std. Deviation	N of Items
20.04	15.752	3.969	6



## Intention to Use

### **Case Processing Summary**

		N	%
Cases	Valid	313	100.0
	Excluded <sup>a</sup>	0	.0
	Total	313	100.0

a. Listwise deletion based on all variables in the procedure.

### **Reliability Statistics**

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.712	.711	5

### **Item Statistics**

	Mean	Std. Deviation	N
IU1	3.68	.980	313
IU2	3.17	1.063	313
IU3	3.30	1.037	313
IU4	3.67	.956	313
IU5	3.45	.980	313

**Inter-Item Correlation Matrix**

	IU1	IU2	IU3	IU4	IU5
IU1	1.000	.385	.154	.217	.303
IU2	.385	1.000	.540	.252	.158
IU3	.154	.540	1.000	.446	.496
IU4	.217	.252	.446	1.000	.345
IU5	.303	.158	.496	.345	1.000

**Inter-Item Covariance Matrix**

	IU1	IU2	IU3	IU4	IU5
IU1	.961	.401	.156	.203	.291
IU2	.401	1.130	.595	.256	.165
IU3	.156	.595	1.076	.442	.504
IU4	.203	.256	.442	.914	.323
IU5	.291	.165	.504	.323	.960

**Item-Total Statistics**

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
IU1	13.60	8.652	.365	.266	.704
IU2	14.11	7.751	.479	.431	.661
IU3	13.98	7.243	.608	.538	.603
IU4	13.61	8.354	.443	.233	.675
IU5	13.83	8.188	.458	.359	.669

**Scale Statistics**

Mean	Variance	Std. Deviation	N of Items
17.28	11.716	3.423	5

## Overall Results

### Case Processing Summary

		N	%
Cases	Valid	313	100.0
	Excluded <sup>a</sup>	0	.0
	Total	313	100.0

a. Listwise deletion based on all variables in the procedure.

### Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.905	.904	45

### Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Item Means	3.439	3.131	3.978	.847	1.270	.054	45
Item Variances	.998	.713	1.135	.422	1.592	.010	45
Inter-Item Covariances	.174	-.215	1.131	1.346	-5.269	.065	45
Inter-Item Correlations	.174	-.224	1.000	1.224	-4.462	.064	45

### Scale Statistics

Mean	Variance	Std. Deviation	N of Items
154.76	389.197	19.728	45

## Appendix 4: Descriptive Statistics

### Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	153	48.9	48.9	48.9
	Female	160	51.1	51.1	100.0
	Total	313	100.0	100.0	

### AgeGroup

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	18-25	44	14.1	14.1	14.1
	26-33	121	38.7	38.7	52.7
	34-41	65	20.8	20.8	73.5
	42-49	74	23.6	23.6	97.1
	50_and_above	9	2.9	2.9	100.0
	Total	313	100.0	100.0	

### Race

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Malay	121	38.7	38.7	38.7
	Chinese	101	32.3	32.3	70.9
	Indian	52	16.6	16.6	87.5
	Others	39	12.5	12.5	100.0
	Total	313	100.0	100.0	

### EducationLevel

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Degree	288	92.0	92.0	92.0
	Master	15	4.8	4.8	96.8
	PhD	10	3.2	3.2	100.0
	Total	313	100.0	100.0	

### EmploymentStatus

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Self_employed	30	9.6	9.6	9.6
	Employed_full-time	236	75.4	75.4	85.0
	Employed_part-time	33	10.5	10.5	95.5
	Unemployed	14	4.5	4.5	100.0
	Total	313	100.0	100.0	

### HouseholdIncome

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Less_than_RM4000	25	8.0	8.0	8.0
	RM4000-RM7000	67	21.4	21.4	29.4
	RM7000-RM10000	162	51.8	51.8	81.2
	More_than_RM10000	59	18.8	18.8	100.0
	Total	313	100.0	100.0	

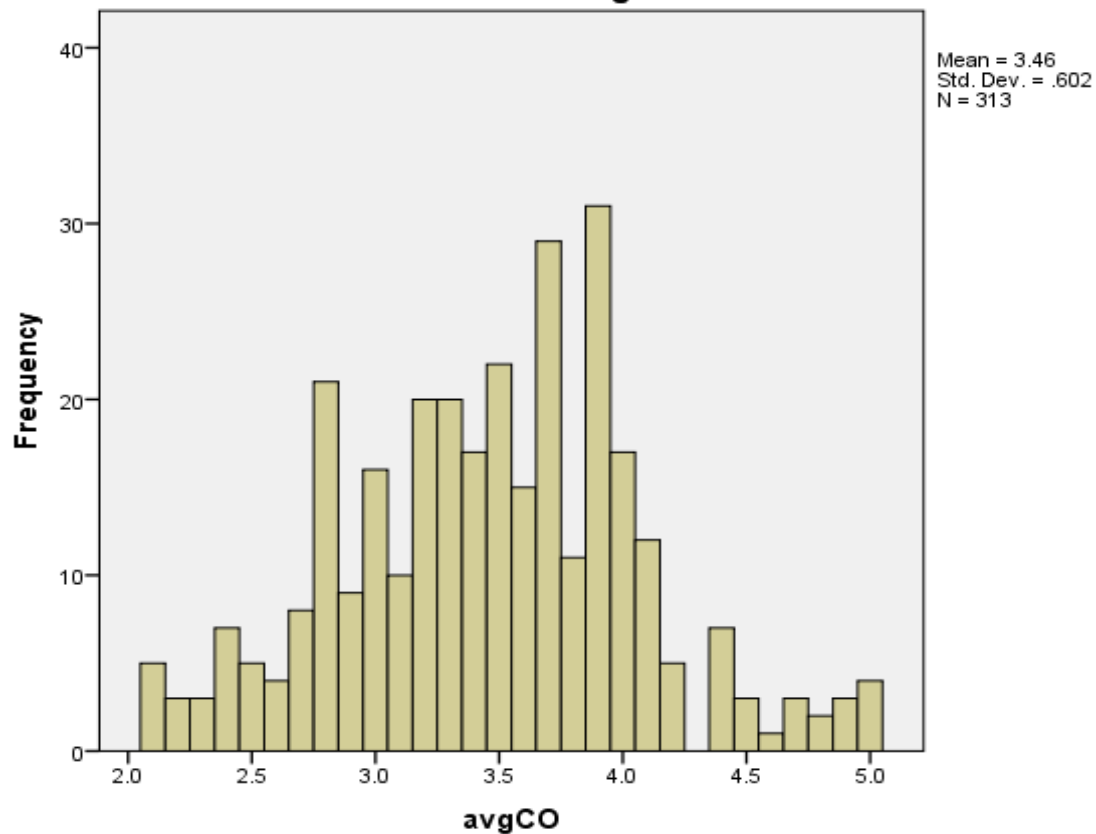
## Appendix 5: Normality Testing (Skewness and Kurtosis): Pre-Refinement

### Convenience

**Descriptives**

			Statistic	Std. Error
avgCO	Mean		3.46	.034
	95% Confidence Interval for Mean	Lower Bound	3.39	
		Upper Bound	3.53	
	5% Trimmed Mean		3.46	
	Median		3.50	
	Variance		.363	
	Std. Deviation		.602	
	Minimum		2	
	Maximum		5	
	Range		3	
	Interquartile Range		1	
	Skewness		.050	.138
	Kurtosis		-.054	.275

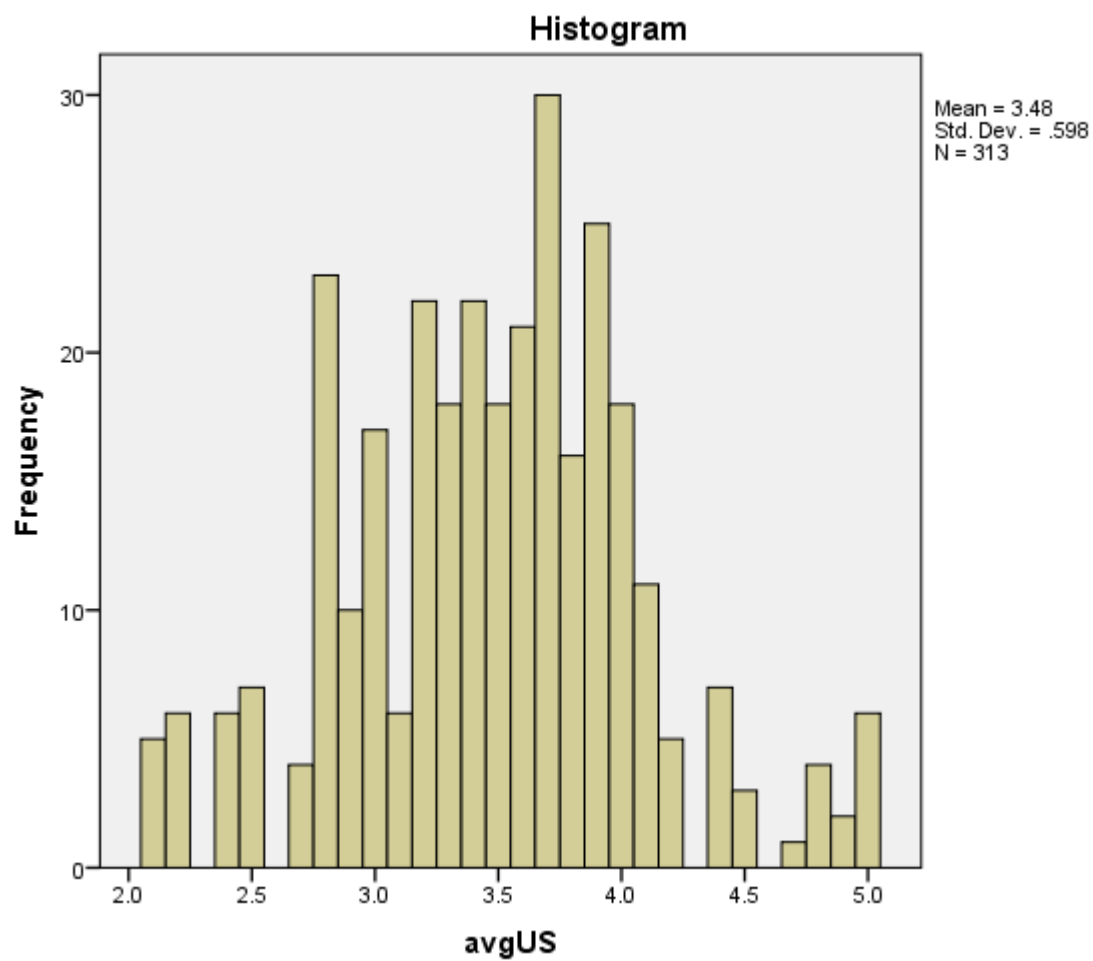
**Histogram**



## Usefulness

**Descriptives**

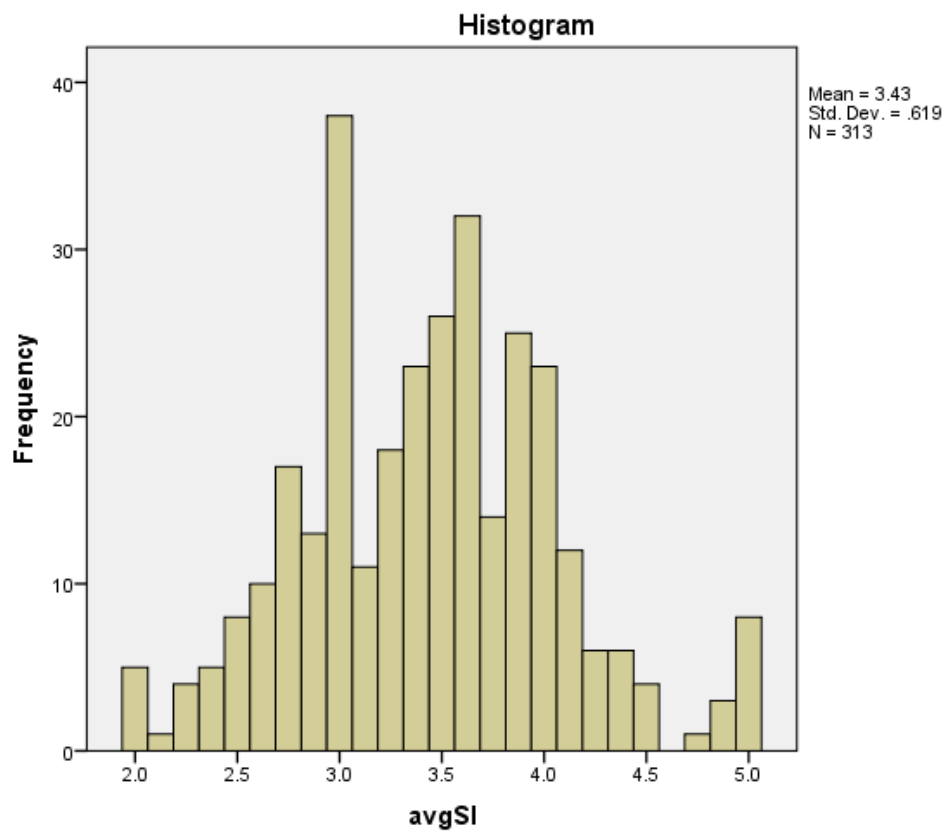
			Statistic	Std. Error
avgUS	Mean		3.48	.034
	95% Confidence Interval for Mean	Lower Bound	3.41	
		Upper Bound	3.54	
	5% Trimmed Mean		3.47	
	Median		3.50	
	Variance		.358	
	Std. Deviation		.598	
	Minimum		2	
	Maximum		5	
	Range		3	
	Interquartile Range		1	
	Skewness		.057	.138
	Kurtosis		.179	.275



## Social influence

**Descriptives**

			Statistic	Std. Error
avgSI	Mean		3.43	.035
	95% Confidence Interval for Mean	Lower Bound	3.37	
		Upper Bound	3.50	
	5% Trimmed Mean		3.42	
	Median		3.50	
	Variance		.384	
	Std. Deviation		.619	
	Minimum		2	
	Maximum		5	
	Range		3	
	Interquartile Range		1	
	Skewness		.181	.138
	Kurtosis		.030	.275

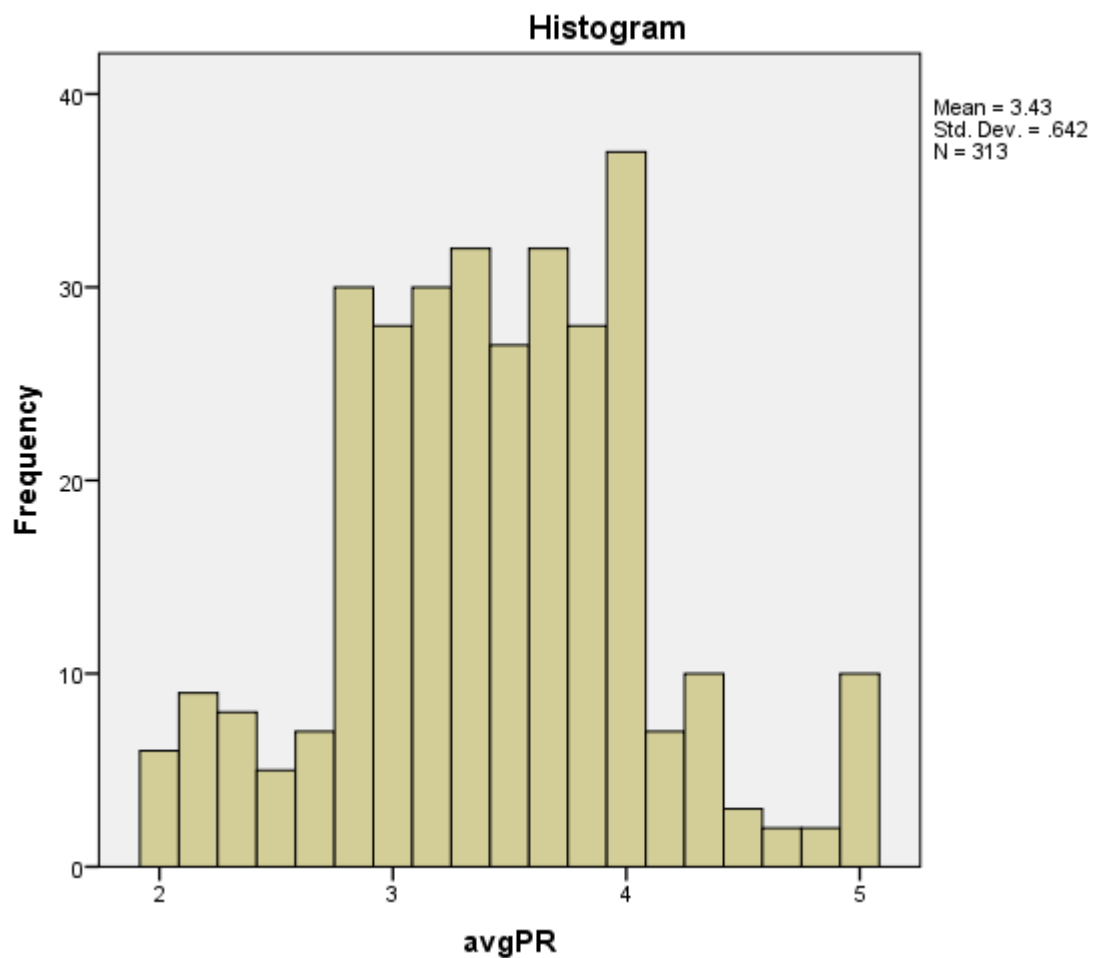




## Promotions

**Descriptives**

			Statistic	Std. Error
avgPR	Mean		3.43	.036
	95% Confidence Interval for Mean	Lower Bound	3.36	
		Upper Bound	3.50	
	5% Trimmed Mean		3.42	
	Median		3.50	
	Variance		.412	
	Std. Deviation		.642	
	Minimum		2	
	Maximum		5	
	Range		3	
	Interquartile Range		1	
	Skewness		.094	.138
	Kurtosis		.078	.275

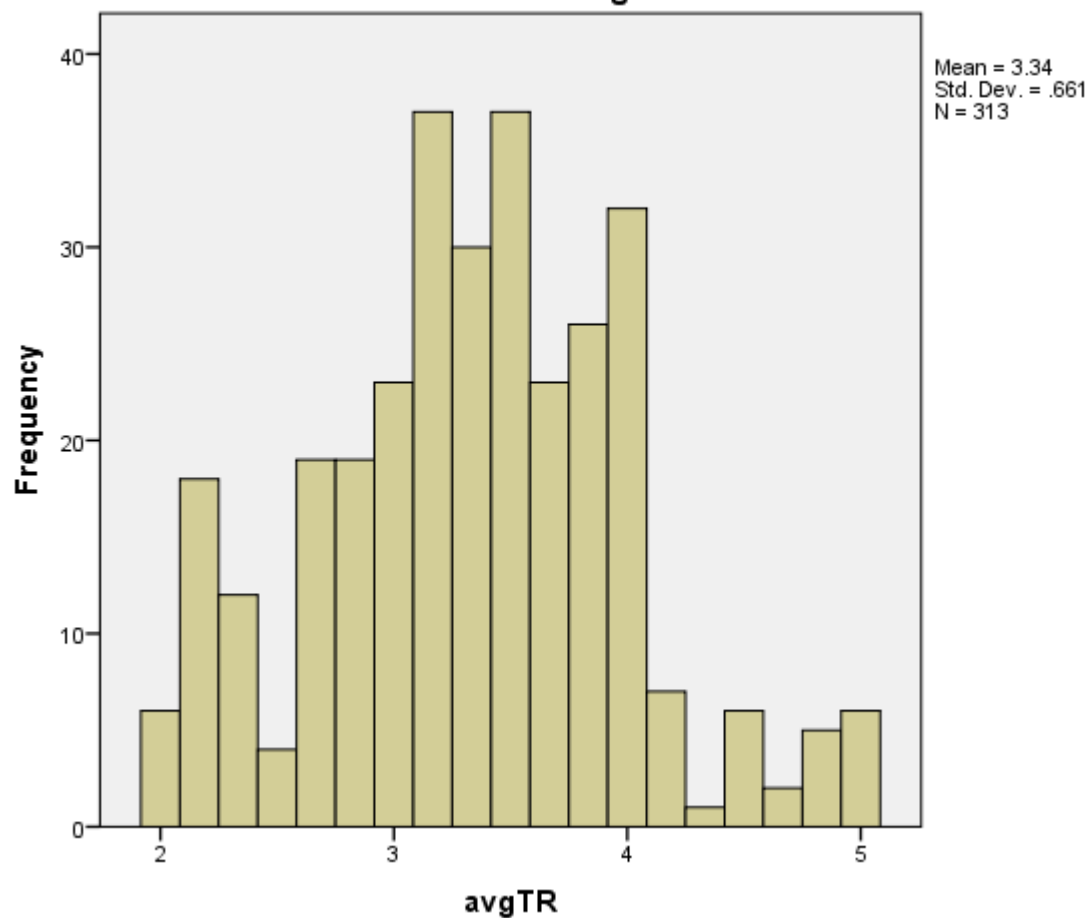


## Trust

**Descriptives**

			Statistic	Std. Error
avgTR	Mean		3.34	.037
	95% Confidence Interval for Mean	Lower Bound	3.27	
		Upper Bound	3.41	
	5% Trimmed Mean		3.33	
	Median		3.33	
	Variance		.438	
	Std. Deviation		.661	
	Minimum		2	
	Maximum		5	
	Range		3	
	Interquartile Range		1	
	Skewness		.102	.138
	Kurtosis		-.078	.275

**Histogram**

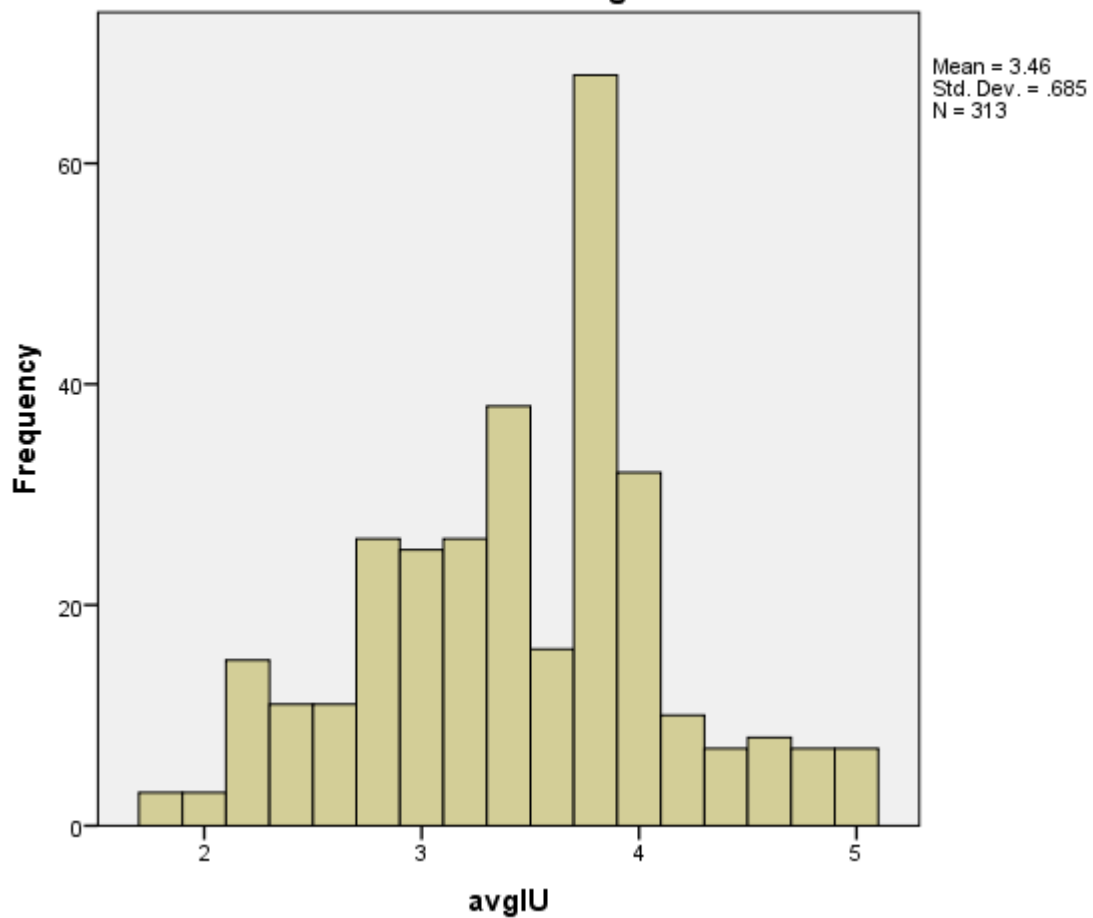


## Intention to Use

**Descriptives**

			Statistic	Std. Error
avglU	Mean		3.46	.039
	95% Confidence Interval for Mean	Lower Bound	3.38	
		Upper Bound	3.53	
	5% Trimmed Mean		3.45	
	Median		3.40	
	Variance		.469	
	Std. Deviation		.685	
	Minimum		2	
	Maximum		5	
	Range		3	
	Interquartile Range		1	
	Skewness		-.101	.138
	Kurtosis		-.237	.275

**Histogram**



## Appendix 6: Pearson Correlations: Pre-Refinement

Correlations		avgCO	avgUS	avgSI	avgPR	avgTR	avgIU
avgCO	Pearson Correlation	1	-.050	.960**	-.037	.911**	.930**
	Sig. (2-tailed)		.381	.000	.520	.000	.000
	Sum of Squares and Cross-products	113.200	-5.588	111.797	-4.401	113.237	119.655
	Covariance	.363	-.018	.358	-.014	.363	.384
	N	313	313	313	313	313	313
avgUS	Pearson Correlation	-.050	1	-.064	.950**	-.098	-.055
	Sig. (2-tailed)	.381		.257	.000	.082	.331
	Sum of Squares and Cross-products	-5.588	111.630	-7.432	113.705	-12.156	-7.038
	Covariance	-.018	.358	-.024	.364	-.039	-.023
	N	313	313	313	313	313	313
avgSI	Pearson Correlation	.960**	-.064	1	-.062	.950**	.876**
	Sig. (2-tailed)	.000	.257		.275	.000	.000
	Sum of Squares and Cross-products	111.797	-7.432	119.719	-7.677	121.392	115.835
	Covariance	.358	-.024	.384	-.025	.389	.371
	N	313	313	313	313	313	313
avgPR	Pearson Correlation	-.037	.950**	-.062	1	-.094	-.055
	Sig. (2-tailed)	.520	.000	.275		.097	.328
	Sum of Squares and Cross-products	-4.401	113.705	-7.677	128.435	-12.458	-7.600
	Covariance	-.014	.364	-.025	.412	-.040	-.024
	N	313	313	313	313	313	313
avgTR	Pearson Correlation	.911**	-.098	.950**	-.094	1	.846**
	Sig. (2-tailed)	.000	.082	.000	.097		.000
	Sum of Squares and Cross-products	113.237	-12.156	121.392	-12.458	136.517	119.530
	Covariance	.363	-.039	.389	-.040	.438	.383
	N	313	313	313	313	313	313
avgIU	Pearson Correlation	.930**	-.055	.876**	-.055	.846**	1
	Sig. (2-tailed)	.000	.331	.000	.328	.000	
	Sum of Squares and Cross-products	119.655	-7.038	115.835	-7.600	119.530	146.210
	Covariance	.384	-.023	.371	-.024	.383	.469
	N	313	313	313	313	313	313

\*\* . Correlation is significant at the 0.01 level (2-tailed).

## Appendix 7: Regression Analysis: Pre-Refinement

**Variables Entered/Removed<sup>a</sup>**

Model	Variables Entered	Variables Removed	Method
1	avgTR, avgPR, avgCO, avgUS, avgSI <sup>b</sup>	.	Enter

a. Dependent Variable: avgIU

b. All requested variables entered.

**Model Summary<sup>b</sup>**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.935 <sup>a</sup>	.874	.872	.245	.874	426.668	5	307	.000	1.970

a. Predictors: (Constant), avgTR, avgPR, avgCO, avgUS, avgSI

b. Dependent Variable: avgIU

**ANOVA<sup>a</sup>**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	127.817	5	25.563	426.668	.000 <sup>b</sup>
	Residual	18.394	307	.060		
	Total	146.210	312			

a. Dependent Variable: avgIU

b. Predictors: (Constant), avgTR, avgPR, avgCO, avgUS, avgSI

**Coefficients<sup>a</sup>**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	-.172	.118		-1.463	.145					
	avgCO	1.336	.083	1.175	16.034	.000	.930	.675	.325	.076	13.115
	avgUS	.169	.074	.147	2.267	.024	-.055	.128	.046	.097	10.330
	avgSI	-.447	.106	-.405	-4.214	.000	.876	-.234	-.085	.044	22.510
	avgPR	-.174	.070	-.163	-2.497	.013	-.055	-.141	-.051	.097	10.361
	avgTR	.164	.067	.159	2.444	.015	.846	.138	.049	.097	10.313

a. Dependent Variable: avgIU

### Coefficient Correlations<sup>a</sup>

Model			avgTR	avgPR	avgCO	avgUS	avgSI
1	Correlations	avgTR	1.000	-.003	.006	.041	-.646
		avgPR	-.003	1.000	-.132	-.949	.100
		avgCO	.006	-.132	1.000	.112	-.738
		avgUS	.041	-.949	.112	1.000	-.105
		avgSI	-.646	.100	-.738	-.105	1.000
	Covariances	avgTR	.005	-1.533E-005	3.618E-005	.000	-.005
		avgPR	-1.533E-005	.005	-.001	-.005	.001
		avgCO	3.618E-005	-.001	.007	.001	-.007
		avgUS	.000	-.005	.001	.006	-.001
		avgSI	-.005	.001	-.007	-.001	.011

a. Dependent Variable: avgIU

### Collinearity Diagnostics<sup>a</sup>

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions					
				(Constant)	avgCO	avgUS	avgSI	avgPR	avgTR
1	1	5.902	1.000	.00	.00	.00	.00	.00	.00
	2	.080	8.569	.00	.00	.01	.00	.01	.01
	3	.012	22.051	.93	.00	.01	.00	.02	.01
	4	.003	44.587	.01	.33	.01	.01	.00	.65
	5	.002	61.312	.05	.00	.91	.03	.89	.03
	6	.001	80.930	.01	.66	.07	.95	.07	.30

a. Dependent Variable: avgIU

### Residuals Statistics<sup>a</sup>

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	1.96	5.11	3.46	.640	313
Residual	-.951	.646	.000	.243	313
Std. Predicted Value	-2.332	2.584	.000	1.000	313
Std. Residual	-3.886	2.639	.000	.992	313

a. Dependent Variable: avgIU

## Appendix 8: Reliability Testing (Cronbach's Alpha): Post-Refinement

### Convenience

**Case Processing Summary**

		N	%
Cases	Valid	313	100.0
	Excluded <sup>a</sup>	0	.0
	Total	313	100.0

a. Listwise deletion based on all variables in the procedure.

**Reliability Statistics**

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.733	.739	2

**Item Statistics**

	Mean	Std. Deviation	N
CO3	3.27	.844	313
CO7	3.34	.984	313

**Inter-Item Correlation Matrix**

	CO3	CO7
CO3	1.000	.586
CO7	.586	1.000

**Inter-Item Covariance Matrix**

	CO3	CO7
CO3	.713	.487
CO7	.487	.968

### Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Item Means	3.307	3.275	3.339	.064	1.020	.002	2
Item Variances	.841	.713	.968	.256	1.359	.033	2
Inter-Item Covariances	.487	.487	.487	.000	1.000	.000	2
Inter-Item Correlations	.586	.586	.586	.000	1.000	.000	2

### Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
CO3	3.34	.968	.586	.343	.
CO7	3.27	.713	.586	.343	.

### Scale Statistics

Mean	Variance	Std. Deviation	N of Items
6.61	2.655	1.629	2



## Usefulness

### Case Processing Summary

		N	%
Cases	Valid	313	100.0
	Excluded <sup>a</sup>	0	.0
	Total	313	100.0

a. Listwise deletion based on all variables in the procedure.

### Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.763	.768	3

### Item Statistics

	Mean	Std. Deviation	N
US3	3.29	.925	313
US4	3.16	1.021	313
US7	3.20	1.054	313

### Inter-Item Correlation Matrix

	US3	US4	US7
US3	1.000	.525	.622
US4	.525	1.000	.426
US7	.622	.426	1.000

### Inter-Item Covariance Matrix

	US3	US4	US7
US3	.856	.496	.606
US4	.496	1.043	.458
US7	.606	.458	1.112

### Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Item Means	3.218	3.157	3.294	.137	1.044	.005	3
Item Variances	1.003	.856	1.112	.256	1.300	.018	3
Inter-Item Covariances	.520	.458	.606	.148	1.323	.005	3
Inter-Item Correlations	.524	.426	.622	.196	1.461	.008	3

### Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
US3	6.36	3.071	.680	.469	.597
US4	6.50	3.180	.524	.291	.763
US7	6.45	2.889	.594	.400	.686

### Scale Statistics

Mean	Variance	Std. Deviation	N of Items
9.65	6.131	2.476	3

## Social influence

### Case Processing Summary

		N	%
Cases	Valid	313	100.0
	Excluded <sup>a</sup>	0	.0
	Total	313	100.0

a. Listwise deletion based on all variables in the procedure.

### Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.788	.791	5

### Item Statistics

	Mean	Std. Deviation	N
SI2	3.40	1.057	313
SI3	3.28	.901	313
SI4	3.17	1.007	313
SI6	3.69	.962	313
SI7	3.21	1.025	313

### Inter-Item Correlation Matrix

	SI2	SI3	SI4	SI6	SI7
SI2	1.000	.471	.348	.473	.348
SI3	.471	1.000	.476	.396	.602
SI4	.348	.476	1.000	.389	.405
SI6	.473	.396	.389	1.000	.394
SI7	.348	.602	.405	.394	1.000

### Inter-Item Covariance Matrix

	SI2	SI3	SI4	SI6	SI7
SI2	1.118	.449	.371	.481	.378
SI3	.449	.812	.432	.343	.556
SI4	.371	.432	1.015	.377	.419
SI6	.481	.343	.377	.925	.389
SI7	.378	.556	.419	.389	1.052

**Summary Item Statistics**

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Item Means	3.351	3.173	3.693	.521	1.164	.044	5
Item Variances	.984	.812	1.118	.306	1.378	.014	5
Inter-Item Covariances	.419	.343	.556	.213	1.621	.004	5
Inter-Item Correlations	.430	.348	.602	.254	1.730	.006	5

**Item-Total Statistics**

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
SI2	13.36	8.833	.534	.324	.759
SI3	13.47	8.936	.661	.478	.720
SI4	13.58	9.097	.526	.289	.761
SI6	13.06	9.205	.545	.313	.754
SI7	13.54	8.775	.573	.400	.745

**Scale Statistics**

Mean	Variance	Std. Deviation	N of Items
16.75	13.308	3.648	5

## Promotions

### Case Processing Summary

		N	%
Cases	Valid	313	100.0
	Excluded <sup>a</sup>	0	.0
	Total	313	100.0

a. Listwise deletion based on all variables in the procedure.

### Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.711	.711	3

### Item Statistics

	Mean	Std. Deviation	N
PR1	3.16	1.021	313
PR4	3.20	1.054	313
PR5	3.35	1.043	313

### Inter-Item Correlation Matrix

	PR1	PR4	PR5
PR1	1.000	.426	.397
PR4	.426	1.000	.529
PR5	.397	.529	1.000

### Inter-Item Covariance Matrix

	PR1	PR4	PR5
PR1	1.043	.458	.422
PR4	.458	1.112	.582
PR5	.422	.582	1.088

**Summary Item Statistics**

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Item Means	3.237	3.157	3.351	.195	1.062	.010	3
Item Variances	1.081	1.043	1.112	.069	1.066	.001	3
Inter-Item Covariances	.487	.422	.582	.159	1.377	.006	3
Inter-Item Correlations	.450	.397	.529	.132	1.334	.004	3

**Item-Total Statistics**

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
PR1	6.56	3.363	.470	.222	.692
PR4	6.51	2.975	.572	.335	.568
PR5	6.36	3.071	.549	.316	.597

**Scale Statistics**

Mean	Variance	Std. Deviation	N of Items
9.71	6.167	2.483	3

## Trust

### Case Processing Summary

		N	%
Cases	Valid	313	100.0
	Excluded <sup>a</sup>	0	.0
	Total	313	100.0

a. Listwise deletion based on all variables in the procedure.

### Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.702	.704	2

### Item Statistics

	Mean	Std. Deviation	N
TR2	3.23	.905	313
TR6	3.20	1.007	313

### Inter-Item Correlation Matrix

	TR2	TR6
TR2	1.000	.544
TR6	.544	1.000

### Inter-Item Covariance Matrix

	TR2	TR6
TR2	.819	.495
TR6	.495	1.014

#### Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Item Means	3.216	3.201	3.230	.029	1.009	.000	2
Item Variances	.916	.819	1.014	.195	1.238	.019	2
Inter-Item Covariances	.495	.495	.495	.000	1.000	.000	2
Inter-Item Correlations	.544	.544	.544	.000	1.000	.000	2

#### Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
TR2	3.20	1.014	.544	.295	.
TR6	3.23	.819	.544	.295	.

#### Scale Statistics

Mean	Variance	Std. Deviation	N of Items
6.43	2.823	1.680	2



## Intention to Use

### Case Processing Summary

		N	%
Cases	Valid	313	100.0
	Excluded <sup>a</sup>	0	.0
	Total	313	100.0

a. Listwise deletion based on all variables in the procedure.

### Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.704	.704	4

### Item Statistics

	Mean	Std. Deviation	N
IU2	3.17	1.063	313
IU3	3.30	1.037	313
IU4	3.67	.956	313
IU5	3.45	.980	313

### Inter-Item Correlation Matrix

	IU2	IU3	IU4	IU5
IU2	1.000	.540	.252	.158
IU3	.540	1.000	.446	.496
IU4	.252	.446	1.000	.345
IU5	.158	.496	.345	1.000

### Inter-Item Covariance Matrix

	IU2	IU3	IU4	IU5
IU2	1.130	.595	.256	.165
IU3	.595	1.076	.442	.504
IU4	.256	.442	.914	.323
IU5	.165	.504	.323	.960

#### Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Item Means	3.399	3.173	3.671	.498	1.157	.046	4
Item Variances	1.020	.914	1.130	.217	1.237	.010	4
Inter-Item Covariances	.381	.165	.595	.430	3.607	.024	4
Inter-Item Correlations	.373	.158	.540	.381	3.407	.020	4

#### Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
IU2	10.42	5.489	.408	.308	.694
IU3	10.30	4.492	.701	.504	.497
IU4	9.93	5.697	.447	.220	.666
IU5	10.14	5.707	.424	.283	.680

#### Scale Statistics

Mean	Variance	Std. Deviation	N of Items
13.60	8.652	2.941	4

### Overall

#### Case Processing Summary

	N	%
Cases Valid	313	100.0
Excluded <sup>a</sup>	0	.0
Total	313	100.0

a. Listwise deletion based on all variables in the procedure.

#### Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.848	.851	19

#### Scale Statistics

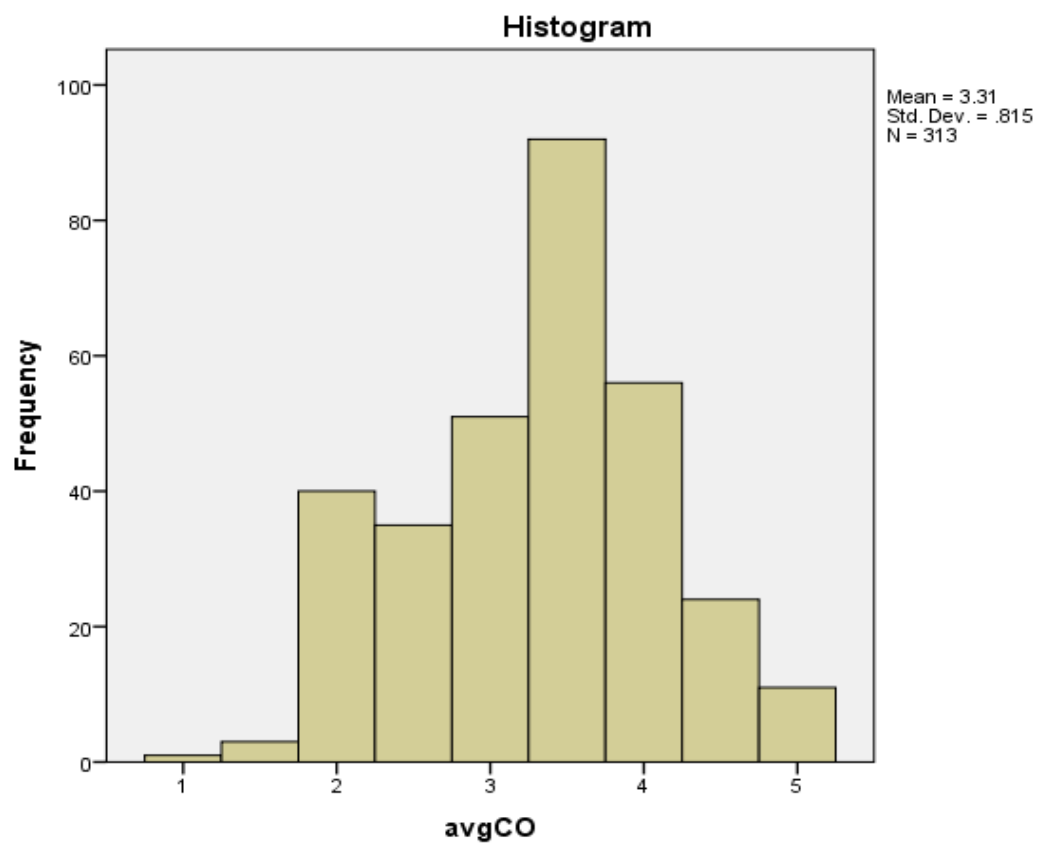
Mean	Variance	Std. Deviation	N of Items
62.76	95.668	9.781	19

## Appendix 9: Normality Testing (Skewness and Kurtosis): Post-Refinement

### Convenience

**Descriptives**

			Statistic	Std. Error
avgCO	Mean		3.31	.046
	95% Confidence Interval for Mean	Lower Bound	3.22	
		Upper Bound	3.40	
	5% Trimmed Mean		3.30	
	Median		3.50	
	Variance		.664	
	Std. Deviation		.815	
	Minimum		1	
	Maximum		5	
	Range		4	
	Interquartile Range		2	
	Skewness		-.152	.138
	Kurtosis		-.475	.275

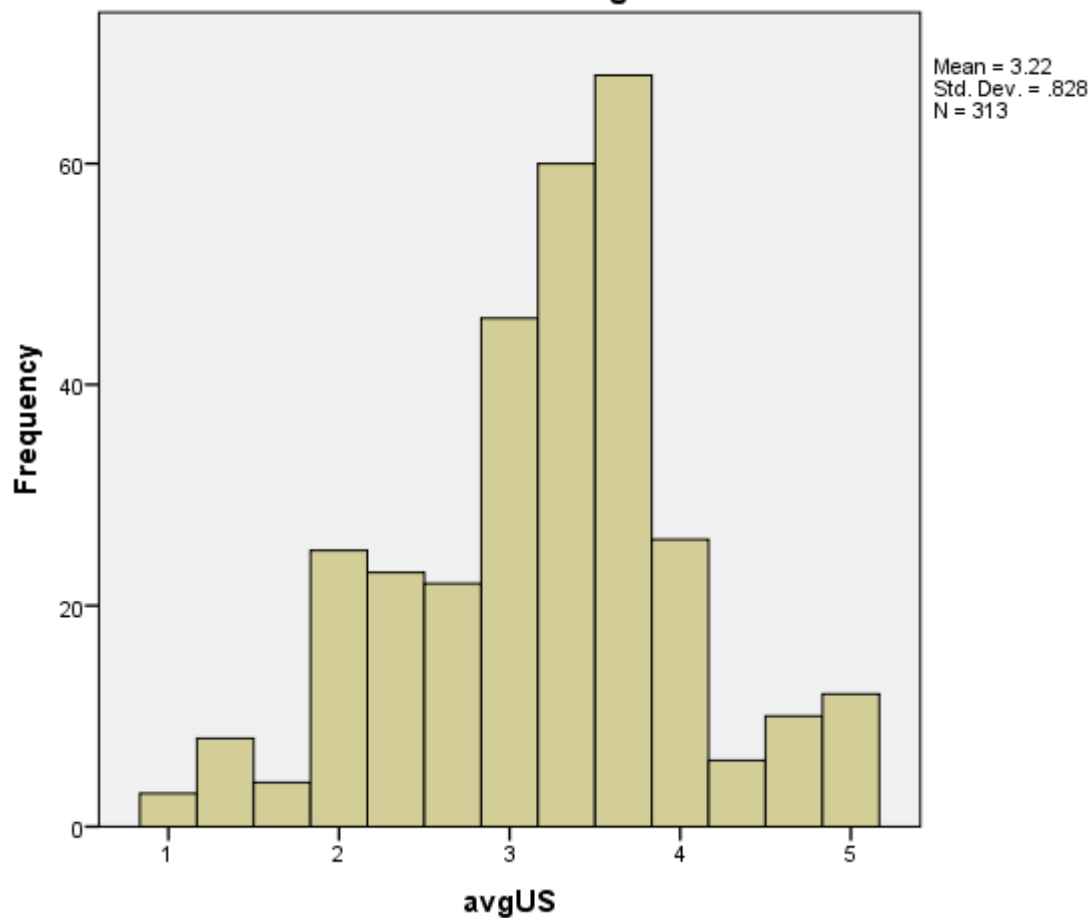


## Usefulness

**Descriptives**

			Statistic	Std. Error
avgUS	Mean		3.22	.047
	95% Confidence Interval for Mean	Lower Bound	3.12	
		Upper Bound	3.31	
	5% Trimmed Mean		3.22	
	Median		3.33	
	Variance		.685	
	Std. Deviation		.828	
	Minimum		1	
	Maximum		5	
	Range		4	
	Interquartile Range		1	
	Skewness		-.228	.138
	Kurtosis		.136	.275

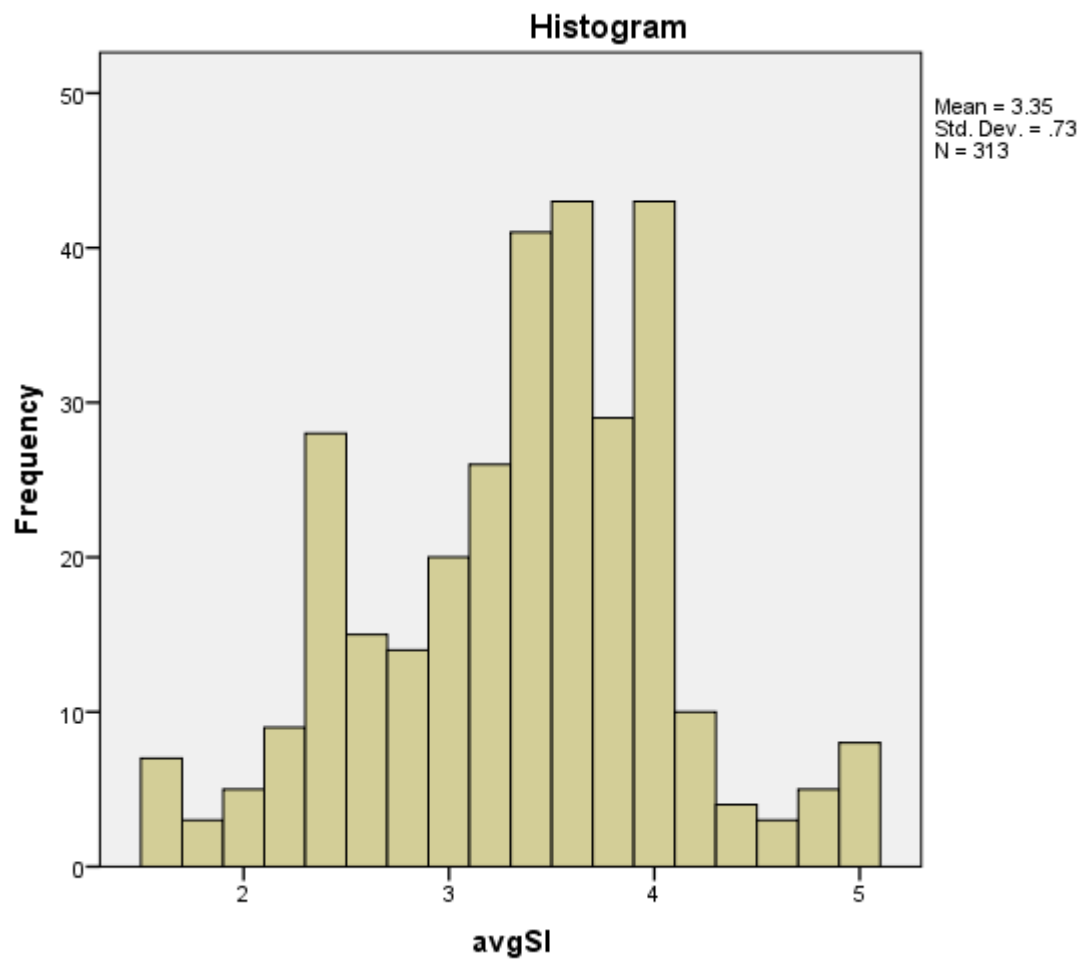
**Histogram**



## Social influence

**Descriptives**

			Statistic	Std. Error
avgSI	Mean		3.35	.041
	95% Confidence Interval for Mean	Lower Bound	3.27	
		Upper Bound	3.43	
	5% Trimmed Mean		3.35	
	Median		3.40	
	Variance		.532	
	Std. Deviation		.730	
	Minimum		2	
	Maximum		5	
	Range		3	
	Interquartile Range		1	
	Skewness		-.214	.138
	Kurtosis		-.119	.275

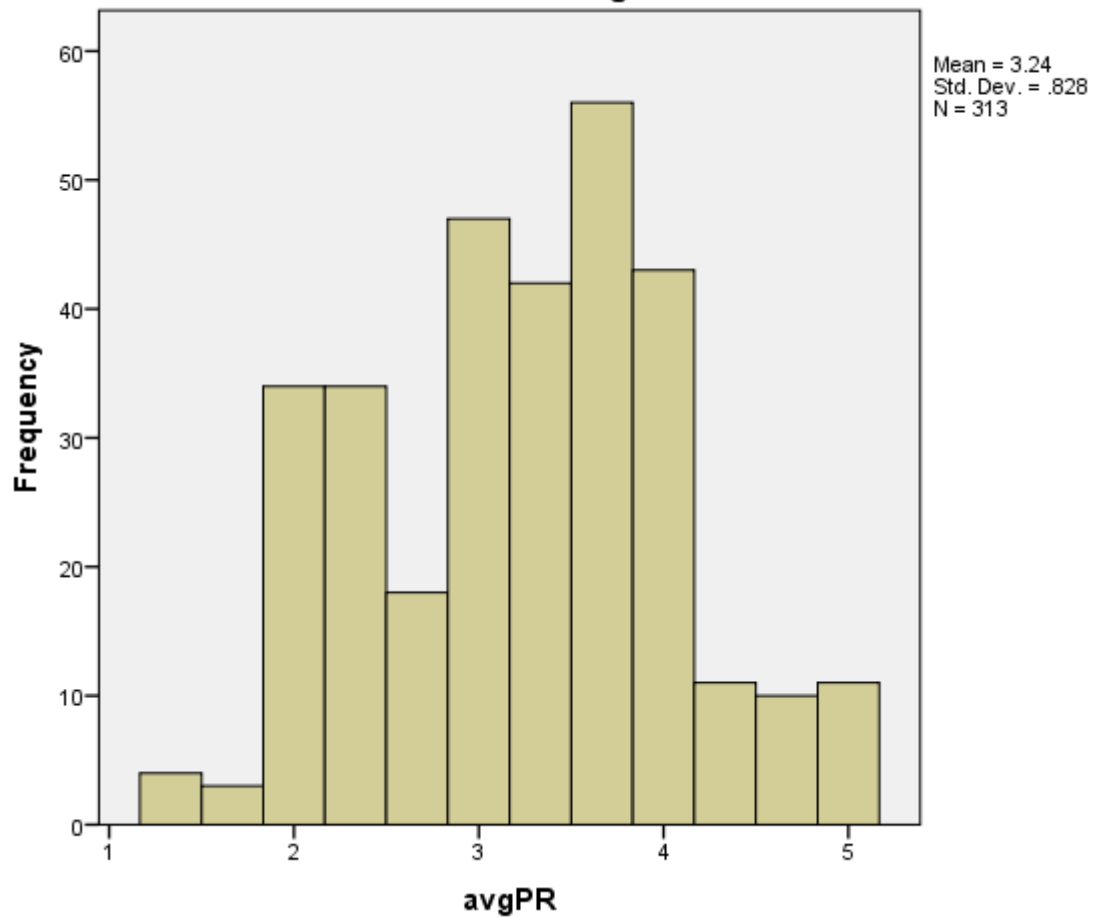


## Promotions

**Descriptives**

			Statistic	Std. Error
avgPR	Mean		3.24	.047
	95% Confidence Interval for Mean	Lower Bound	3.15	
		Upper Bound	3.33	
	5% Trimmed Mean		3.23	
	Median		3.33	
	Variance		.685	
	Std. Deviation		.828	
	Minimum		1	
	Maximum		5	
	Range		4	
	Interquartile Range		1	
	Skewness		-.030	.138
	Kurtosis		-.555	.275

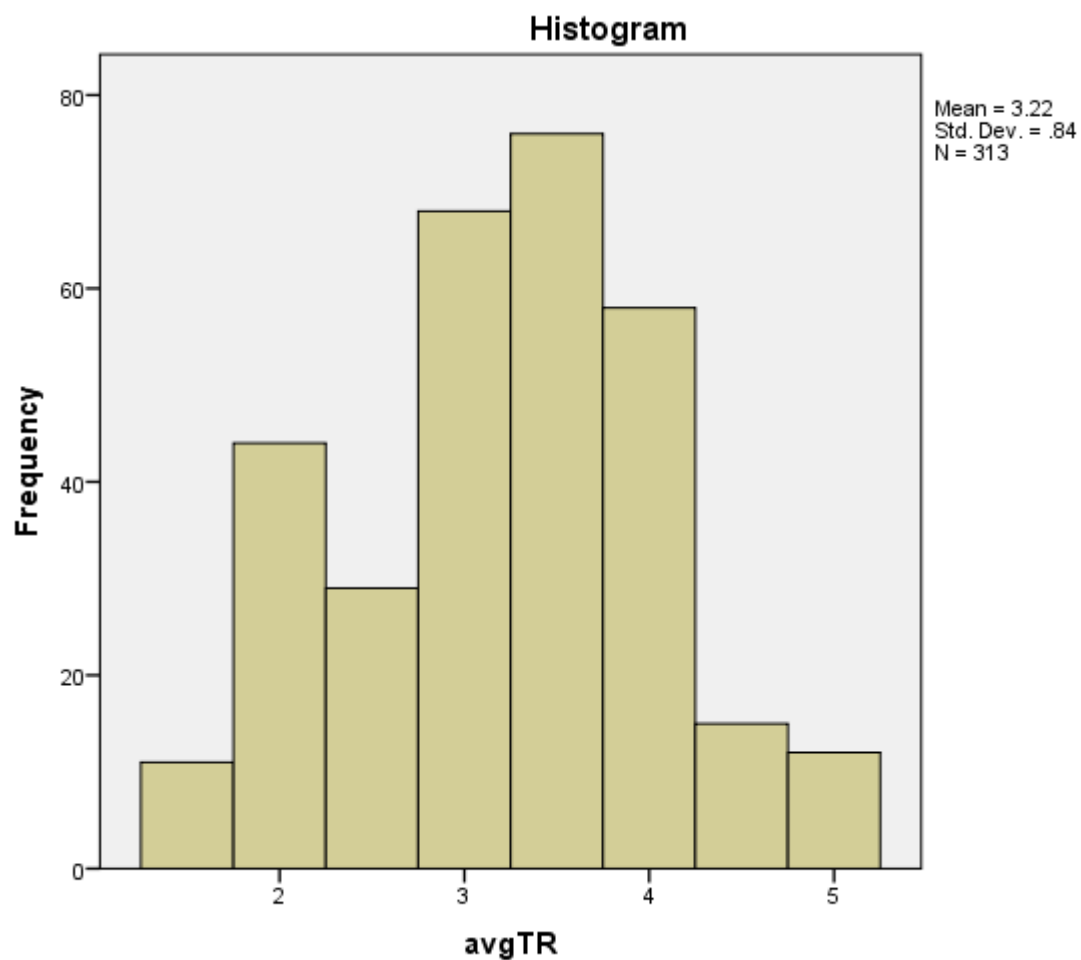
**Histogram**



## Trust

**Descriptives**

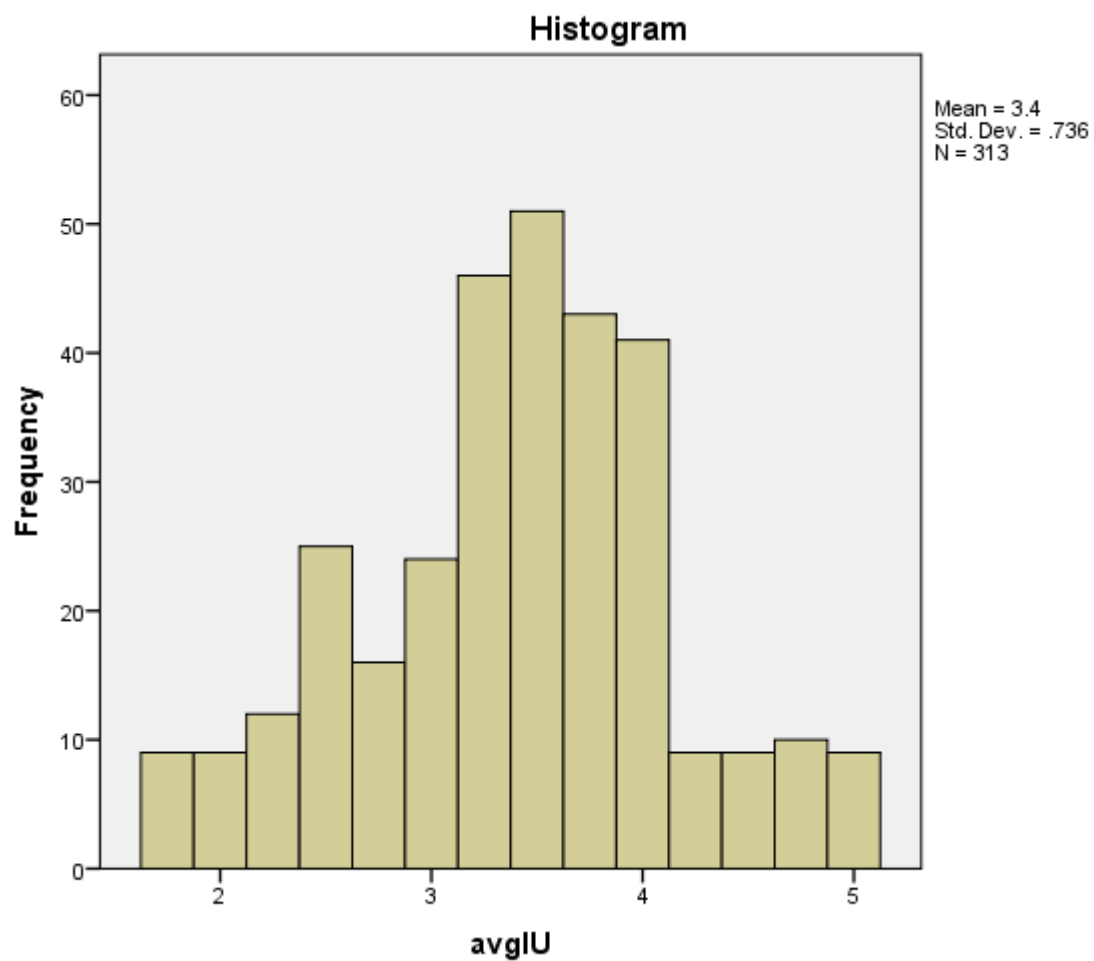
			Statistic	Std. Error
avgTR	Mean		3.22	.047
	95% Confidence Interval for Mean	Lower Bound	3.12	
		Upper Bound	3.31	
	5% Trimmed Mean		3.21	
	Median		3.50	
	Variance		.706	
	Std. Deviation		.840	
	Minimum		2	
	Maximum		5	
	Range		4	
	Interquartile Range		2	
	Skewness		-.088	.138
	Kurtosis		-.510	.275



## Intention to Use

**Descriptives**

			Statistic	Std. Error
avglU	Mean		3.40	.042
	95% Confidence Interval for Mean	Lower Bound	3.32	
		Upper Bound	3.48	
	5% Trimmed Mean		3.40	
	Median		3.50	
	Variance		.542	
	Std. Deviation		.736	
	Minimum		2	
	Maximum		5	
	Range		3	
	Interquartile Range		1	
	Skewness		-.139	.138
	Kurtosis		-.158	.275





## Appendix 10: Regression Analysis (Pre-Refined Questionnaire)

**Variables Entered/Removed<sup>a</sup>**

Model	Variables Entered	Variables Removed	Method
1	avgTR, avgPR, avgCO, avgUS, avgSI <sup>b</sup>	.	Enter

a. Dependent Variable: avgIU

b. All requested variables entered.

**Model Summary<sup>b</sup>**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.935 <sup>a</sup>	.874	.872	.245	.874	426.668	5	307	.000	1.970

a. Predictors: (Constant), avgTR, avgPR, avgCO, avgUS, avgSI

b. Dependent Variable: avgIU

**ANOVA<sup>a</sup>**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	127.817	5	25.563	426.668	.000 <sup>b</sup>
	Residual	18.394	307	.060		
	Total	146.210	312			

a. Dependent Variable: avgIU

b. Predictors: (Constant), avgTR, avgPR, avgCO, avgUS, avgSI

**Coefficients<sup>a</sup>**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	-.172	.118		-1.463	.145					
	avgCO	1.336	.083	1.175	16.034	.000	.930	.675	.325	.076	13.115
	avgUS	.169	.074	.147	2.267	.024	-.055	.128	.046	.097	10.330
	avgSI	-.447	.106	-.405	-4.214	.000	.876	-.234	-.085	.044	22.510
	avgPR	-.174	.070	-.163	-2.497	.013	-.055	-.141	-.051	.097	10.361
	avgTR	.164	.067	.159	2.444	.015	.846	.138	.049	.097	10.313

a. Dependent Variable: avgIU

### Coefficient Correlations<sup>a</sup>

Model			avgTR	avgPR	avgCO	avgUS	avgSI
1	Correlations	avgTR	1.000	-.003	.006	.041	-.646
		avgPR	-.003	1.000	-.132	-.949	.100
		avgCO	.006	-.132	1.000	.112	-.738
		avgUS	.041	-.949	.112	1.000	-.105
		avgSI	-.646	.100	-.738	-.105	1.000
	Covariances	avgTR	.005	-1.533E-005	3.618E-005	.000	-.005
		avgPR	-1.533E-005	.005	-.001	-.005	.001
		avgCO	3.618E-005	-.001	.007	.001	-.007
		avgUS	.000	-.005	.001	.006	-.001
		avgSI	-.005	.001	-.007	-.001	.011

a. Dependent Variable: avgIU

### Collinearity Diagnostics<sup>a</sup>

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions					
				(Constant)	avgCO	avgUS	avgSI	avgPR	avgTR
1	1	5.902	1.000	.00	.00	.00	.00	.00	.00
	2	.080	8.569	.00	.00	.01	.00	.01	.01
	3	.012	22.051	.93	.00	.01	.00	.02	.01
	4	.003	44.587	.01	.33	.01	.01	.00	.65
	5	.002	61.312	.05	.00	.91	.03	.89	.03
	6	.001	80.930	.01	.66	.07	.95	.07	.30

a. Dependent Variable: avgIU

### Residuals Statistics<sup>a</sup>

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	1.96	5.11	3.46	.640	313
Residual	-.951	.646	.000	.243	313
Std. Predicted Value	-2.332	2.584	.000	1.000	313
Std. Residual	-3.886	2.639	.000	.992	313

a. Dependent Variable: avgIU

## Appendix 11: Rotated Component Matrix

**Rotated Component Matrix<sup>a</sup>**

	Component				
	1	2	3	4	5
CO3		.828			
CO7	.827				
US3			.643		
US4					.919
US7			.965		
SI2		.564		.548	
SI3		.861			
SI4					
SI6					
SI7	.888				
PR1					.919
PR4			.965		
PR5			.647		
TR2		.846			
TR6	.907				
IU2	.904				
IU3	.517			.620	
IU4				.652	
IU5				.825	

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 8 iterations.

## Appendix 12: Questionnaire (Pre-refinement)

Section	Variable	Questions
A	Demographic	<ul style="list-style-type: none"> <li>• Gender</li> <li>• Age group</li> <li>• Race</li> <li>• Educational level</li> <li>• Employment status</li> <li>• Household income</li> </ul>
B	Convenience	<ol style="list-style-type: none"> <li>1. I find FinTech application not cumbersome to use.</li> <li>2. Learning to operate FinTech application is easy for me.</li> <li>3. Interacting with FinTech applications is not frustrating to me.</li> <li>4. I find it easy to get the FinTech application do what I want it to do.</li> <li>5. FinTech application is flexible for me to interact with.</li> <li>6. I can easily remember how to perform tasks using FinTech applications.</li> <li>7. Interacting with FinTech applications requires minimal effort from me.</li> <li>8. My interaction with FinTech application is clear and understandable.</li> <li>9. I find it takes less effort to become skilful at using FinTech applications.</li> <li>10. Overall, I find FinTech application convenient to use.</li> </ol>
C	Usefulness	<ol style="list-style-type: none"> <li>1. Using FinTech applications improves the quality of the tasks I do.</li> <li>2. Using FinTech applications gives me greater control over my tasks.</li> <li>3. FinTech applications enable me to accomplish tasks more quickly.</li> <li>4. FinTech applications support critical aspects of my tasks.</li> <li>5. Using FinTech applications increases my productivity.</li> <li>6. Using FinTech applications improves my job performance.</li> <li>7. Using FinTech applications allows me to accomplish more tasks than would otherwise be possible.</li> <li>8. FinTech applications enhance my effectiveness at my tasks.</li> <li>9. Using FinTech applications makes it easier to do my tasks.</li> <li>10. Overall, I find the FinTech applications useful in my tasks.</li> </ol>
D	Social influence	<ol style="list-style-type: none"> <li>1. People who are important to me are likely to recommend using FinTech applications.</li> <li>2. People who are important to me would probably suggest that I should use FinTech applications.</li> <li>3. People who are important to me expect me to use FinTech applications.</li> <li>4. People around me who use FinTech applications have more prestige than those who do not.</li> <li>5. People who use FinTech applications have a higher profile.</li> <li>6. Using FinTech applications is considered a status symbol among my friends.</li> <li>7. People who influence my behaviour think that I should use FinTech applications.</li> <li>8. My friend thinks that I should use FinTech applications.</li> </ol>
E	Promotions	<ol style="list-style-type: none"> <li>1. Using FinTech applications with promotions is rather pleasant.</li> <li>2. The FinTech application is rather enjoyable.</li> <li>3. If I heard about new FinTech applications, I'd look for ways to experiment with it.</li> <li>4. Among my peers, I am usually the first to explore new FinTech applications.</li> <li>5. I like to experiment with new FinTech applications.</li> <li>6. In general, I am not hesitant to try out new FinTech applications.</li> </ol>
F	Trust	<ol style="list-style-type: none"> <li>1. FinTech applications give me a feeling of trust.</li> <li>2. FinTech applications give a trustworthy impression.</li> <li>3. I have trust in FinTech applications.</li> <li>4. The service provider for FinTech applications can be relied upon to keep promises.</li> <li>5. The service provider for FinTech applications is trustworthy.</li> <li>6. I have full confidence in the service provider for FinTech applications.</li> </ol>
G	Intention to use	<ol style="list-style-type: none"> <li>1. Assuming I have access to a FinTech application, I intend to adopt it.</li> <li>2. Given that I have access to a FinTech application, I predict that I would adopt it.</li> <li>3. I would positively consider FinTech by choice.</li> <li>4. I prefer to use FinTech.</li> <li>5. I intend to continue to use FinTech.</li> </ol>

### Appendix 13: Questionnaire (Post-refinement)

Section	Variable	Questions
A	Demographic	<ul style="list-style-type: none"> <li>• Gender</li> <li>• Age group</li> <li>• Race</li> <li>• Educational level</li> <li>• Employment status</li> <li>• Household income</li> </ul>
B	Convenience	<ol style="list-style-type: none"> <li>1. Interacting with FinTech applications is not frustrating to me.</li> <li>2. Interacting with FinTech applications requires minimal effort from me.</li> </ol>
C	Usefulness	<ol style="list-style-type: none"> <li>1. FinTech applications enable me to accomplish tasks more quickly.</li> <li>2. FinTech applications support critical aspects of my tasks.</li> <li>3. Using FinTech applications allows me to accomplish more tasks than would otherwise be possible.</li> </ol>
D	Social influence	<ol style="list-style-type: none"> <li>1. People who are important to me would probably suggest that I should use FinTech applications.</li> <li>2. People who are important to me expect me to use FinTech applications.</li> <li>3. People around me who use FinTech applications have more prestige than those who do not.</li> <li>4. People within my social circle view FinTech applications as important.</li> <li>5. Using FinTech applications is considered a status symbol among my friends.</li> <li>6. People who influence my behaviour think that I should use FinTech applications.</li> </ol>
E	Promotions	<ol style="list-style-type: none"> <li>1. Using FinTech applications with promotions is rather pleasant.</li> <li>2. Among my peers, I am usually the first to explore new FinTech applications.</li> <li>3. I like to experiment with new FinTech applications.</li> </ol>
F	Trust	<ol style="list-style-type: none"> <li>1. FinTech applications give a trustworthy impression.</li> <li>2. I have full confidence in the service provider for FinTech applications.</li> </ol>
G	Intention to Use	<ol style="list-style-type: none"> <li>1. Given that I have access to a FinTech application, I predict that I would adopt it.</li> <li>2. I would positively consider FinTech as my choice.</li> <li>3. I prefer to use FinTech applications.</li> <li>4. I intend to continue to use FinTech applications.</li> </ol>