FLORIDA INTERNATIONAL UNIVERSITY

Miami, Florida

COUNTRY SOCIO-ECONOMIC LANDSCAPE AS MODERATING FACTOR ON THE RISE, ADOPTION AND USAGE OF DIGITAL PAYMENTS: US, CANADA, UK, AND AUSTRALIA

A dissertation submitted in partial fulfillment of

the requirements for the degree of

DOCTOR OF BUSINESS ADMINISTRATION

by

Fidel E. Chacon

2025

To: Dean William G. Hardin

College of Business

This dissertation, written by Fidel E. Chacon, and entitled COUNTRY SOCIO-ECONOMIC LANDSCAPE AS MODERATING FACTOR ON THE RISE, ADOPTION AND USAGE OF DIGITAL PAYMENTS: US, CANADA, UK, AND AUSTRALIA having been approved in respect to style and intellectual content, is referred to you for judgment.

We have read this dissertation and recommend that it be approved.

Maria Cristina Gonzalez

Miguel Aguirre-Urreta

Ronald Mesia

George Marakas, Co-Major Professor

Alfred Castillo, Co-Major Professor

Date of Defense: June 17, 2025

The dissertation of Fidel E. Chacon is approved.

Dean William G. Hardin

College of Business

Andrés G. Gil

Senior Vice President for Research and Economic Development

and Dean of the University Graduate School

Florida International University, 2025

DEDICATION

"It's kind of fun to do the impossible" -Walt Disney

I dedicate this dissertation to my family, starting with my parents, who showed me that anything is possible with hard work and the will to never give up.

To Alaska, who stood by me in difficult moments and never let go. To my mother-in-law, Mireya, I know you're watching from heaven with pride. And to my extended family and friends: if you heard from me at any point during these three years, please know you mattered then and matter now. Whether it was a word of encouragement, a moment of listening, your help and support or simply your presence, you helped carry me forward.

To my beloved Alena, that I know is also watching this moment from heaven.

This victory is mine, but it was never mine alone. It is also dedicated to those who doubted, those who cheered, and those who quietly inspired. To the believers, the dreamers, and to all the witches, wizards, and sorcerers whom I adore, who have made this journey more thrilling; you know who you are. You are all an endless source of motivation.

"I'm just like my country: young, scrappy, and hungry." — Hamilton, the Musical

And even when the page was blank, you helped me keep writing.

ACKNOWLEDGMENTS

I would like to express my deepest gratitude to all the members of my dissertation committee for their guidance, support, and thoughtful feedback throughout this journey. To Dr. Alfred Castillo, my dissertation co-chair, thank you for your time, patience, effort, and unwavering belief in me. From the summer project until dissertation, your mentorship, along with Dr. Amin Shoja, reminded me that sometimes others see our potential before we see it ourselves. To the entire DBA faculty team, led by Dr. George Marakas and Dr. Miguel Aguirre-Urreta: your support began long before this manuscript. From the admissions process to the very first residency and beyond, your trust made it possible for me to be here today. To the amazing DBA staff: Yasemin Shirazi, Daniela Leon, and the rest of the team, thank you for running this program with such precision and care. Your seamless coordination made it easier for us to focus on the work and the whole experience. To my DBA cohort classmates: even though I rarely made it to happy hours, the experience wouldn't have been the same without your presence, insight, and camaraderie. A special shoutout to Dr. Maria Cristina Gonzalez; thank you for the courage to let me speak from a qualitative theory perspective about my favorite musical, Hamilton. I may have hijacked your class that day, but you gave me space to speak as a rookie scholar and storyteller. Finally, Dr. George Marakas, your phrase "trust the process" carried me through this journey. If I may add a respectful amendment as a soon-to-be practitioner-scholar: it wasn't just the process. It was this extraordinary team you assembled that made the difference.

ABSTRACT OF THE DISSERTATION

COUNTRY SOCIO-ECONOMIC LANDSCAPE AS MODERATING FACTOR ON THE RISE, ADOPTION AND USAGE OF DIGITAL PAYMENTS: US, CANADA, UK, AND AUSTRALIA

by

Fidel E. Chacon

Florida International University, 2025

Miami, Florida

Professor George Marakas, Co-Major Professor

Professor Alfred Castillo, Co- Major Professor

The payments industry continues to serve as a catalyst for global economic growth and innovation, driven by the rapid advancement and adoption of digital payment technologies. As internet access and smartphone usage expand, more individuals across the globe are gaining access to financial tools that reshape how they transact. Despite this momentum, significant gaps remain in understanding how digital payments are adopted and sustainedly used during day-to-day transactions across diverse national and cultural environments. This study aims to contribute on the ongoing effort of addressing those gaps by examining user behavior and adoption patterns across four developed markets: the United States, Canada, the United Kingdom, and Australia, using established technology acceptance frameworks.

Grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Technology Acceptance Model (TAM), the study evaluated key constructs that influence digital payment behavior, including performance expectancy, effort expectancy, social influence, trust, attitude, but also introducing cash preference. A quantitative, cross-sectional survey was conducted with 191 participants, and regression analysis was used to assess core predictors of behavioral intention (BI). Due to subgroup sample size limitations, the analysis focused on baseline regression to ensure internal validity. Although country-level subgroup analysis was limited by sample size, the study initially operationalized the country as a moderating variable and subsequently emphasized cash preference as a more contextual proxy. Findings revealed that Attitude, Performance Expectancy (PE), Effort Expectancy (EE), Trust (T), and Cash Preference (CP) significantly predicted BI, with Attitude emerging as the strongest individual predictor. Conversely, Social Influence (SI) and Price Value (PV) did not significantly influence BI, suggesting a behavioral shift in mature digital ecosystems toward self-driven, efficiency-based adoption behaviors.

These findings reinforce the continued relevance of TAM and UTAUT constructs while highlighting the need for greater customization of digital payment adoption models. The study offers both theoretical and practical contributions, including a refined view of cash preference as an individual-level contextual moderator. Practically, it provides insights into evolving user expectations, highlighting the role of intuitive design, transparent pricing, and reduced reliance on social cues or external validation in influencing digital payment decisions within advanced economies.

TABLE OF CONTENTS

TABLE OF CONTENTS		VIII
LIST OF TABLES		XII
LIST OF FIGURES		XII
INTRODUCTION		1
1.1	Background and Context of the Study	3
1.2	Problem Statement	5
1.3	Purpose of the Study	7
1.4	Research Questions	8
1.5	Significance of Study	8
1.6	Research Gap	11
1.7	Definition of Key Terms	15
1.8	Scope Limitations and Assumptions	18
1.9	Organization of the Dissertation	21
LITERATURE REVIEW		22
2.1	Technology Acceptance Model (TAM)	26
2.2	Unified Theory of Acceptance and Use of Technology (UTAUT)	29
2.3	Cross-Country Comparisons in Digital Payment Behavior	39
2.4	Gaps in Literature	41
2.5	Chapter Summary	42
RESEARCH MODEL AND HYPOTHESIS		43

3.1 Overview 43

3.2 Research Design and Strategy 44

3.3 Conceptual Model 46

3.4 Hypotheses Development 51

DATA ANALYSIS AND RESULTS 52

4.1 Overview 52

4.2 Data Preparation and Cleaning. 53

4.3 Population of Interest and Sampling Procedures 54

4.4 Data Collection Procedures 55

4.5 Ethical Considerations 56

4.6 Data Analysis Plan 57

4.7 Descriptive Statistics (Demographics & Construct Measures). 59

4.8 Measurement Model Validation (Factor Analysis & Reliability). 61

4.8.1 Exploratory Factor Analysis (EFA) 61

4.8.2 Correlation Matrix and Multicollinearity Check 64

4.8.3 Reliability Analysis 65

4.8.4 Composite Scores and Descriptive Statistics 68

4.9 Assumption Testing (Normality, Linearity). 69

4.10 Hypothesis Testing (Regression/Model Results). 70

4.11 Summary of Results 72

4.12 Moderation Analysis: 73

4.12.1 Moderation of PE → BI by CP Across Countries 74

4.12.2 CP as a Moderator of Trust → BI (Pooled Sample) 76

4.12.3 Summary of Moderation Analysis 77

4.13 Chapter Summary 79

DISCUSSION, CONCLUSION AND RECOMMENDATIONS. 80

5.1 Summary of Key Findings. 80

5.2 Interpretation of Findings. 82

5.3 Theoretical Implications. 83

5.4 Practical/Managerial Implications. 84

5.5 Limitations of the Study. 86

5.6 Recommendations for Practice and Policy 88

5.7 Directions for Future Research. 89

5.8 Final Thoughts and Concluding Remarks 91

REFERENCES 92

APPENDIX 103

VITA 136

LIST OF TABLES

Table 1 Digital payments adoption: an analysis of literature. 34

Table 2 Systematic Literature Review on Digital Payment Technologies 35

Table 3 Key Constructs & Definitions... 47

Table 4 Table 4 Research Hypotheses& Path Source: Author’s research (2025) 51

Table 5 Demographics Overview of the Total Sample (N = 190) 60

Table 6 Exploratory Factor Analysis 62

Table 7 Pearson Bivariate Correlation Matrix 64

Table 8 Internal Consistency (Cronbach's Alpha) 67

Table 9 Composite Scores & Descriptivie Statistics of Construct (M=190) 68

Table 10 Regression Coefficients Predicting Behavioral Intention................................. 71

Table 11 Summary of Hypothesis Testing Results.. 72

Table 12 Moderation Analysis Summary: Country-Level Moderation Effects................ 75

Table 13 Moderation Analysis Summary: Cash Preference and Country 78

LIST OF FIGURES

Figure 1 Digital Payment Technologies 23

Figure 2 TAM model applied to Digital Payments Adoption... 27

Figure 3 An Extended TAM 28

Figure 4 Extended TAM Older Adults 29

Figure 5 Extending UTAUT Retailers 30

Figure 6 Mobile UTAUT 31

Figure 7 Digital Payments Studies by Category 36

Figure 8 Systematic Literature Review... 37

Figure 9 Research Model 49

INTRODUCTION

The World Payment Report (2020) reported that global non-cash transactions grew by more than 14% in 2019, reaching over 708 billion transactions, the highest rate in recent decades.(Roncancio, 2020) The volume is not only significant but also highly diverse, encompassing a wide variety of payment methods across different countries, ranging from global platforms like PayPal, Visa, MC and Apple Pay to domestic networks such as Interac in Canada. Global differences in digital payment adoption remain significant, often influenced by variations in regulatory frameworks, technological infrastructure, and user readiness across regions (Malaguti, 2015; De Luna et al., 2019). These disparities reflect the importance of context-specific analysis, as explored in this study. The rapid evolution of digital payment systems over the past decade has significantly reshaped global financial ecosystems. Governments, financial institutions, and fintech companies have invested heavily in digital transformation, with different levels of success depending on economics, infrastructure, overall country landscape and even cultural differences.

These ecosystems involve a mix of business models, technology adoption rates, product characteristics, and regulatory environments, making it difficult to analyze the global or even national digital payments landscape through a single research framework.

From an academic standpoint, the existing literature on traditional payment systems, largely defined by card usage, e-commerce, and money transfers, was already complex. The traditional payment model, composed of banks, merchants, consumers, and card brands, have long posed definitional and organizational challenges, as distinct models rely on different sets of participants and variables (Chiu & Lai, 2007). The rise of fully digital payments has basically added layers of complexity (Effah, 2016) with new players and use cases for payment application interaction, making it increasingly difficult to generalize how the model(s) features translate into payments trends, and even more so to predict consumers, stakeholders and governments behavior in response to these offerings.

The global trend toward digital payments saw a major acceleration during and after the COVID-19 pandemic (Jonker et al., 2022; Musyaffi et al., 2021). The lockdowns acted as a catalyst, shifting consumer behavior toward safer, contactless transaction methods, including mobile payments, digital wallets and real-time transfers. The crisis also highlighted the potential of digital payments to support vulnerable populations, allowing governments to deliver aid faster and more securely than traditional methods like checks (Fabris, 2022).

As a result, the digital payments ecosystem has become a major topic of global academic and policy debate (Khando et al., 2022). However, despite the global push for innovation, adoption and usage patterns remain as diverse as the payment methods available themselves. Different regions, countries, and communities exhibit diverse behaviors toward financial technologies, driven by disparities in infrastructure, banking penetration, regulatory environments, domestic options and cultural preferences (Patil et al., 2018). For instance, EMV chip technology, introduced in Europe and Canada in the 1990s and Latin America in the early 2000s, wasn’t fully implemented in the United States until 2015, despite the country’s position as a leader in technological innovation (Conroy, 2012).

Additionally, while mobile apps, card transactions, and digital wallets have surged in usage, the path toward full adoption is not uniform. Adoption patterns of digital payments vary widely across countries, influenced by local market maturity, financial inclusion rates, and even cultural norms around trust, privacy, and cash preferences. This is an ongoing debate with considerable room for new contributions. The wide spectrum of payment options and the global diversity in consumer behavior call for deeper, comparative studies (Wu & Liu, 2023).

This study focuses on gaining deeper insight into the drivers of adoption and usage behavior for digital payment technologies in four mature markets: the United States, Canada, the United Kingdom, and Australia. It explores how socio-economic profiles, market maturity, and cultural dynamics, particularly those reflected in cash preferences, influence digital payment adoption and sustained usage. While country-level differences were considered, the study ultimately emphasizes user-centered insights and consumer behaviors that transcend national borders. Using established theoretical frameworks such as the Unified Theory of Acceptance and Use of Technology (UTAUT), this research aims to contribute new findings and regional nuance to the ongoing global conversation around innovation, trust, digitalization, and financial behavior, highlighting the need for greater customization of digital payment adoption models.

1.1 Background and Context of the Study

The global payments ecosystem has undergone significant transformation over the past two decades. What was once dominated by traditional card networks and bank-driven transactions has evolved into a complex digital landscape, shaped by mobile technologies, fintech innovation, and shifting consumer preferences. The COVID-19 pandemic further accelerated the adoption of contactless and mobile payments, making digital transactions a standard part of daily life (Jonker et al., 2022). As technology advances and new players, such as Apple, Google, and fintechs enter the arena, digital payment options have expanded to include digital wallets, real-time payments, and peer-to-peer transfers.

Despite similar levels of economic development and infrastructure, countries vary in how digital payment solutions are adopted and used. For example, while the U.S. is a major player in financial innovation, its adoption of Real-Time Payments (RTP) only began in 2017, years after countries like the UK and India (Prabhakar, 2019). These national differences are shaped by factors such as regulation, consumer habits, cultural preferences, and the maturity of payment systems. Understanding how these factors influence digital payment adoption is critical for policymakers, banks, and technology providers worldwide.

Besides a growing consumer interest in faster, more efficient options, these trends were also aligned with financial inclusion goals by expanding access to the unbanked population via mobile and internet technologies (Gupta et al., 2024). This growth has also revealed persistent inequalities and gaps in digital infrastructure, particularly in emerging economies, where digital payment adoption is uneven due to technological, regulatory, and socioeconomic barriers (Malaguti, 2015; Gupta et al., 2024). The debate around the "cashless society" is ongoing and diverse, with proponents highlighting increased efficiency, reduced transaction costs, and enhanced transparency. Critics, however, raise concerns about financial exclusion, particularly for unbanked and underbanked populations, privacy concerns, and increased vulnerability to cyber threats (Gupta et al., 2024). Despite these divergent views, what remains clear is that digital payment adoption and growth do not follow a uniform, linear trend across the globe. This study adopts a neutral stance in this debate, focusing instead on mapping observable user behaviors across diverse national contexts to explore how behavioral predictors interact with country-specific characteristics. What remains clear is that digital payment adoption and growth do not follow a uniform, linear trend across the globe.

1.2 Problem Statement

The central problem addressed in this study is the influence of country-specific factors on the adoption and usage of digital payments in the United States, Canada, Australia, and the United Kingdom. As highlighted in the introduction, digital payment adoption does not follow uniform trends globally, even when products are customized to meet local market requirements. Although these target countries are considered advanced in terms of digital payment infrastructure and usage, they differ significantly in terms of preferences for payment methods (e.g., digital wallets, cards, real-time payments), regulatory frameworks, infrastructure, cash reliance, cultural norms, and consumer behavior.

This variation raises a critical question in digital payments research: What are the driving factors behind the adoption and sustained usage of digital payment solutions across different countries? The topic holds significant relevance, as electronic payments are widely considered an enabler of greater economic efficiency and inclusion (Elkins, n.d.).

While much of the current literature focuses on consumer behavior, technology acceptance, and the natural shift away from cash, results also show that market maturity levels and country context play a substantial role in adoption outcomes. For example, Augsburg and Hedman's (2017) study in Denmark, where mobile and card usage is already mature, found high intention to use mobile payments, which may not be as applicable in less digitally mature markets. The authors of this research talked about the need for further comparative research between advanced economies and emerging markets to better understand how local factors impact adoption and usage across different digital payment technologies.

Despite the increased adoption of digital payments worldwide, the mechanisms behind their adoption and usage remain complex and significantly vary across geographies. Prior research has heavily focused on consumer behavior and technology acceptance but often lacks nuanced perspectives that account for local culture, economic infrastructure, and the residual reliance on cash. There is a need for more comprehensive, country-specific analysis to understand how demographics, economic and society landscape factors moderate adoption behavior. Without this understanding, digital payment strategies may fail to address the barriers unique to each region, limiting their effectiveness and potentially widening financial inequality .(Al-Saedi et al., 2019). Recognizing these contextual differences, this study narrows its focus by operationalizing one key national variable, cash preference, as a proxy for broader country-level influences, aiming to explore its potential moderating effect on digital payment adoption.

1.3 Purpose of the Study

The purpose of this study is to explore how country-specific economic and structural dynamics moderate the adoption and usage of digital payment technologies across four mature markets: the United States, Canada, Australia, and the United Kingdom. While these countries are often grouped as mature economies with relatively advanced digital infrastructure (World Bank, 2023; OECD, 2022), their adoption patterns diverge due to local preferences, regulatory environments, trust levels, and cash reliance, among other factors.

Applying the Unified Theory of Acceptance and Use of Technology (UTAUT2) as the guiding framework, the research investigates how constructs like performance expectancy, effort expectancy, social influence, trust, influence behavioral intention and use behavior, with the addition to cash preference. The goal is not just to validate these drivers but to evaluate how their impact shifts across different national contexts.

This study aims to bridge the gap between global adoption models and localized realities, providing a nuanced understanding for banks, fintechs, and policymakers navigating increasingly complex digital economies.

The findings will contribute to the body of research that today is shaping digital payment strategies for governments, banks, and fintech innovators navigating increasingly complex consumer behaviors. By exploring cross-country dynamics, this study also seeks to bridge the gap between global trends and local realities in the adoption of digital payments

1.4 Research Questions

This study seeks to understand the key drivers and moderators influencing the adoption and usage of digital payments across four developed countries: the United States, Canada, the United Kingdom, and Australia. Specifically, it explores how user perceptions and country context impact behavioral intention and actual usage of digital payment technologies. The following are the proposed research questions for the purpose of this study:

What behavioral factors significantly influence users' intention to adopt digital payment technologies in mature economies?

Does Cash Preference (CP) moderate the relationship between Behavioral Intention (BI) and key predictors (EE, PE, SI, PV, A, T) and if so, which ones demonstrate statistical significance?

How do country-level factors contribute conceptually to digital payment adoption, even when not statistically significant in this study?

The hypotheses guiding this research are presented in chapter 3, following a detailed review of the literature and theoretical foundations.

1.5 Significance of Study

Until the early 2000s, the traditional payments model operated within a four-party system: payment networks (Visa, MasterCard, American Express), merchants, consumers, and banks (issuers and acquirers). This system also included closed-loops and domestic networks, such as Macy’s proprietary card and Canada’s Interac (Leblebici, 2012). At that time, the primary business goal was to convert traditional cash and check transactions into card payments, initially physical and later digital through e-commerce channels. Growth relied heavily on financial institutions, card brands, and national schemes.

The payments ecosystem has evolved into a dynamic and highly complex landscape. The widespread adoption of mobile phones and internet access has brought non-traditional players, including Google, Apple, and various fintechs into the payments arena. These entrants have expanded digital payment offerings to include wallets, bill payment apps, online banking, and real-time payment systems (Wenting, 2021), as well as back-end and data mining solutions. Even from a merchant perspective, major retailers like Amazon have added domestic and digital transfer options, while smaller players have embraced mobile-first models offering services such as paycheck advances, stock trading, and digital money transfers (Franciska & Sahayaselvi, 2017).

Although convenience remains central to the digital payments value proposition, its broader implications are far-reaching. Research in this space offers insights into consumer behavior while also addressing economic development and financial inclusion (Gupta et al., 2024). Digital payments are increasingly viewed as drivers of economic efficiency, supporting tax collection, reducing cash-related risks, expanding customer bases, and lowering operational costs (Lee et al., 2021). However, these benefits are accompanied by significant challenges, including privacy concerns, fraud, cybersecurity threats, and infrastructure investment requirements. Digital readiness during times of crisis has also emerged as a growing concern, particularly in terms of enabling the secure and rapid disbursement of government assistance (e.g., FEMA support).

Amid these challenges, understanding the broader economic implications of digital payments becomes essential. Aguilar et al. (2024) highlight this macroeconomic impact, noting that a one percentage-point increase in digital payments usage is associated with a two-year growth of per capita GDP by 0.10 percentage points. Their study emphasizes the value of government policies that encourage adoption of digital payments while also pointing to the importance of complementary efforts to expand access to financial accounts and internet connectivity.

Beyond macroeconomic metrics, the behavioral dimension of digital payments adoption has been extensively explored through models such as the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), and their respective extensions. These frameworks focus on individual perceptions, including perceived usefulness, ease of use, trust, and behavioral intention, as key predictors of adoption. Recent studies have adopted these models to reflect the nuances of digital payment systems, incorporating constructs such as perceived security, risk, and innovativeness to capture evolving consumer concerns (Venkatesh et al., 2022).

Despite the robustness of these models, their predictive power is not absolute. Variations across geographies, demographic profiles, and cultural contexts often reveal discrepancies between theoretical expectations and real-world behaviors. For instance, while trust consistently emerges as a critical factor, its antecedents and weight in the adoption decision can differ significantly between developed and emerging markets (Hernandez et al., 2023). This underscores the importance of customizing adoption studies within specific environments, recognizing that a one-size-fits-all approach is insufficient.

There is a growing body of research focused on understanding how digital payments influence economic systems and consumer behavior. They provide valuable insight into governments, financial institutions, and technology providers aiming to expand or refine their digital payment offerings.

This study contributes to academic literature by exploring how economic and contextual considerations may influence digital payment adoption across four advanced economies. Rather than modeling each country individually, the study explores cash preference as an individual-level moderator that may reflect underlying country-specific tendencies related to digital payment behavior, regulatory frameworks, and financial systems. By applying the UTAUT2 framework and testing the influence of behavioral drivers like performance expectancy, effort expectancy, trust, and social influence, the study offers a more nuanced understanding of what drives (or limits) digital payment adoption. The findings aim to support both theoretical refinement and practical decision-making for governments, banks, and fintech providers navigating diverse payment landscapes.

1.6 Research Gap

A considerable body of research has explored the rise and effects of digital payments, including specific methods such as mobile payments and e-commerce transactions (Patil et al., 2018). The COVID-19 pandemic significantly accelerated digital payment adoption, leading to a surge in consumer interest and behavior change. As Jonker et al. (2022) note, "Electronic payment instruments gained further ground" as retailers promoted contactless payments and banks enabled easier access to them. The social distancing requirements during the pandemic made digital payments not just a convenience, but a necessity, one whose behavioral impact has persisted in the post-COVID era.

Despite these advancements, there is still a significant opportunity in understanding how country-specific and regional factors influence the adoption and sustained usage of digital payments. Much of the current research emphasizes consumer behavior or the adoption of specific technologies, but does not fully account for how economic, infrastructural, regulatory, or cultural variables shape outcomes across different national contexts. For example, while some countries followed a gradual evolution, from physical cards to internet banking and digital wallets; others, like India, leapfrogged directly into large-scale digital mobile payments (Pal et al., 2018).

Furthermore, although many studies have identified factors that drive digital payments adoption, relatively few have examined inhibitors such as persistent cash preferences or multichannel choices, like using the online channel to look for information about a service but then going to the branch to enroll (Hummel, 2017). Similar logic in digital payments would be seeing a bill online but paying it via ACH or at the store. Other research efforts have focused narrowly on singular payment technologies, such as blockchain-based systems (Casino et al., 2019), central bank digital currency pilots like FED Boston/ MIT Project Hamilton (Elson & Elson, 2021), or mobile payments (Dahlberg et al., Kabir et al.).

This study contributes to addressing some of those gaps by examining digital payment behavior in four advanced economies, each with distinct regulatory, trust, and infrastructure landscapes. While the UTAUT2 framework guides individual-level analysis, this study introduces cash preference as a moderator, a practical element to explore how national-level differences may influence technology adoption patterns. By operationalizing this construct, the research provides a more nuanced view of how individual behavioral factors interact with broader environmental influences. While prior studies have explored the role of technology adoption and external shocks like COVID-19 (Musyaffi et al., 2021b), there is still limited research that systematically compares cross-country adoption patterns in a unified framework. As Patil et al. (2018) note, "Existing studies have mainly examined mobile payment methods. Future studies should also focus on examining other forms of digital payment methods for a holistic development of digital payments ecosystems and emerging FinTech applications." This study responds to that call by integrating a broader set of digital payment types, including debit/credit/prepaid cards, digital wallets and real-time payments, into a four-target country behavioral analysis.

Some research, such as Wu and Liu (2023), has examined cultural factors by incorporating Hofstede's dimensions into mobile payment adoption studies. Their findings suggest that the predictive power of models like UTAUT2 varies across countries, particularly in markets where mobile payment systems are already widely adopted. As they state, "It would be interesting to further examine the robustness of the UTAUT2 model in other developing and developed countries," and they call for future studies to explore the role of additional cultural dimensions in shaping adoption.

Rather than evaluating culture or macroeconomic indicators directly, this study focuses on observable user preferences toward cash as an interpretable variable with national implications. The aim is to enhance our understanding of how adoption drivers may shift in different environments, not by modeling each country separately, but by identifying moderating effects through shared survey constructs. This approach aligns with recent calls in the literature to expand existing frameworks in ways that are both scalable and sensitive to landscape related variance. Besides theoretical relevance, Digital Payments related studies also seek to inform future research and policy discussions about the enablers and barriers to digital payment adoption at both the national and global levels. The findings may even support efforts to improve economic efficiency, enhance transparency, and advance financial inclusion goals, widely cited by researchers and policymakers alike (Gupta et al., 2024).

As digital payments continue to grow, understanding the behavioral and unique drivers of adoption becomes critical. By applying an extended UTAUT2 framework (Venkatesh et al., 2012), is research extends traditional behavioral analysis by introducing cash preference as a proxy contextual moderator, revealing how adoption drivers may shift across countries with similar infrastructure but varying financial habits. By examining these interactions within a unified model, the dissertation offers practical insights for institutions and policymakers seeking to design effective digital payment strategies across varied regions. The findings may help bridge the gap between global frameworks and local realities, supporting informed decisions around financial inclusion, transparency, and user adoption beyond the boundaries of individual-level predictors alone.

1.7 Definition of Key Terms

To ensure consistency throughout the study, the following key terms are defined:

Digital Payments: The transfer of value (goods, services, or funds) between two parties using electronic devices, platforms, or channels such as mobile phones, online banking, or point-of-sale terminals (Khando et al., 2022).

Digital Wallets (electronic (e) wallets/mobile wallets): A type of digital payment solution that stores payment information on a smartphone or similar device, enabling consumers to make payments electronically (e.g., Apple Pay, Google Pay, Samsung Pay).

Real-Time Payments (RTP): Instant digital payment systems that allow the immediate transfer of funds between banks or financial institutions, available 24/7, with immediate confirmation.(Prabhakar, 2019), such as FedNow.

Behavioral Intention (BI): A consumer's expressed intent or likelihood to use digital payments. The combination of factors that will contribute to consumers willing to adopt this technology. "*a person's intentions to perform a variety of behaviors*" (Thakur & Srivastava, 2014)

Actual Use (AU): The observed or self-reported act of using digital payments in real-life transactions. Directly and positively influenced by BI, but also moderated by country, culture, demographics. Not only adoption, but also the actual level of transactions conducted by the consumers.

Performance Expectancy (PE): The belief that using digital payments will enhance transactional efficiency or outcomes, hence, that the consumer believes the digital payment offering will contribute to their goals and it is expected to positively influence users' behavioral intention (BI) to use digital payments (Venkatesh et al., 2012).

Attitude (A): Determined by expectation of ease, satisfaction and effort, conditioned as well but cultural differences (Hofstede, 2011) as well as a collectivist or individualist society (Kohun et al., 2012).

Effort Expectancy (EE): The perceived ease or simplicity of learning and using digital payment systems. Determined by the existing capabilities in the country to use an additional service. "*The degree of ease related to consumers' use of technology. also known as perceived ease of use in the TAM model, is one of the important predictors of behavioral intention to use* "(Venkatesh et al., 2012). If the expected effort to use digital payments is considered low, Behavioral intention increases.

Social Influence (SI): The impact that peers, family, or society have on an individual's intention to adopt digital payments. Adoption, initial attempts to do transactions, not necessarily a significative volume. Learning curve, Customer registered for the service; the question is if the issue will be consistent day to day. Questions will show differentiation between strong users vs. just limited transaction type users. The actual frequency of using digital payments (Venkatesh et al., 2012). The community information received about digital payment options, such as family, friends, social media as a potential driver for adoption and usage. "*Social influence consists of two factors: (1) consumers' beliefs about* *people they consider important (e.g. family members or close friends) to influence their behavior; (2) the motivation to consult important others about their attitude towards new technologies."*(Venkatesh et al., 2012). There's a cultural component that will be moderating the effects on the behavioral intention to adopt digital payments. This will be also driven by the type of society and background, that also moderates the effect of this construct. (Hofstede, 2011)

Trust (T): A consumer's confidence in the security, privacy, and reliability of digital payment methods and platforms.

Price Value (PV): The user's evaluation of the financial benefits or cost-savings of digital payment usage, weighed against any perceived costs. Price value has been defined as "consumers' cognitive tradeoff between the perceived benefits of the applications and the monetary cost for using them" (Venkatesh et al., 2012). It positively affects users' behavioral intention (BI) to use digital payments. If the PV relationship increases, the Behavioral intention moves in the same direction. Costs vary by country in terms of owning the devices, internet service costs and other fees (if they applies).

Cash Preference (CP): A consumer's tendency to favor cash over digital payment methods, shaped by personal habits, economic context, and local acceptance norms. In this study, CP is treated as a moderator, reflecting country-level variation in cash usage and digital convenience perceptions.

Country Landscape: Defined as national-level economic and infrastructural conditions, such as digital readiness, regulatory frameworks, and payment infrastructure, that influence user adoption patterns. While not a direct construct, these factors inform the moderating role of CP across countries.

1.8 Scope Limitations and Assumptions

This study focuses on the factors influencing the adoption and use of digital payments by consumers across four (4) developed, English-speaking countries: the United States, Canada, the United Kingdom, and Australia. The research applies constructs from the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), including effort expectancy, performance expectancy, trust, attitude, price value, and social influence. These variables are analyzed alongside behavioral intention and actual use, with cash preference introduced as a moderating factor.

This study focuses on digital payment adoption across several countries, incorporating cultural and economic diversity. The research assumes that survey respondents provide honest and accurate responses. Limitations include the potential for bias in self-reported data and the challenge of generalizing findings beyond the selected sample countries.

The **scope** of this study is limited to:

Individual consumers make personal purchasing and payment decisions.

Four countries with developed payment infrastructure and high technology penetration.

Cross-sectional data collected via self-reported online surveys.

Digital payment methods, including cards, digital wallets, contactless payments, and banking apps (see full list in Chapter 2).

While the study focuses on consumer behavior, it acknowledges that merchant and business-related factors, such as payment acceptance, infrastructure availability, and transaction design, may indirectly influence consumer perceptions and adoption. These environmental influences are considered within the broader constructs of performance expectancy and price value.

The **delimitations** of the study are as follows:

Cultural and political factors are not explored in depth, though the country's context is partially represented through cash preference.

Other potential influences on digital payment adoption, such as perceived risk, cost, or facilitating conditions, are not directly examined to maintain focus on the selected constructs. However, relevant aspects are captured through existing model components. Specifically:

Trust encompasses user confidence in the security, reliability, and integrity of digital payment systems.

Price value accounts for cost sensitivity and perceived financial benefit.

Effort expectancy reflects usability and accessibility.

The study does not assess longitudinal changes in behavior, as data is captured at a single point in time.

The research is limited to English-speaking populations, which may restrict the generalizability of findings to other global regions with different linguistic, infrastructural, or economic conditions.

The **assumptions** of the study are as follows:

First, it was assumed that respondents answered truthfully and understood the questions presented in the survey. Second, it was assumed that the Likert-scale items accurately reflected the intended constructs, based on prior validation from earlier studies. Finally, it was assumed that digital payment experiences were sufficiently comparable across countries to allow for meaningful interpretation of the aggregated data.

While the initial design and research questions of this study sought to explore potential moderation effects by country of residence and cash preference on digital payment adoption, data limitations emerged during the analysis phase that restricted the feasibility of executing these advanced statistical procedures. Specifically, the sample sizes within key subgroups did not meet the thresholds required for reliable moderation or multi-group analyses. Consequently, the study strategically focused on delivering a robust baseline regression analysis, identifying the primary predictors of behavioral intention to adopt digital payments across the entire sample. This approach allowed the study to maintain analytical rigor and generate actionable insights, while positioning moderation effects as a critical area for future research, as discussed throughout the dissertation.

1.9 Organization of the Dissertation

This dissertation is structured into five chapters:

Chapter 1 – Introduction: Provides the background, problem statement, purpose, research questions, theoretical framework, and scope of the study.

Chapter 2 – Literature Review: Explores the current academic and industry research on digital payments, technology adoption models (TAM and UTAUT), and factors influencing adoption and usage across countries.

Chapter 3 – Research Design and Methodology: Describes the study's research model, hypotheses, survey design, sampling strategy, and data collection approach.

Chapter 4 – Data Analysis Procedures: Presents the data preparation steps, statistical methods, and techniques used to analyze the collected responses. Data Analysis and Results: Reports the results of descriptive statistics, reliability testing, regression analysis, and hypotheses testing.

Chapter 5 – Discussion, Conclusion and Recommendations: Interprets the results in the context of existing literature, discusses theoretical and practical implications, and evaluates the role of moderating factors like cash preference and country context. Summarizes the study's key findings, acknowledges limitations, and offers recommendations for future research and policymaking.

LITERATURE REVIEW

During the literature review process for this research, a keyword-based search was used to identify relevant studies in the digital payments field. The keywords used included: "Digital Payments", "Digital Payments and COVID", "Cashless society", "unbanked population", and "digital payments". As described in chapter 1, Digital payments, also called electronic payments, is the transfer of value (goods, services, funds) from one payment account to another using a digital device or channel (Khando et al., 2022). Digital payments can be partially digital, primarily digital, or fully digital.

From the various existing categorizations of digital payments, this study adopts the classification proposed by Khando et al. (2022): 1) Card Payments (Credit/debit/prepaid cards) 2) E-payments (Fast funds, digital wallets), 3) Mobile Payments (P2P funds transfer, mobile apps) 4) Cryptocurrencies (bitcoin, DCC).

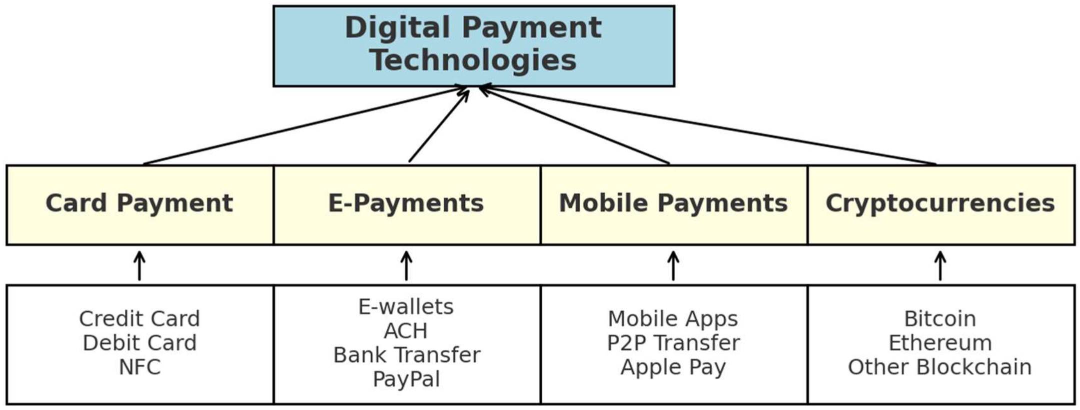


Figure 1 Digital Payment Technologies- Adapted from Khando K, Islam M.S, Gao, S "The emerging technologies of Digital Payments and Associated Challenges" (2022)

Despite the diverse nature of digital payment offerings worldwide (Franciska & Sahayaselvi, 2017), for research purposes, all forms of payment options, whether domestic or international, are considered under these four categories, including country-specific services like the Interac Debit product in Canada. There are several other categorizations, such as (Wenting, 2021), focused on digital wallets and not including cryptocurrencies. The adopted classification is mostly driven by the nature of the research and the target market/subjects. Plus, digital payments are also extremely diverse in business cases, for example, digital wallet (Apple/Samsung/Bank proprietary), Real Time Payments: Person to Person (P2P), Business to person or Business (B2P/B2B).

Khando et al. (2022) provide one of the most extensive systematic literature reviews in the field. Their framework categorizes studies by product type and channel, and identifies challenges across technical, social, awareness, economic, and legal domains. This study draws on those classifications to explore country-level moderating factors such as culture, demographics, and infrastructure.

Analyzing these categories through the lenses of consumer behavior, technology acceptance (Ariffin et al., 2020), and moderated by the country landscape, contributes with valuable insights into the adoption and usage of digital payments. This research incorporates infrastructure, culture (Gelfand et al., 2011), and the economic context of the selected countries, recognizing their influence on adoption trends (Pal et al., 2018).

Given the variety of options offered by digital payments, from traditional plastic to ecommerce and mobile payments, it is necessary to integrate these Constructs to the overall model focused on getting a better understanding of these drivers, given different countries' socio-economic landscape. There are other theories also used to explain the consume adoption of new technologies and digital payment applications, such as UTAUT (Patil et al., 2018).

Economic literature traditionally explains the reduction in the use of cash and the transition to digital payment as part of the natural evolution of monetary and payment systems *(Trautwein ,1997),* basically arguing that innovation and digital payments evolution will eventually shape the entire world. Several studies have been focused on evaluating the digitalization of payments and an eventual "cashless society" as a key goal(Hummel, 2017), but also as a natural result of the evolution of technology (Mohd Thas Thaker et al., 2023). On the other hand, the opposition to the cashless benefit thesis relies on potential distortions in aggregate consumption, investment, and output, as well as misallocation of productive efforts across the economy, not to mention consider it unrealistic (*Lagos and Zhang 2019, Cohen 2020),*(Fabris, 2019) . A study by Cohen (2020) argues that cash plays an essential role in facilitating transactions between the banked and unbanked sectors, and that its elimination can disrupt productive exchange, especially in economies with high cash reliance.

This research does not aim to take a stance in this broader debate but rather focuses on how cash preference interacts with country-level conditions, such as digital infrastructure or policy environments, to shape digital payment adoption. Instead of comparing countries head-to-head, the study uses cash preference as a proxy moderator to capture how broader economic and contextual dynamics may influence adoption outcomes. The Digital Payments space is extremely diverse dynamic, driven by innovation and financial opportunities. Therefore, implementation and adoption might have different results even within developed nations, given the product offering vs. the country landscape, regulations, cash preference, among other factors. For instance, while the U.S. is often considered a leader in financial innovation, it only began widespread adoption of Real-Time Payments (RTP) in 2017, years after countries like the UK and India (Patil et al., 2018; Prabhakar, 2019). This highlights how even advanced markets can differ in adoption timelines due to regulatory, infrastructural, or preference-based factors.

2.1 Technology Acceptance Model (TAM)

Originally developed by Davis to explain individual reactions to computers, TAM focuses on two central constructs: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). These constructs have been adapted to digital payments research (Rigopoulos & Askounis, 2007), especially for services like mobile payments, where subjective perceptions significantly influence behavior (Agarwal & Karahanna, 1998). The adoption and usage of digital payments is traditionally studied under similar theoretical frameworks as Online banking, mobile adoption, internet usage and other applications.

Extended TAM models have been used in specific contexts such as mobile payments in the USA (Bailey et al., 2017). This version separates ease of use (PEOUMP), mobile payment usefulness (PUMP), and incorporates privacy concerns and technology anxiety. The study notes the need for further research into demographic and cultural moderators, as well as a broader analysis beyond tap-and-go use cases.

Recent studies have expanded TAM further by incorporating Risk into a broader Trust construct (Yang et al., 2023), which considers privacy, performance, financial, and time risks. These studies emphasize limitations such as geographic and demographic differences that may require longitudinal designs.

This model is also being used for Digital Payments research and constructs are fundamentally focused on the subjective Perceived Usefulness and Ease to Use of the new offering, or in our case, a new digital payments option (Rigopoulos & Askounis, 2007)

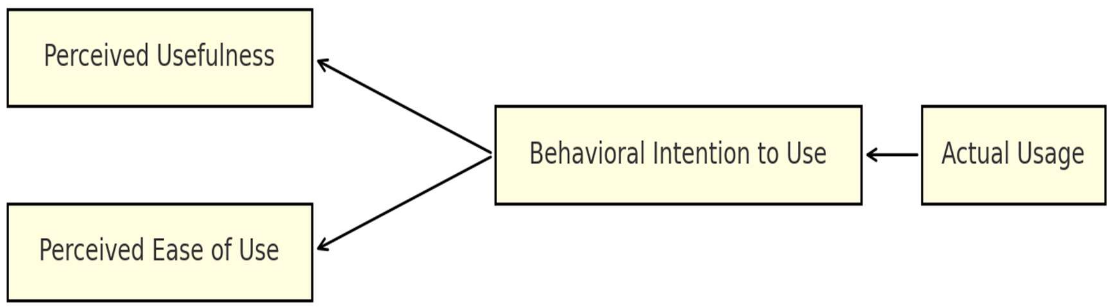


Figure 2 Adapted from Rigopoulos, G., & Askounis, D. (2007). TAM model applied to Digital Payments Adoption

Specifically for mobile payments, the TAM model has been evaluated in terms of an extended version, to get a better understanding of consumer behavior (Bailey et al., 2017), evaluating different functionalities, such as “Tap and go”, privacy concerns and “technology anxiety”. It’s important to mention that this research was conducted in 2017, pre COVID era and additional mobile payment options. Nevertheless, the model required a certain level of customization focused on getting a better understanding of consumer behavior towards mobile and digital payment options, in this case in the USA.

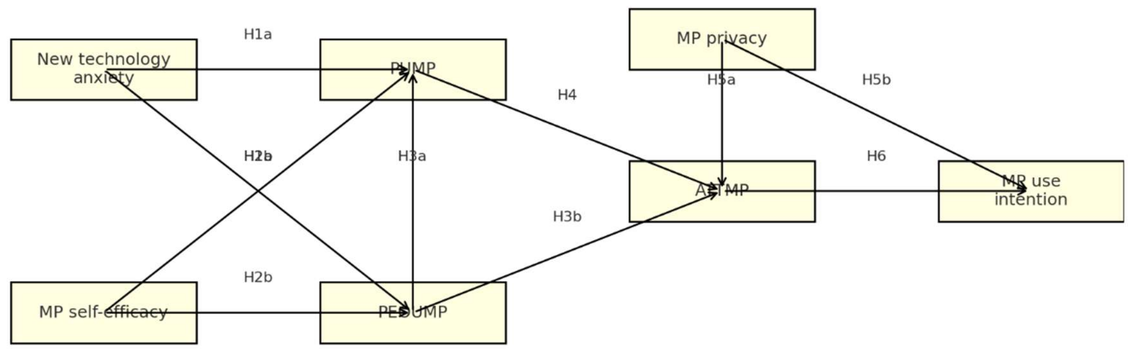


Figure 3 An Extended TAM Adapted from (Bailey et al., 2017)

This model tries to separate the perception of ease to use (PEOUMP), mobile payments usefulness (PUMP), as well as privacy and new technologies anxiety. The author also acknowledges the complexity of the digital payments adoption and usage, especially given cultural and geographical differences, acknowledging the need of studying the impact of demographics, different kind of payments and even evaluating potential cultural related impacts (Bailey et al., 2017).

More recent studies, such as (Yang et al., 2023), extended the TAM model even more, adding additional variables, such as Risk (Privacy, performance, financial, time) as component of a more robust Trust construct.

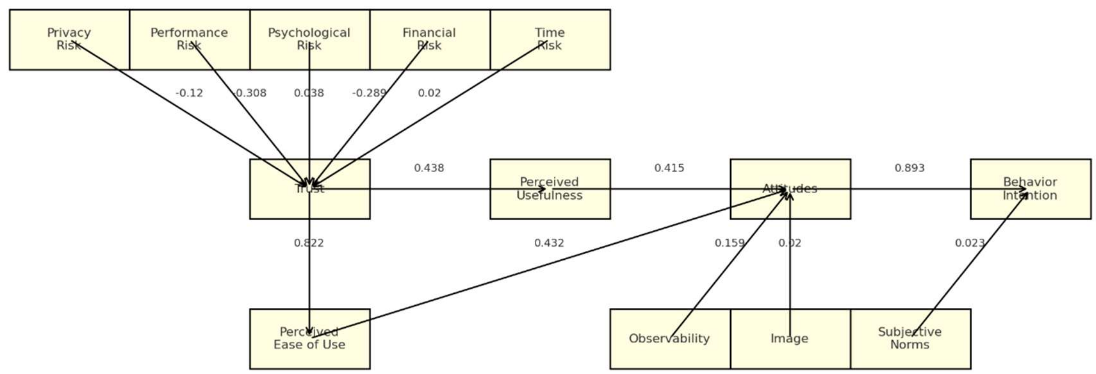


Figure 4 Extended TAM Older Adults-Adapted from “An Extended TAM Predicting older adults’ mobile payment adoption” (Yang et al., 2023)

The study also acknowledged the limitations of the research, due to other variables, such as geography, usage trends, education and demographics, plus a long-term perspective in order to understand trends and changes in user behavior (Yang et al., 2023).

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

UTAUT, developed by Venkatesh et al. (2003), consolidates constructs from multiple acceptance models and introduces Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions. UTAUT has been extended with constructs such as Trust, Risk, Innovativeness, and Habit in digital payments research (Slade et al., 2015; Ariffin et al., 2020).

Researchers such as Al-Saedi et al. (2019) argue that UTAUT offers a more comprehensive model than TAM for analyzing digital payment behavior to close gaps in previous studies with the TAM and other conceptual models, considering UTAUT a more robust model for this analysis. Ariffin et al. (2020) further validate this by applying UTAUT in a retail context.

Sahi et al. (2021) and Patil et al. (2018) highlight additional constructs and propose future research directions, emphasizing gaps such as cross-cultural and socioeconomic variations. Patil et al. also recommends extending technology acceptance frameworks to include fintech tools beyond traditional mobile payments, such as bill payments and pay advances.

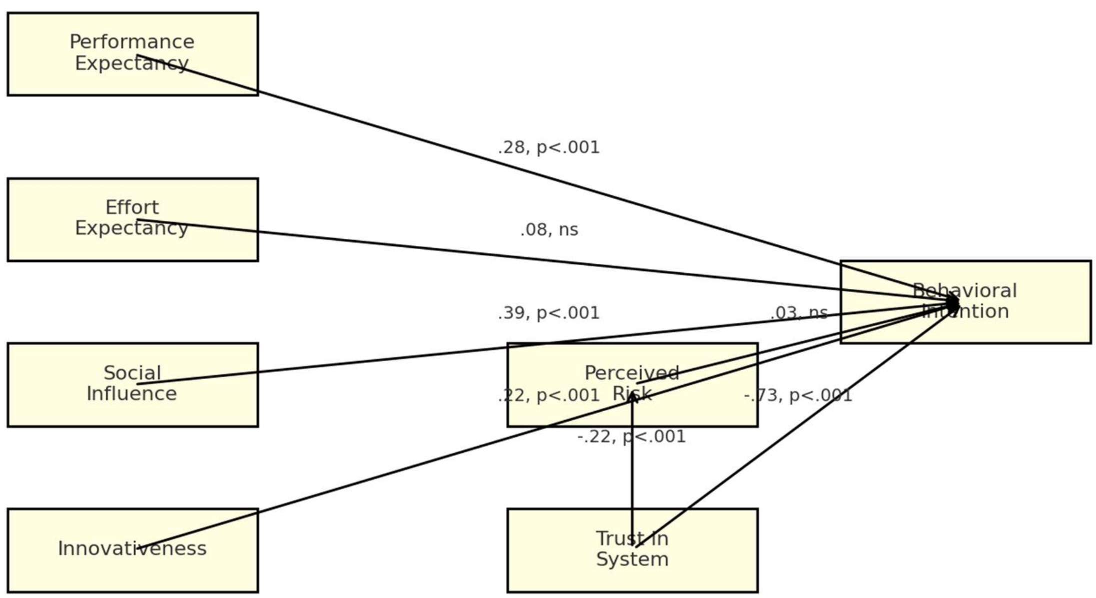


Figure 5 Extending UTAUT

Adapted from Modeling Consumers' Adoption Intentions of Remote Mobile Payments in the United Kingdom: Extending UTAUT with Innovativeness, Risk, and Trust (Slade et al., 2015)

Other external factors have been added to an extended version of the model, to get a more comprehensive view of adoption, such as facilitating conditions and habit. (Ariffin et al., 2020)

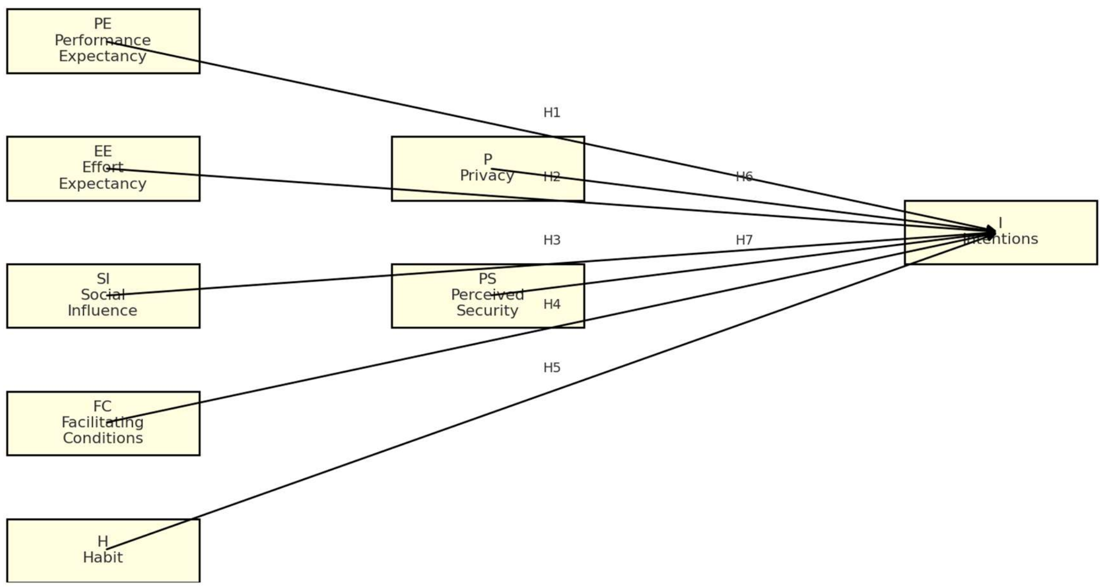


Figure 6 Mobile UTAUT Adapted from Ariffin et al. (2020). "Acceptance of Mobile Payments by Retailers Using UTAUT Model". (Ariffin et al., 2020)

Multiple researchers have consistently concluded that the complexity of electronic payments extends beyond mere consumer behavior factors, encompassing technological, infrastructural, and regulatory challenges (Alduais & Al-Smadi, 2022; Sahi et al., 2021). For instance, Alduais and Al-Smadi (2022) emphasize the need for complementary research focusing on determinants of e-payment adoption beyond user attitudes, while Sahi et al. (2021) highlight how external factors, such as policy frameworks and technological readiness, significantly influence adoption patterns. These studies advocate for a broader analytical scope, urging scholars to explore variables that impact payment adoption across different contexts and to continually update research models in line with technological advancements.

Building on prior behavioral research, subsequent studies have expanded technology acceptance frameworks by integrating complementary factors that address the multifaceted nature of digital payment adoption. A notable example is the work of Sahi et al. (2021), which offers a comprehensive synthesis of these dynamics.

Sahi et al. (2021) provides a comprehensive synthesis of digital payment adoption by integrating behavioral, technological, and contextual dimensions. Their framework highlights how factors such as user trust, perceived risk, financial literacy, and regulatory environments interact with technological readiness to influence adoption decisions. Sahi et al. (2021) examined cross-country variations and identified emerging trends. Their study offers a holistic perspective that extends existing technology acceptance models and uncovers critical gaps for future research. This synthesis serves as a valuable foundation for framing the broader digital payment adoption landscape and underscores the need for multi-dimensional approaches. In contrast, the present study did not model country-level differences directly due to sample constraints. Instead, it explored cash preference as an individual-level moderator that may reflect certain contextual influences across countries.

Other studies have continued the behavioral focused research, introducing additional elements to the technology acceptance models, such as the Behavioral Intention Model of

Electronic payments (Sahi et al., 2021), which integrates a wide range of individual, technological, and risk-related factors impacting adoption intentions.

Patil et al. (2018) conducted a systematic analysis of literature focused on theoretical anchors such as TAM and UTAUT, while also expanding on contextual factors influencing electronic payment adoption. Their work synthesized over a decade of empirical studies, highlighting determinants beyond consumer behavior, including infrastructure readiness, regulatory support, and socio-economic disparities. Additionally, they identified key research gaps, such as the limited scope of cross-country comparative analyses, the underrepresentation of non-mobile payment methods, and the lack of studies examining the behavioral impact of emerging fintech services. While this study does not conduct a formal cross-country comparative analysis, it includes participants from four developed economies to explore how individual preferences, such as cash usage, may serve as contextual signals. This approach offers exploratory insights into potential variations in adoption behavior across mature markets, without claiming direct country-level comparisons.

Table 1 Adapted from Patil, Pushp P., Yogesh K. Dwivedi, and Nripendra P. Rana. "Digital payments adoption: an analysis of literature." Digital Nations–Smart Cities, Innovation, and Sustainability": November 21–23, 2017

Theory/Model	**Frequency**	**Citations**
TAM	14	[4, 11, 17, 21–30, 33]
UTAUT	5	[6, 19–21, 33]
DOI	3	[12, 15, 19]
IDT	3	[4, 15, 33]
Mallat (2007)	1	[13]
Dahlberg and Oorni Factor (2007)	1	[36]
Tornatzky and Klein (1982)	1	[16]
Trust Based Acceptance Model	1	[16]

LEGEND: *DOI: Diffusion of Innovations Theory; IDT Innovation Diffusion Theory; TAM: Technology Acceptance Model; UTAUT: Unified Tehory of Acceptance and Use of Technology.*

It's also important to mention the systematic literature review by digital payment offering conducted by (Khando et al., 2022), classified its findings as follows:

Table 2 Systematic Literature Review on Digital Payment Technologies and Associated Challenges (Khando et al., 2022)

Review by	No. of Papers	Focus of the Study
Khandro et al. (2022)	58	Emerging technologies of digital payment and associated challenges
Ahmad & Hanza (2021)	51	Mobile e-wallet in emerging economies
Kabir, Sadiq & Ahmi (2019)	51	Adoption of e-payment systems
Castro, Diniz & Hassens (2017)	54	Applications related to blockchain technology
Diniz, Porto & Cerney (2014)	192	Mobile money and payment
Dahlberg et al. (2015)	73	Past, present, and future of mobile payment technology
Patil, Dwivedi & Rana (2022)	21	Adoption of digital payment technologies
Karsen, Chandra & Juwitasary (2019)	54	Technological factors of mobile payment

As of today, the (Khando et al., 2022) literature review is considered one of the most complete in the rapidly changing digital payments research space, presenting a classification of existing studies by electronic channel option. The author also presented a classification of studies based on product type and digital payment challenges: Technical, Social, Awareness, Economic and Legal. This research will be focused on identifying some of these components, such as country, culture, demographics, acting as moderators of electronic payments' evolution. As discussed in the introduction, the evolution of digitalization of payments does not follow a straight line across different countries, being more than a challenge, a permanent (at least mid-term) element conditioning the country/region adoption and usage of these payment options.

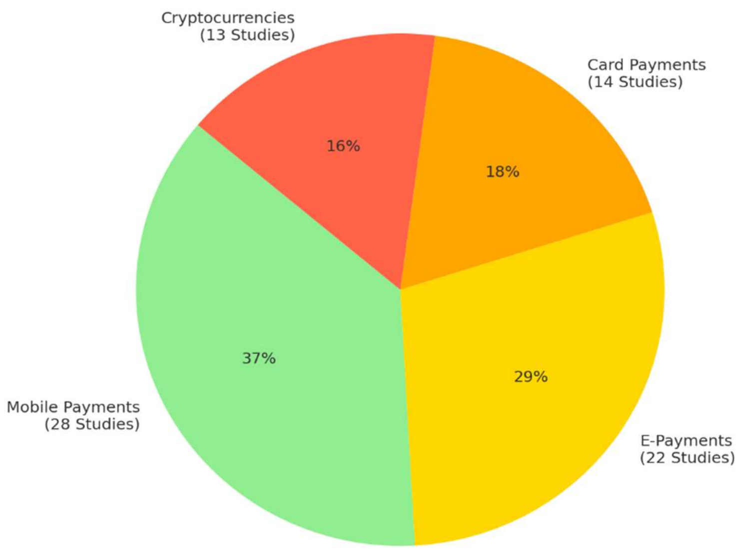


Figure 7 Digital Payments Studies by Category Adapted from Khando et al. (2022). "Percentage and Number of Studies Conducted in Each Category of Digital Payment Technologies."

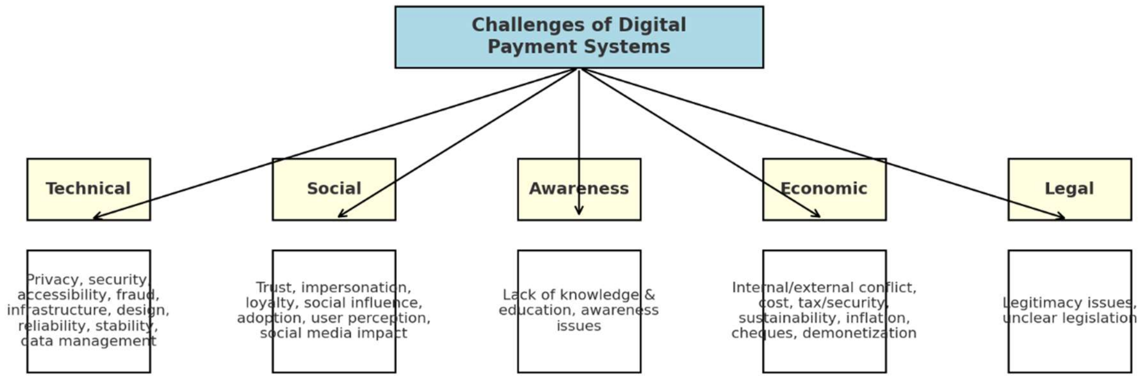


Figure 8 Systematic Literature Review- Adapted from Khando et al. (2022). "The Emerging Technologies of Digital Payments and Associated Challenges: A Systematic Literature Review"

Some studies have discussed country differences and cultural elements (Gelfand et al., 2011), as well as connecting with the theoretical technology model UTAUT (Wu & Liu, 2023), specifically among the mobile payments research. The study acknowledges the existence of different stages of mobile adoption that could affect the results and suggests further research compared to other countries. This behavior is similar to other more specific digital payment offerings, such as Electronic wallets (Lwin, 2022).

Another element attributed to digital payments is its potential to be a path to financial formality for unbanked population (Gupta et al., 2024). Previous research also outlined a relationship between cash transactions and the unbanked population, or a link between socio-economic inequality and still heavy reliance on cash. Given the level of digitalization and banked population in the economy, how will new advances in the payments landscape impact financial inclusion and socio-economic equality in each country? Are the government policies a potential driver/inhibitors? (Gupta et al., 2024).

Based on the initial analysis and existing literature review, this research will be focused on the result of the interaction between a country's economic landscape and the digital payments consumer behavior. It will consider the cash usage in the economy, under the UTAUT2 theoretical lens (Ariffin et al., 2020), as anchor of this research, as well as the potential benefits into the economy as a whole and eventually in terms of financial inclusion moderating the digital economy trends in the country. The above-mentioned differentiation between adoption and usage, as well as the cultural elements driving consumer habits will be key drivers for the research (Wu & Liu, 2023).

The influence of country-level effects can also intersect with demographic factors such as age, income, and education, which have been shown to impact digital payments usage (Lohana & Roy, 2023). Furthermore, it is important to understand if there are specific events that acted as drivers or inhibitors of the digital payments' adoption and usage. Economic crises, like the cash shortage in Venezuela, have driven accelerated adoption of digital solutions, both domestically through banking infrastructure and internationally via platforms like Zelle (Boshkov, 2018).

The cultural component is being analyzed from the perspective of tight or loose cultures (Gelfand et al., 2011), as a moderator factor for the consumer behavior towards digital payments.. Theres also a study about payment culture differences by (Busse et al., 2020) , also acknowledging the gap on the body of research in terms of social norms in place as traditions or given the specific country's economic landscape. Like use candy or gums to substitute small change in Iran or a cash shortages in Venezuela that started in 2016, also allowing barter type of transactions, until 2019 (Boshkov, 2018). Financial inclusion is another central theme. Gupta et al. (2024) connect digital payments with reduced cash dependency among unbanked populations, raising questions about how socio-economic inequality and government policy impact digital payment adoption. These types of scenarios accelerated the use of digital payments options, such as cards in Iran, Real Time Payments in Venezuela and Mobile Payments in India. Based on the literature review for this research, these economic driven habits offer potential opportunities for future work.

2.3 Cross-Country Comparisons in Digital Payment Behavior

Preliminary findings suggest performance disparities in digital payments between countries. For example, in Denmark, the most popular transaction type comes from credit cards, while the mobile application Swipp, leads the market for Real Time Payments transactions, but mostly coming from Debit, with different use cases (P2P, B2P among others). (Staykova & Damsgaard, 2015). Country-specific elements also shape mobile payment adoption and digital wallet usage (Lwin, 2022).

Several studies highlight the widespread adoption of digital payments in developed economies, illustrating the maturity of these markets. While adoption rates are high across countries like our target ones for this study: UK, Canada, Australia, and the US, underlying drivers, such as infrastructure, regulations, and digital readiness can still vary. Building on these insights, this study focuses on behavioral determinants of adoption, emphasizing user-level perceptions and intent, rather than drawing direct country-to-country comparisons.

Regarding these specific markets, recent data confirms the high digital infrastructure maturity and banking penetration levels in each country: Digital payment penetration across the UK, Canada, Australia, and the USA reflects a high level of digital infrastructure maturity. For example, over 86% of UK adults use online or remote banking (Statista, 2024), while 89% of Canadians reported using online banking services, with nearly half citing it as their primary method (Canadian Banking Association, 2024). Australia reports 20.8 million banking customers across 97 institutions (Statista, 2024), and in the USA, digital banking users are projected to surpass 217 million by 2025 (Statista, 2024). The data illustrate the widespread adoption of digital financial services in developed markets and support the decision to focus this study on behavioral factors influencing sustained usage.

This study builds on the extended UTAUT2 framework by incorporating Cash Preference as a moderator. Rather than testing individual cultural or regulatory variables, the model uses cash preference and country context to explore how broader economic environments may shape digital payment behaviors. This approach allows for an initial step toward understanding adoption variance across mature markets, particularly where cash remains a prevalent method.

2.4 Gaps in Literature

Despite the growing body of work on digital payments, several important gaps remain: While many studies use models like TAM and UTAUT, there's limited cross-national research that systematically compares countries with different economic, cultural, and infrastructure profiles. Studies often focus on single-country data, leaving a gap in understanding how adoption drivers vary globally (Patil et al., 2018; Wu & Liu, 2023). Additionally, cash remains a strong behavioral and cultural anchor in many countries, yet few studies have explored cash usage as a moderating variable affecting behavioral intention to adopt digital payments. This gap limits the practical understanding of how digital and cash preferences coexist.

Much of the research emphasizes individual behavioral constructs (e.g., ease of use, performance expectancy) while underrepresenting structural and policy-level factors, such as financial infrastructure, digital literacy, or regulatory environments (Gupta et al., 2024).

There is a lack of targeted research on how digital payments influence or are influenced by financial inclusion efforts, particularly in economies with large underbanked populations (Gupta et al., 2024; Boshkov, 2018). It is also significant that a large portion of foundational studies were conducted before or during the early stages of the COVID-19 pandemic. The long-term effects of accelerated digitalization, changing privacy concerns, and new technologies like real-time payments and digital wallet ecosystems are still to be seen and underexplored (Yang et al., 2023; Khando et al., 2022).

This study aims to explore how selected behavioral constructs, such as performance expectancy, trust, and cash preference, interact with broader national characteristics to shape digital payment behavior. It leverages the extended UTAUT2 model, incorporating cash preference as a potential moderating variable, and explores how national context may shape behavioral intention and usage. While it draws on data from four developed countries (U.S., Canada, U.K., and Australia), the primary objective is not to compare these countries directly, but to understand behavioral patterns and potential moderating effects of national context. Due to data limitations, the moderation analysis serves more as an exploratory lens than a conclusive comparative tool. The study contributes to the growing literature on digital payment adoption by highlighting the need to contextualize behavioral models within the realities of specific economic and technological landscapes. It provides preliminary insight into behavioral patterns and subtle cross-market dynamics, offering a foundation for future comparative research.

2.5 Chapter Summary

This chapter provided an in-depth review of the literature surrounding digital payment adoption, focusing on key theoretical frameworks and constructs relevant to consumer behavior. Beginning with an exploration of TAM and its extensions, the review transitioned into the more robust and widely applied Unified Theory of Acceptance and Use of Technology (UTAUT) and UTAUT2. These models serve theoretical anchors of the proposed research, incorporating constructs such as Performance Expectancy, Effort Expectancy, Price Value, Trust, Social Influence, Attitude, and Behavioral Intention.

RESEARCH MODEL AND HYPOTHESIS

3.1 Overview

This study adopts a quantitative research approach using a cross-sectional survey design to examine the factors influencing the adoption and usage of digital payments. The research is grounded in the extended UTAUT2 model, integrated with constructs from TAM and recent digital payments literature. This theoretical foundation supports the examination of behavioral intention and usage behavior across digitally mature, English-speaking economies, accounting for key predictors from the UTAUT2 framework and recent literature. The primary goal is to test the hypothesized relationships between core constructs: Performance Expectancy, Effort Expectancy, Price Value, Trust, Social Influence, Attitude, and Behavioral Intention. The study also incorporates Cash Preference as a moderator to explore its influence on these relationships.

Although the study was initially designed to explore moderation effects at the country level, reflecting broader contextual factors such as infrastructure, culture, and economic environment, the final design prioritized Cash Preference as a key country-level proxy due to sample size limitations. This decision aligns with the study's multi-country comparative focus, which balances both shared adoption drivers and country-level diversity while maintaining methodological rigor. As a result, moderation analysis is performed using Cash Preference as a contextual factor, highlighting its role in shaping adoption behaviors.

Given the global relevance of digital payments, a multi-country sample was selected to account for economic, cultural, and infrastructural diversity. This strategy involves analyzing both shared patterns and individual differences in adoption behavior, offering exploratory insight into how country-specific trends may influence digital payment usage in advanced economies.

This chapter outlines the methodological foundation of the study, detailing the research design, strategy, conceptual framework, and hypotheses. The primary objective is to examine the factors influencing the adoption and use of digital payments across the target countries using the UTAUT model. The chapter begins with the overall research strategy, followed by a discussion of the conceptual model guiding the investigation. The research questions and hypotheses are revisited considering the final instrument and theoretical alignment. Together, these sections establish the groundwork for the data collection, analysis, and interpretation stages presented in subsequent chapters.

3.2 Research Design and Strategy

This study employs a quantitative, cross-sectional survey design, leveraging a structured questionnaire to gather data on individuals' attitudes, preferences, and behaviors regarding digital payment systems. The strategy is designed to test a set of predefined hypotheses derived from an extended UTAUT2 framework. The study aims to explore how behavioral constructs and country-level proxies, such as individual cash preference, may reflect broader contextual factors (e.g., infrastructure or economic environments) influencing digital payment adoption

Although data was collected across four advanced economies, the study does not conduct direct cross-country comparisons, focusing instead on shared behavioral patterns and individual-level insights. Key features of the research strategy include:

Deductive approach, starting from theory (UTAUT2) and testing specific hypotheses.

Structured instrument developed from validated scales in prior studies.

Convenience sampling with efforts to ensure representation across demographics (e.g., age, income, education).

Statistical analysis including Exploratory Factor Analysis (EFA) and regression analysis.

Initially, the study also aimed to conduct a moderation analysis to explore country-level factors, represented here through cash preference, might influence the adoption & dynamics of digital payments. However, due to sample size constraints within subgroups, a formal multi-group moderation analysis was not executed in the final model. This limitation is acknowledged, and the study focuses instead on examining the direct effects of the core constructs on Behavioral Intention, complemented by an extended moderation analysis using cash preference as a continuous moderator variable.

This strategy supports the empirical validation of relationships between constructs like Performance Expectancy, Effort Expectancy, Price Value, Trust, Social Influence, Attitude, and Behavioral Intention, while ensuring an efficient assessment of perceptions and behaviors at a single point in time. This is particularly relevant when studying technology adoption across diverse regions.

Data was collected via an online questionnaire distributed across the four target countries, ensuring a broad and diverse respondent base. The use of a structured survey supports consistency in responses and aligns with best practices for validating theory-driven models in information systems research. While this design does not capture longitudinal effects, it enables an effective assessment of current adoption factors and cross-country comparisons.

3.3 Conceptual Model

The conceptual model for this study is grounded in the extended Unified Theory of Acceptance and Use of Technology (UTAUT2), incorporating elements from the Technology Acceptance Model (TAM) and recent literature on digital payments. The model aims to identify and test the key factors that influence individuals' Behavioral Intention (BI) to adopt digital payments and their subsequent Use Behavior (UB).

This study was initially designed to examine both direct effects and potential moderating relationships among constructs. Specifically, the role of Cash Preference was conceptualized as a potential moderator of relationships between key predictors and Behavioral Intention. However, as noted in the research design, due to sample size constraints within subgroups, a formal moderation analysis was not executed in the final model. Instead, Cash Preference was analyzed as a direct predictor of Behavioral Intention. This adjustment ensures methodological robustness while still acknowledging the theoretical relevance of Cash Preference as a potential moderating factor in digital payment adoption.

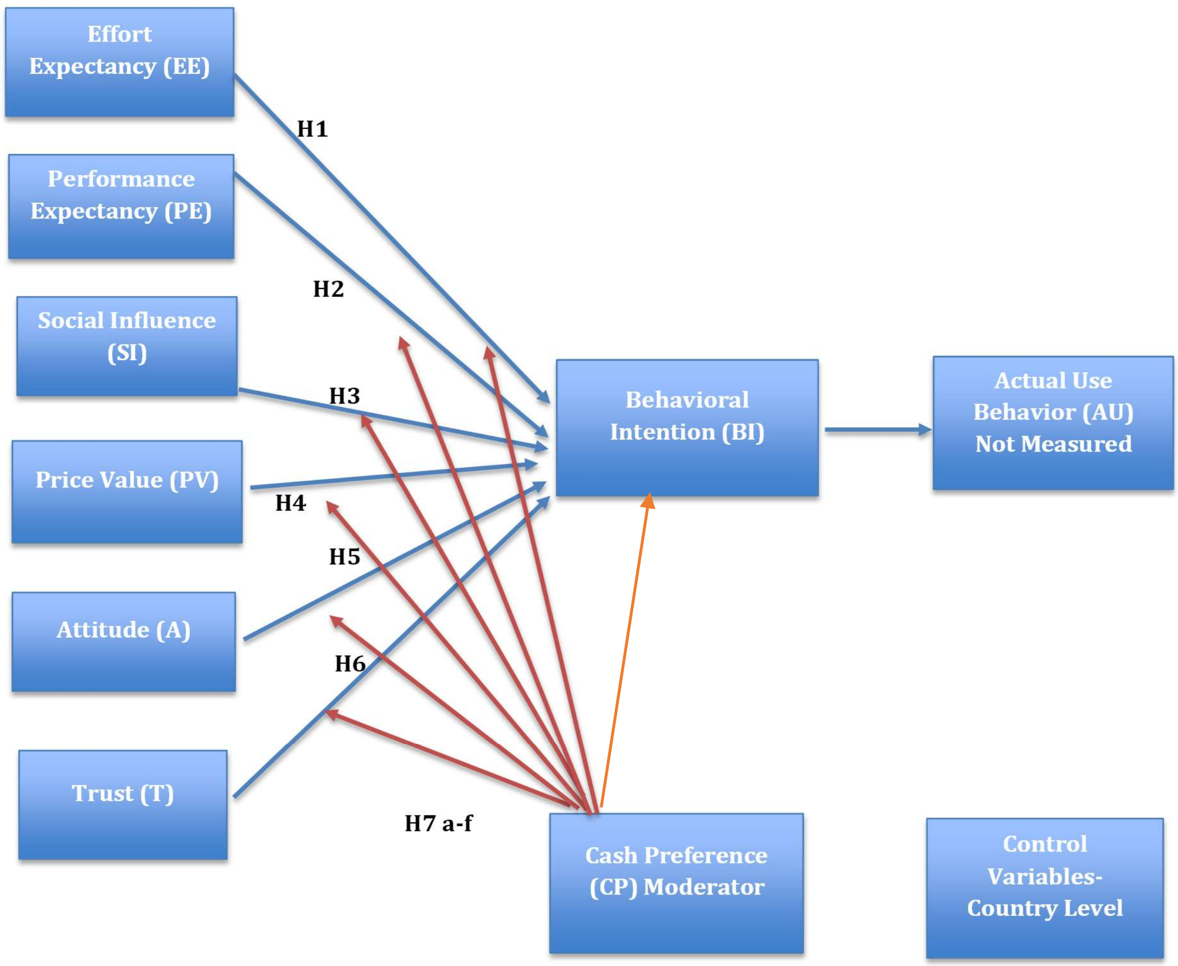
Given the study's international scope, the conceptual model includes core constructs derived from UTAUT2 and relevant literature, as summarized in Table X. The conceptual model hypothesizes that users' Behavioral Intention to adopt digital payments is primarily influenced by the four UTAUT constructs, and that this relationship is moderated by the user's cultural context and, potentially, other demographic variables (e.g., age, income, education). The model also reflects a practical application of theory, designed to provide actionable insights for financial institutions and policymakers seeking to expand the reach of digital payment platforms in different cultural settings.

Table 3 Key Constructs & Definitions

Construct	**Code**	**Definition**
Performance Expectancy	PE	Degree to which using digital payments provides benefits.
Effort Expectancy	EE	Degree of ease associated with digital payment usage.
Price Value	PV	Perceived value and cost trade-off of digital payments.
Social Influence	SI	Degree to which users perceive others expect them to use digital payments.

Construct	Code	Definition
Attitude	A	Overall positive or negative feelings toward digital payments.
Trust	T	Degree to which users feel secure and confident in using digital payments, especially in terms of platform reliability, privacy, and institutional safeguards.
Behavioral Intention	BI	Intention to adopt digital payment technologies.
Cash Preference	CP	User's preference for cash over digital payments (direct predictor and key moderator).
Use Behavior	UB	Real frequency and extent of digital payment usage by participants.

The model reflects both theoretical and practical perspectives, offering insights for financial institutions, technology developers, and policymakers aiming to understand adoption dynamics in diverse cultural and economic contexts. Figure 9 presents the proposed conceptual model guiding this study.



Digital Payments Adoption – H1-H7 and CP Moderation

Figure 9 Research Model– Source: Author (2025)

The proposed research model with IV, DV and mediator/dependent construct is based on the UTAUT model but adding not only the Use Behavior (adoption), but also the Actual transaction (Usage). Table 2 provides definition for the proposed constructs. Then the mediation effect is defined by the country landscape and the cultural differences (tight and loose cultures), considering also external shocks such as COVID. The actual transaction (DV) will be determined by a combination of all these factors by target country.

The proposed research model is based on the UTAUT2 framework, incorporating key constructs such as Performance Expectancy (PE), Effort Expectancy (EE), Price Value (PV), Social Influence (SI), Attitude (A), and Cash Preference (CP) as direct predictors of Behavioral Intention (BI) to adopt digital payments. Behavioral Intention is further linked to Use Behavior (UB), representing actual usage.

Although the initial design conceptualized Cash Preference as a moderating variable, due to methodological limitations and sample size constraints within subgroups, the final analysis focused solely on direct relationships. Consequently, Cash Preference was analyzed as a direct predictor of Behavioral Intention. This approach ensures methodological rigor while acknowledging that Cash Preference may still influence the strength and direction of relationships between key constructs and Behavioral Intention in future research.

Additionally, while the initial model intended to explore Cash Preference's moderating role across variables such as Performance Expectancy, Effort Expectancy, Price Value, Trust, and Social Influence, the final model treats Cash Preference as a significant and contextually relevant direct factor. This decision aligns with the study's emphasis on exploring core adoption drivers across diverse markets, laying a foundation for future studies to incorporate more nuanced moderation analyses.

3.4 Hypotheses Development

This section presents the hypotheses guiding the study, refined based on pilot feedback and methodological limitations encountered during data collection. The study explores the direct relationships between UTAUT and TAM constructs and Behavioral Intention (BI) to adopt digital payments, as well as the link between Behavioral Intention and Use Behavior (UB).

Although the original model intended to examine moderation effects of cash preference and country differences, these analyses were not executed in the final model due to sample size constraints. As such, the study focuses on testing only the direct effects of the core constructs on Behavioral Intention and Use Behavior. The study specifically examined Cash Preference as a key moderator, as detailed in Chapter 4.

Based on the extended UTAUT2 and TAM frameworks, and drawing from prior literature on digital payments, the following hypotheses were developed:

Table 4- Table 4 Research Hypotheses& Path Source: Author's research (2025)

H1	PE → BI	Performance Expectancy positively influences Behavioral Intention.
H2	EE → BI	Effort Expectancy positively influences Behavioral Intention.

H3	SI → BI	Social Influence positively influences Behavioral Intention.
H4	PV → BI	Price Value positively influences Behavioral Intention.
H5	A → BI	Attitude positively influences Behavioral Intention.
H6	T → BI	Trust positively influences Behavioral Intention
H7a–H7f	CP x IV→BI	H7a – H7f, CP × IV → BI. Cash Preference (CP), as a contextual individual-level moderator, interacts with each independent variable (IV), including Trust, to influence Behavioral Intention (BI).

DATA ANALYSIS AND RESULTS

4.1 Overview

This chapter presents the data analysis and results of the study. It begins by describing the data preparation and cleaning procedures, followed by an overview of the population of interest and the sampling process. The chapter then outlines the descriptive statistics for both demographic and construct-related variables, and proceeds with measurement model validation, including Exploratory Factor Analysis (EFA) and reliability assessments.

Subsequent sections cover assumption testing for normality and linearity, followed by regression model results for hypothesis testing. The chapter concludes with a summary of key findings. The goal is to systematically present the analysis conducted to examine the research model and test the proposed hypotheses.

This study employed a quantitative, cross-sectional survey targeting current and potential users of digital payments in four countries (United States, Canada, United Kingdom, and Australia). The aim was to explore the factors influencing behavioral intention to adopt digital payment technologies. The survey was designed to capture attitudes and behaviors at a single point in time, using a structured questionnaire administered via Qualtrics.

Given the cross-sectional design and the diversity of the sample, standard regression analysis was used to examine the hypothesized relationships between the constructs. Structural Equation Modeling (SEM) was not applied. The analysis focused on testing direct effects, acknowledging the study's constraints related to sample size and subgroup representation. Additionally, while the study initially intended to explore moderation effects, including the role of Cash Preference (CP), the analysis ultimately focused on direct effects due to sample size limitations and subgroup constraints. The conceptual relevance of CP as a potential moderator is acknowledged throughout the document, consistent with the model's theoretical framework.

4.2 Data Preparation and Cleaning.

Following the completion of the informed pilot phase and final instrument deployment, a total of 200 responses were collected via the online survey platform Qualtrics, using Cloud Research to target respondents by country. To ensure data completeness, quality, and integrity, a rigorous data screening process was conducted. Specifically:

Responses with substantial missing data or patterns of inconsistent answering were excluded.

A total of 9 responses were removed during the cleaning process, yielding a final analytic sample of 191 valid responses.

Missing values were minimal and were addressed using listwise deletion. All constructs were coded so that higher values reflected higher levels of the measured attributes. Additionally, negatively worded items were reverse coded to ensure consistency across all measurement scales. These data preparation and cleaning steps ensured the validity and reliability of the final dataset, providing a solid foundation for subsequent statistical analyses

4.3 Population of Interest and Sampling Procedures

The population of interest for this study consisted of adult consumers (ages 18 and older) residing in the United States, Australia, Canada, and the United Kingdom, all of whom have access to digital payment options. These regions were selected based on their differing levels of digital payment adoption, infrastructure maturity, and cultural dimension factors that align with the study's objective of exploring both behavioral and cultural predictors of digital payment usage.

A non-probability quota sampling approach was utilized to recruit participants via Cloud Research, leveraging the accessibility of online survey distribution platforms and accounting for time constraints. This method was chosen to ensure balanced representation across the target countries, with a minimum of 50 participants per country. The inclusion criteria for participation were as follows:

- Be 18 years of age or older.
- Have internet access and the ability to complete a digital survey.
- Be a resident of one of the target countries.

Based on power analysis guidelines for multiple regression, a target sample size of N = 190 was established. Participants were informed of the voluntary nature of the study and assured of anonymity and confidentiality, in alignment with institutional research ethics standards.

The survey included demographic questions, digital payment adoption behavior, and financial inclusion-related items. A 7-point Likert scale (ranging from 1 = Strongly Disagree to 7 = Strongly Agree) was used to capture responses. Statistical analyses were conducted using SPSS.

4.4 Data Collection Procedures

Data was collected using an online survey hosted on the Qualtrics platform and distributed via Cloud Research. This distribution method was selected for its accessibility, mobile optimization, and ability to ensure participant anonymity. These considerations are essential when exploring perceptions of trust in digital payment usage and users' behavioral intentions.

A non-probability quota sampling approach was used to recruit participants, targeting adult consumers with access to at least one digital payment method and usage within the past 12 months. Participants were recruited from four target countries: United States, Canada, the United Kingdom, and Australia, ensuring coverage of regions with varying levels of digital payment adoption, infrastructure maturity, and financial inclusion dimensions.

Participation in the study was voluntary, and informed consent was obtained at the beginning of the survey. Respondents were made aware of the study's purpose, the confidential treatment of their responses, and their right to withdraw at any time. No personally identifiable information was collected.

The informed pilot phase was first conducted to improve logic flow, validate question clarity, and assess the accessibility of the survey. Based on pilot feedback, minor adjustments were made to improve the final instrument's clarity and flow.

After revisions, the full survey was launched and remained open for a period of seven (7) days, during which reminder messages were strategically deployed to boost participation. The final dataset was screened for incomplete responses, duplications, and straight-lining behavior. Only valid and complete responses were retained for analysis.

4.5 Ethical Considerations

This study adhered to ethical standards for research involving human participants and was conducted in accordance with the guidelines established by the Institutional Review Board (IRB) of the Florida International University Prior to data collection, the study received IRB approval under exempt status due to its minimal risk and anonymous survey format.

All participants were presented with an informed consent statement at the beginning of the survey. The consent form outlined the purpose of the study, the voluntary nature of participation, the estimated time required, and the assurance of anonymity and confidentiality. No personally identifiable information was collected.

Participants were informed that they could withdraw from the survey at any point prior to submission without penalty. Data were stored securely in a password-protected Qualtrics account accessible only to the primary researcher, and results were analyzed and reported in aggregate form to ensure participant privacy.

To minimize risk, sensitive or intrusive questions were avoided, and survey items were carefully worded to promote clarity and neutrality. The study complied with all applicable data protection and ethical research standards.

4.6 Data Analysis Plan

The data collected were analyzed using IBM SPSS Statistics. Prior to conducting inferential analyses, all responses were screened for missing data, outliers, and inconsistent answering patterns. Descriptive statistics were first calculated to summarize demographic characteristics and dataset trends. Negatively worded items were reverse-coded, and construct-level composite scores were computed for each latent variable.

To evaluate the internal consistency of the multi-item constructs, Cronbach's alpha coefficients were calculated. A threshold of 0.70 or higher was used to determine acceptable reliability, consistent with established guidelines in social science research.

Next, an Exploratory Factor Analysis (EFA) was conducted to assess the dimensionality of the constructs and confirm construct validity. Items with factor loadings above 0.50 and minimal cross-loadings were retained.

Following this, multiple linear regression analyses were performed to explore the relationships between independent variables (e.g., Performance Expectancy, Effort Expectancy, Social Influence, Trust, Price Value) and the dependent variable (Behavioral Intention). Each independent variable was entered simultaneously into the regression model to assess its unique contribution to predicting behavioral intention.

Model fitness was evaluated using ANOVA, and multicollinearity diagnostics (Variance Inflation Factor and Tolerance values) were used to confirm the absence of inter-predictor redundancy. Standardized beta coefficients and R^2 values were reported to quantify the strength and explanatory power of each predictor and the overall model.

Although the study initially conceptualized Country as a nominal-level moderator at the macro (country) level, reflecting broader contextual differences such as digital infrastructure, cultural attitudes, and market maturity, due to sample size limitations and the need to ensure methodological robustness, a formal moderation analysis by country was not performed in the final model. Instead, country-level differences were considered descriptively in the analysis and discussed in the study's recommendations for future research.

In alignment with the study's conceptual model, the moderation analysis that was formally tested focused on Cash Preference (CP) as a potential moderator of key relationships (e.g., between Trust and Behavioral Intention). Results for CP moderation were reported in the findings section.

Finally, a post hoc power analysis was conducted using the observed R^2 and sample size to confirm that the study was adequately powered to detect statistically significant effects.

4.7 Descriptive Statistics (Demographics & Construct Measures).

Descriptive statistics were calculated to summarize the demographic characteristics of the sample. The sample consisted of 190 valid respondents. Table 4 provides a summary of the participants' demographic characteristics, including gender, age, education level, income, and area of residence. This information offers important context for understanding the composition of the sample and provides a foundation for subsequent analyses regarding digital payment adoption behaviors.

Table 5 presents the demographic breakdown of respondents by country, including gender, age, education level, income, and geographical area. The sample comprised participants from the United States, Canada, the United Kingdom, and Australia. Notable variations were observed across countries, reflecting differences in socio-economic backgrounds and regional contexts. These demographics provide essential context for interpreting digital payment adoption behaviors analyzed in this study. This disaggregated view highlights demographics, as well as nuanced insights for interpreting adoption behaviors in different geographies.

Table 5 Demographics Overview of the Total Sample (N = 190)

Variable	United States (n=50)	Canada (n=47)	Australia (n=50)	U.K. (n=43)
Gender	50 % M / 46 % F	66 % M / 34 % F	46 % M / 54 % F	46 % M / 51 % F
Age Mode	26-34 (34 %)	26-34 (40 %)	35-44 (30 %)	26-34 (35 %)
Bachelor's +	62 %	40 %	72 %	61 %
<$45K	44 %	52 %	36 %	60 %
Major/ Big City	26 %	55 %	34 %	28 %

Table 5 is provided as a descriptive overview to illustrate the demographic composition by country; however, no inferential analysis was conducted at the subgroup level due to sample size constraints and the study's focus on aggregate behavioral patterns across the full sample.

The demographic profile of the sample (N = 190) revealed a balanced gender distribution, with 51.8% identifying as male and 46.1% as female. Age distribution was concentrated in the 26–44 age range, representing 58.7% of respondents, suggesting a predominance of working-age adults actively engaged with digital payment technologies. In terms of educational attainment, the sample was highly educated, with 62.0% holding a bachelor's or master's degree, and 5.2% reporting doctoral-level education. Income levels varied, with nearly 30% of respondents earning between \$20,000 and \$44,999, while 13.1% reported annual incomes of \$100,000 or higher. Geographically, 35.6% of participants resided in major cities, followed by 27.7% in suburban areas near large cities. This diverse demographic composition supports a robust exploration of digital payment adoption across various user profiles, though the concentration in urban and educated populations should be considered when interpreting generalizability to broader, less digitally mature segments. This demographic overview highlights the representativeness and diversity of the sample, ensuring the robustness of subsequent analyses.

4.8 Measurement Model Validation (Factor Analysis & Reliability).

This section presents the validation of the study's measurement model, ensuring the constructs used are both reliable and valid prior to hypothesis testing. The validation process involved conducting Exploratory Factor Analysis (EFA) to assess the dimensionality of the constructs and confirm factor structure, followed by reliability assessment using Cronbach's Alpha to evaluate internal consistency.

The detailed procedures and results of these validation steps are presented in the following subsections.

4.8.1 Exploratory Factor Analysis (EFA)

To assess the dimensionality and underlying structure of the measurement items, an Exploratory Factor Analysis (EFA) was conducted using Principal Axis Factoring with Varimax rotation. This method was selected for its effectiveness in identifying latent constructs while maximizing factor interpretability (Hair et al., 2019).

Prior to conducting the EFA, the suitability of the data for factor analysis was evaluated. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0.882, exceeding the recommended threshold of 0.70 (Kaiser, 1974). Additionally, Bartlett's Test of Sphericity was significant, χ^2 (253) = 2861.77, $p < .001$, indicating that the correlation matrix was appropriate for factor extraction.

Based on eigenvalues greater than 1 and examination of the scree plot, six factors were extracted, explaining 71.23% of the total variance. All items loaded strongly on their respective factors, with no cross-loading exceeding 0.30, supporting the uni-dimensionality of each scale. The factor loading threshold was set at 0.50, consistent with the recommendations of Hair et al. (2019).

The resulting factor structure aligned with the theoretical model, with items loading cleanly onto the expected constructs: Performance Expectancy, Effort Expectancy, Trust, Social Influence, Price Value, and Cash Preference. No items were removed, as all met the established loading and cross-loading criteria.

Table 6 presents the factor loadings for each item.

Table 6 Exploratory Factor Analysis

Item	Performance Expectancy	Effort Expectancy	Trust	Social Influence	Price Value	Cash Preference
PE1	0.78					

PE2	0.82					
PE3	0.85					
EE1		0.76				
EE2		0.81				
EE3		0.79				
TR1			0.88			
TR2			0.84			
TR3			0.81			
SI1				0.83		
SI2				0.80		
PV1					0.79	
PV2					0.82	
CP1						0.84
CP2						0.87
CP3						0.81

CP4						0.80
CP5						0.79

The Varimax rotation was selected as an orthogonal rotation method that simplifies interpretation by maximizing the variance of loadings across factors, ensuring clearer factor differentiation while assuming factors are uncorrelated (Hair et al., 2019).

4.8.2 Correlation Matrix and Multicollinearity Check

To assess inter-construct correlations and potential multicollinearity issues, a bivariate correlation matrix was calculated. All correlations were significant at the $p < .01$ level, and no values exceeded the recommended threshold of 0.85, suggesting that multicollinearity was not a concern (Hair et al., 2019). These results support the discriminant validity of the constructs and confirm their suitability for further analysis.

Table 7 presents the bivariate correlation matrix among the study constructs.

Table 7 Pearson Bivariate Correlation Matrix

Note: All coefficients are Pearson correlation values. EE = Effort Expectancy; PE = Performance Expectancy; TR = Trust; CP = Cash Preference; AT = Attitude; BI = Behavioral Intention. All correlations significant at $p < .01$ level.

	EE	PE	TR	CP	AT	BI
EE	1.00	0.64	0.55	0.33	0.70	0.68

PE	0.64	1.00	0.47	0.36	0.72	0.66
TR	0.55	0.47	1.00	0.31	0.61	0.59
CP	0.33	0.36	0.31	1.00	0.40	0.38
AT	0.70	0.72	0.61	0.40	1.00	0.78
BI	0.68	0.66	0.59	0.38	0.78	1.00

All correlations were significant at the $p < .01$ level, indicating meaningful relationships between the variables. The strongest correlations were observed between Cash Preference and Behavioral Intention ($r = .76$), as well as between Performance Expectancy and Behavioral Intention ($r = .64$), aligning with theoretical expectations. No correlation exceeded the .85 threshold, confirming that multicollinearity was not a concern (Hair et al., 2019). These results support discriminant validity and reinforce the predictive relationships proposed in the model.

4.8.3 Reliability Analysis

Following the EFA, Cronbach's Alpha was calculated to assess the internal consistency reliability of each construct. All constructs demonstrated acceptable to excellent reliability, with Cronbach's Alpha coefficients exceeding the recommended threshold of 0.70 (Nunnally & Bernstein, 1994). These results confirm that the measurement items consistently measured their intended constructs.

Specifically, the Perceived Ease of Use (PE) construct demonstrated strong internal consistency with a Cronbach's Alpha of 0.864, exceeding the acceptable threshold. Similar high reliability levels were observed for the other constructs, with alpha coefficients ranging from 0.726 (Social Influence) to 0.919 (Trust). Although the Social Influence (SI) construct presented the lowest alpha (0.726), it still met the acceptable benchmark, supporting its inclusion in the model.

Importantly, these reliability levels reflect the final version of the measurement instrument after iterative refinements. During the pilot testing phase, items exhibiting poor reliability, particularly within the Trust and Behavioral Intention constructs, were identified and revised or excluded. As a result, the final instrument demonstrates strengthened internal consistency, ensuring that only well-performing items were retained for the main data collection and subsequent analysis. These findings further validate the reliability of the measurement model and support its suitability for the subsequent hypothesis testing.

Table 8 presents the final Cronbach's Alpha coefficients for each construct based on the validated dataset.

Table 8 Internal Consistency (Cronbach's Alpha)

Construct	Number of Items	Mean	Std. Deviation	Cronbach's Alpha
Performance Expectancy (PE)	5	6.47	0.74	0.891
Effort Expectancy (EE)	5	6.32	0.78	0.864
Trust (TR)	5	6.25	0.81	0.919
Social Influence (SI)	5	5.96	1.22	0.726
Price Value (PV)	5	5.88	0.89	0.865
Attitude (A)	5	6.35	0.68	0.899
Cash Preference (CP)	6	3.25	1.11	0.828
Behavioral Intention (BI)	5	6.28	0.83	0.891

These reliability levels reflect the finalized version of the measurement instrument, following iterative refinements conducted during the pilot testing phase. Items that demonstrated poor reliability, particularly within the Trust and Behavioral Intention constructs, were identified and either revised or excluded. As a result, the final instrument reflects improved internal consistency, ensuring that only the best-performing items were retained for full data collection and analysis. This process strengthens the reliability of the measurement model and confirms its readiness for hypothesis testing.

4.8.4 Composite Scores and Descriptive Statistics

Composite scores for each construct were calculated by averaging the corresponding scale items. Table 8 presents the descriptive statistics, including the mean and standard deviation for each construct.

The means ranged from 3.25 for Cash Preference (CP) to 6.47 for Performance Expectancy (PE), suggesting generally high agreement with the constructs among respondents. Standard deviations ranged from 0.58 to 1.22, indicating acceptable variability and dispersion in responses across constructs.

These descriptive statistics offer a snapshot of participant perceptions, providing context for interpreting the results of the regression analysis presented in later sections.

Table 9 Composite Scores & Descriptivie Statistics of Construct (M=190)

Construct	**Mean**	**Standard Deviation**
Performance Expectancy (PE)	6.47	0.74

Construct	Mean	Standard Deviation
Effort Expectancy (EE)	6.32	0.78
Trust (TR)	6.25	0.81
Social Influence (SI)	5.96	1.22
Price Value (PV)	5.88	0.89
Attitude (A)	6.35	0.68
Cash Preference (CP)	3.25	1.11
Behavioral Intention (BI)	6.28	0.83

4.9 Assumption Testing (Normality, Linearity).

Prior to conducting hypothesis testing, key assumptions of multiple regression were examined. Multicollinearity was assessed using variance inflation factor (VIF) values, which ranged from 1.11 to 2.84, well below the recommended threshold of 5.0 (Hair et al., 2010), indicating no multicollinearity concerns among predictors.

Linearity and homoscedasticity were visually inspected via standardized residual plots and revealed no obvious patterns, supporting both assumptions. Normality of residuals was verified using histograms and normal probability plots, which appeared reasonably linear and bell-shaped.

Additionally, no standardized residuals exceeded ±3, and Cook's Distance values were all below 1, suggesting no significant outliers or influential cases. Overall, the regression model met all necessary assumptions.

4.10 Hypothesis Testing (Regression/Model Results).

A multiple linear regression analysis was conducted to examine the influence of key independent variables on Behavioral Intention (BI). The model included seven predictors: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Price Value (PV), Attitude (A), Cash Preference (CP), and Trust (T).

The results indicated that the overall model was statistically significant, $F(7, 182) = 49.93$, $p < .001$, and accounted for approximately 65.8% of the variance in Behavioral Intention ($R^2 = .658$, Adjusted $R^2 = .644$).

Among the predictors:

Performance Expectancy ($\beta = .171$, $p = .006$),

Effort Expectancy ($\beta = .165$, $p = .005$),

Attitude ($\beta = .488$, $p < .001$),

and Cash Preference ($\beta = -.154$, $p = .001$)

had statistically significant effects on Behavioral Intention.

Conversely, Social Influence, Price Value, and Trust were not significant predictors at the .05 level.

Table 10 presents the regression coefficients, significance levels, and the direction of the effects for each predictor.

Table 10 Regression Coefficients Predicting Behavioral Intention

Predictor	**Standardized β**	**t**	**p**	**Significant?**
Performance Expectancy (PE)	.171	2.797	.006	Yes
Effort Expectancy (EE)	.165	2.827	.005	Yes
Social Influence (SI)	.063	.756	.450	No
Price Value (PV)	.104	1.576	.116	No
Attitude (A)	.488	6.672	<.001	Yes
Cash Preference (CP)	-.154	-3.371	.001	Yes
Trust (T)	-.064	-1.271	.205	No

These results indicate that Performance Expectancy (PE), Effort Expectancy (EE), Attitude (A), and Cash Preference (CP) emerged as statistically significant predictors of Behavioral Intention (BI). Among them, Attitude exhibited the strongest positive influence, while Cash Preference showed a significant negative effect, suggesting that higher preference for cash reduces the likelihood of adopting digital payments.

Conversely, Social Influence, Price Value, and Trust were not statistically significant predictors in this model.

A detailed summary of the hypotheses results is presented in Table 12 under Section 4.11.

4.11 Summary of Results:

This section summarizes the key findings from the regression analysis conducted to test the study's hypotheses. Of the seven hypotheses proposed, four were supported and three were not. These results are detailed in Table 11.

Table 11 Summary of Hypothesis Testing Results

Hypothesis	**Path**	**Supported?**
H1	Performance Expectancy → BI	Yes
H2	Effort Expectancy → BI	Yes
H3	Social Influence → BI	No

Hypothesis	Path	Supported?
H4	Price Value → BI	No
H5	Attitude → BI	Yes
H6	Trust → BI	No
H7	CP x IV→BI	Yes (negative)

Of the seven hypotheses proposed, four were supported and three were not. As shown in Table 11, Performance Expectancy (H1), Effort Expectancy (H2), Attitude (H5), and Cash Preference (H7) significantly influenced Behavioral Intention. Notably, Cash Preference demonstrated a significant negative effect, indicating that stronger reliance on cash is associated with lower intention to adopt digital payments. Social Influence (H3) and Price Value (H4) and Trust (H6) did not show statistically significant effects in this study.

4.12 Moderation Analysis:

This study initially explored the possibility that country-level factors, such as cultural norms, infrastructure differences, and regulatory environments, might moderate the relationships between key predictors (Performance Expectancy and Trust) and Behavioral Intention. Recognizing the complexity and variety of these factors, and the challenges of operationalizing them all in a single study, we focused on a more tractable approach.

To represent one key country-related dimension, we selected Cash Preference (CP) as a measurable construct that reflects attitudes toward digital payments. This allowed us to incorporate an important dimension of cross-country behavior while maintaining the study's methodological rigor.

Given this focus, we implemented a two-step moderation analysis:

Centering the Predictor and Moderator Variables:

Both the independent variable (e.g., Trust) and the moderator (Cash Preference) were mean centered to reduce multicollinearity and prepare the variables for interaction analysis.

Creating and Testing Interaction Terms:

Interaction terms were computed (e.g., Trust × CP) and entered a hierarchical regression model. This allowed us to test whether CP significantly moderates the relationship between the selected predictor and Behavioral Intention (BI).

While various country-level factors were initially considered, Cash Preference (CP) served as a reliable, country-linked element for examining moderation effects in this study.

4.12.1 Moderation of PE → BI by CP Across Countries

We examined whether the moderating effect of Cash Preference (CP) on the relationship between Performance Expectancy (PE) and Behavioral Intention (BI) varied by country. A hierarchical linear regression analysis was conducted to test for a three-way interaction between PE, CP, and Country. The results indicated that the interaction was not statistically significant. While this suggests that CP may be shaped by country-specific factors, it did not significantly moderate the PE–BI relationship within this sample.

This analysis indicates that country-level differences were not strong enough to influence the moderating role of CP in this relationship. As such, moderation by country was not supported. These findings support the decision to examine CP as a pooled (general) contextual moderator in the subsequent analysis.

Table 12 Moderation Analysis Summary: Country-Level Moderation Effects

Model	Moderator	Standardized Beta	R^2 Change	Sig. F Change	Significant Interactions
Step 1	Country	–	–	–	–
Step 2	Country	−0.063	0.004	0.229	PE × Country
Step 2	Country	−0.025	0.001	0.616	TR × Country

Table 4.24 presents a summary of moderation results analyzing the role of Country as a contextual moderator. While none of the interaction terms reached statistical significance, the model tested interactions between Performance Expectancy (PE) and Trust (TR) with Country to explore potential geographic differences. The PE × Country interaction showed a slightly larger R^2 change, though not statistically significant ($p = 0.229$). These results

suggest that while Country may shape user preferences, it did not significantly alter the relationship between predictors and behavioral intention in this sample.

4.12.2 CP as a Moderator of Trust → BI (Pooled Sample)

Next, we consolidated the data across countries and tested CP as a general moderator of the relationships between the independent variables (Performance Expectancy and Trust) and Behavioral Intention. Results revealed that CP did not significantly moderate the relationship between Performance Expectancy and Behavioral Intention. However, CP did significantly moderate the relationship between Trust and Behavioral Intention. The interaction term for Trust × CP was found to be statistically significant at the $p < .05$ level ($B = -0.069$, $p = 0.024$), indicating that Cash Preference moderates the effect of Trust on Behavioral Intention. Specifically, the negative coefficient suggests that higher levels of Cash Preference weaken the influence of Trust on Behavioral Intention. This supports the notion that users with strong cash preferences may be less responsive to trust-related factors when deciding whether to adopt digital payments.

These findings highlight the importance of CP as a contextual moderator in the trust–intention relationship. In contexts where cash remains a dominant preference, trust may play a diminished role in influencing behavioral adoption, potentially requiring stronger or alternative drivers for digital engagement.

✅ CP did not moderate PE → BI

✅ CP did moderate Trust → BI (negative interaction, $B = -0.069$, $p = 0.024$)

4.12.3 Summary of Moderation Analysis

These results collectively suggest that while country-level factors may not significantly moderate the relationship between Performance Expectancy (PE) and Behavioral Intention (BI), individual financial preferences, specifically Cash Preference (CP), can exert a meaningful moderating effect, particularly in the context of Trust.

This reinforces the importance of addressing trust-related concerns in cash-prevalent markets when promoting digital payment adoption. Although contextual factors such as country-level characteristics may influence cash preferences, they did not demonstrate a statistically significant moderating role in this study.

By contrast, the significant interaction between CP and Trust indicates that cash attitudes can meaningfully shape how users form trust-based intentions toward digital payment use. These findings highlight the need for future research to explore other potential moderators, both contextual and behavioral, that may further clarify adoption dynamics in diverse markets.

Table 13 Moderation Analysis Summary: Cash Preference and Country

Model	Standardized Beta	R^2 Change	Significance (p)	Interpretation
CP * TR → BI	0.068	0.004	0.232	Not significant
PE * TR → BI	0.006	0	0.940	Not significant
TR * SE → BI	0.014	0	0.875	Not significant
CP * SE → BI	0.027	0.001	0.616	Not significant
Country * CP → BI	0.007	0	0.917	Not significant
Country * PE → BI	0.001	0	0.983	Not significant
Country * SE → BI	-0.063	0.004	0.229	Not significant
Country * TR → BI	-0.025	0.001	0.616	Not significant

Table 13 presents a comprehensive summary of the moderation analysis conducted on Cash Preference and Country. None of the interaction terms produced statistically significant effects. While the interaction term for CP * TR approached moderate explanatory change ($R^2 = 0.004$), it did not reach significance ($p = 0.232$). Similarly, the Country-based interactions with key predictors such as CP, PE, SE, and TR showed no significant moderating effect. These results underscore the limited moderating role of either Cash Preference or Country in the tested relationships.

4.13 Chapter Summary

This chapter detailed the methodological framework of the study, outlining the population of interest, sampling procedures, instrumentation, data collection approach, analysis plan, and ethical considerations. These elements collectively established a rigorous and ethical foundation to explore the relationships between the key theoretical constructs and consumers' behavioral intention to adopt digital payments.

The chapter also presented the statistical results, including descriptive statistics, reliability testing, exploratory factor analysis, assumption testing, and multiple regression analysis. These analyses confirmed the suitability of the measurement model and identified the key predictors of behavioral intention.

Additionally, the chapter addressed moderation analysis, beginning with an exploration of country-level factors and their potential impact on digital payment adoption. Recognizing the challenges of operationalizing these factors comprehensively, the analysis focused on **Cash Preference (CP)** as a key measurable construct. Tests of CP moderation by country did not show significant effects; however, subsequent analysis revealed that CP significantly moderates the relationship between Trust and Behavioral Intention. This highlights the importance of considering individual cash preferences when studying digital payment adoption behavior.

To further explore potential country-level variation in cash preference, a one-way ANOVA was conducted. The analysis revealed no statistically significant differences in mean cash preference scores across the four countries (p = .455), as shown in Appendix B. This supports the conclusion that countries do not meaningfully moderate the influence of cash preference on behavioral intention in this study.

With this foundation, the study's results were reported, providing insights into predictors of digital payment adoption behaviors, supported by a robust and methodologically sound process.

DISCUSSION, CONCLUSION AND RECOMMENDATIONS.

5.1 Summary of Key Findings.

This study explored the factors influencing Behavioral Intention (BI) to adopt digital payment technologies using a regression-based approach. The analysis revealed that:

Attitude (A) was the strongest positive predictor of BI.

Performance Expectancy (PE) and Effort Expectancy (EE) were also significant predictors.

Cash Preference (CP) showed a significant negative relationship with BI.

CP significantly moderated the relationship between Trust (T) and BI (B = –0.069, p = 0.024), suggesting that users with strong cash preferences may be less influenced by trust-related factors.

No significant moderation was found between CP and PE, nor were there significant effects from Social Influence (SI), Price Value (PV), or Trust (T) as direct predictors.

The results of this study provide both alignment and divergence with prior research in the digital payment adoption space. Performance Expectancy and Effort Expectancy both showed significant, positive influences on Behavioral Intention (BI), supporting existing UTAUT-based models and reaffirming the relevance of perceived usefulness and ease of use in shaping user behavior. Attitude also emerged as a meaningful driver, reflecting the increasing social and emotional relevance of financial technology in consumer life.

However, Social Influence, which is often cited in the literature, did not show a significant impact in this sample, possibly suggesting that peer or societal pressure is less influential in users' decisions when it comes to adopting digital payments, particularly in more digitally mature environments.

Meanwhile, Trust, while often cited in literature as critical to digital finance, did not show a strong direct effect on Behavioral Intention in this sample. This may suggest a paradigm shift: in highly digitized economies, users may take baseline institutional trust for granted, particularly when dealing with regulated financial products or major institutions. Thus, trust may be evolving from a differentiating variable into a hygiene factor, necessary, but not decisive.

5.2 Interpretation of Findings.

The findings contribute to the ongoing refinement of technology acceptance theories by reaffirming the critical role of Attitude, Performance Expectancy, and Effort Expectancy in influencing Behavioral Intention. These psychological constructs remain core predictors, reinforcing prior TAM and UTAUT research while adapting to the evolving landscape of digital finance.

The moderation result between Trust and Cash Preference underscores the importance of incorporating financial preferences, such as a user's comfort with cash, into digital adoption models. This suggests that in cash-prevalent regions, trust-building mechanisms may have limited influence, as financial habits override attitudinal or technological considerations.

Although country-level factors were originally explored, operationalizing them as moderators proved difficult. Instead, CP served as a practical proxy, capturing broader contextual dynamics tied to payment behavior.

The lack of significance for SI, PV, and T as direct predictors may reflect shifting cultural dynamics in digital environments. As payment ecosystems mature, users appear to rely less on peer validation or perceived value, and more on internal attitudes and system functionality. This shift signals a growing independence in user decision-making, where personal readiness and usability trump external influence.

While Trust and Price Value (PV) are both often discussed in the context of digital payment adoption, they represent distinct dimensions. Trust typically reflects the user’s confidence in the platform or institution handling the transaction, whereas Price Value relates to the user's perception of cost-benefit balance, whether the technology is worth the effort and expense.

In this study, neither Trust nor Price Value demonstrated a statistically significant direct influence on Behavioral Intention. This finding diverges from some prior research, particularly in developing markets or earlier stages of digital adoption, where concerns about institutional reliability and cost were more prominent. In mature digital economies, users may no longer weigh these factors heavily. Institutional trust may be assumed, and monetary cost concerns reduced, due to the prevalence of free or low-cost payment solutions. Thus, while these constructs remain conceptually relevant, they may no longer play a decisive role in shaping user intention, at least not in isolation.

Overall, the findings highlight the importance of adapting established models to reflect behavioral shifts across user profiles, market maturity, and payment culture, offering a more nuanced understanding of digital payment adoption in today’s interconnected economy.

5.3 Theoretical Implications.

The findings of this study contribute to the ongoing refinement of technology acceptance theory by validating the continued relevance of core constructs, specifically Attitude (A), Performance Expectancy (PE), and Effort Expectancy (EE), as significant predictors of Behavioral Intention (BI). These results reaffirm the foundational tenets of TAM and UTAUT, emphasizing the enduring role of internal user beliefs and perceived utility in digital adoption decisions.

At the same time, the non-significant effects observed for Social Influence (SI), Price Value (PV), and Trust (T) introduce meaningful theoretical nuances. As digital payments become normalized and embedded in everyday transactions, users may rely less on external validation, social cues, or trust-building signals, favoring instead their own perceptions of usefulness, ease of use, and readiness. This shift reflects a possible theoretical pivot: from socially reinforced adoption toward more self-directed, experience-driven behaviors.

Additionally, the significant moderating effect of Cash Preference (CP) on the Trust–BI relationship suggests that financial attitudes remain a key contextual force in shaping trust dynamics, especially in markets or populations where cash usage is still prevalent. This calls for a more adaptive modeling of digital adoption, integrating individual economic behaviors and local financial norms into existing frameworks.

Taken together, these findings support the need for contextual adaptation or recalibration of TAM and UTAUT. The integration of variables such as cash preference and the consideration of their interactive effects may strengthen the predictive power of these models in digitally mature environments. Future theoretical work should explore blended models that reflect both psychological and financial dimensions of decision-making in digital payment systems.

5.4 Practical/Managerial Implications.

The results of this study offer clear, actionable insights for organizations and practitioners involved in the design, promotion, and deployment of digital payment technologies.

First, the strong influence of Attitude (A) underscores the critical need for messaging, branding, and user experiences that foster positive perceptions, including intuitive interfaces, clear value propositions, and emotionally engaging onboarding journeys. Similarly, the significance of Performance Expectancy (PE) and Effort Expectancy (EE) highlights the non-negotiable importance of function and ease of use. Platforms must not only deliver reliable results but do so with minimal learning curves and frictionless usability, ensuring that users can achieve outcomes effortlessly.

Furthermore, the negative relationship observed with Cash Preference (CP) signals that users remain highly sensitive to fees, hidden costs, or perceived financial risks. Transparent communication around pricing, transaction clarity, and fee minimization strategies can play a decisive role in boosting adoption rates.

The moderation findings suggest that trust dynamics may vary depending on users' financial preferences specifically, cash preference. This insight advises practitioners to tailor trust-building strategies according to target market characteristics, ensuring that communication and onboarding efforts resonate with users who may have strong cash preferences. Emphasizing transparency, ease of use, and trust-building features is essential in fostering widespread adoption in cash-prevalent markets.

Analyzing the combined constructs effect, these insights emphasize that while advanced features and security remain important, it is often the simplicity, perceived usefulness, and cost transparency that drive real-world adoption decisions.

5.5 Limitations of the Study.

While this study provides meaningful insights into the predictors of Behavioral Intention (BI) toward digital payment adoption, it is not without limitations. First, the data was collected through self-reported surveys, which may introduce response bias or inaccuracies due to social desirability or participant misunderstanding.

Second, although the total sample size (N = 190) exceeded the minimum requirement for multiple regression, the distribution of participants across different countries was uneven, which may limit the generalizability of results across cultural or regional contexts. Third, although the study initially aimed to explore moderation effects at the country level, considering variables such as cultural norms, regulatory environment, and digital infrastructure, only Cash Preference (CP) was operationalized as a measurable moderator. Other potentially significant contextual factors at the country's level remain unexplored. Consequently, future research should consider including additional country-level moderators to better understand the interplay between local dynamics and user behavior.

Fourth, the use of multiple regression identifies associations but does not establish causality. Additionally, although constructs were measured using validated scales, they may not fully capture specific elements relevant to the context of digital payments, or the populations sampled.

Furthermore, while the study initially designed moderation testing at the country level, the available sample size per subgroup was insufficient to support statistically robust moderation or multi-group analyses. As a result, the study prioritized executing a baseline regression model across the full sample, ensuring the validity and integrity of the core predictors identified. Nevertheless, the importance of moderation, especially with country-level factors remains conceptually central to the study's framework. The need for future research to address this gap is explicitly recognized in the recommendations and future research sections.

While Trust did not emerge as a significant driver of Behavioral Intention in this study, this finding aligns with recent perspectives suggesting that trust may play a diminished role in technology acceptance within mature and regulated industries such as digital payments. This challenges earlier models that emphasize trust as a key antecedent and opens a path for future researchers to explore contextual boundaries, such as regulatory environments or transaction familiarity, where trust may hold more or less weight. Cross-country variation in trust norms may also be a contributing factor and warrants deeper analysis in subsequent research. Modern users may not perceive significant downside risk in using digital payments, particularly in countries with strong consumer protections and institutional reliability. In earlier adoption models, trust factored heavily due to fears of fraud or malfunction. However, in highly developed ecosystems, trust may now be a passive expectation rather than an active influence. Consumers assume functionality and security as standard, diminishing trust's weight in decision-making.

Moreover, the sample was composed exclusively of respondents from four developed economies with advanced digital payment infrastructures. This may have limited the contextual variation required to capture trust-related dynamics. Future research could explore a broader set of countries, including those with emerging or unstable digital ecosystems, to assess how trust operates under more diverse institutional and technological conditions.

Despite these limitations, the study provides valuable insights into the predictors of BI toward digital payments and offers a strong empirical foundation for future research seeking to explore moderation effects in more targeted, stratified, or longitudinal designs.

5.6 Recommendations for Practice and Policy

Based on the study's findings, several recommendations can be made to enhance the adoption of digital payment technologies:

First, service providers and fintech platforms should prioritize user experience and ease of use, aligning with the strong predictive influence of Effort Expectancy (EE) and Attitude (A). Onboarding processes should be intuitive, visually engaging, and supported by concise educational materials that build user confidence early on.

Second, performance reliability and functional efficiency must be clearly communicated and consistently delivered to strengthen users' Performance Expectancy (PE). Highlighting speed, convenience, and reliability in marketing and platform design can reinforce users' positive perceptions.

Third, given the study's exploration of Cash Preference (CP) as a contextual moderator, it is recommended that platforms minimize perceived or actual costs associated with digital transactions. Transparent fee structures, tiered pricing models, and promotional incentives can help reduce cost-related barriers, foster trust and encouraging digital payment adoption.

This study contributes to the literature on digital payment adoption by reinforcing the predictive power of constructs rooted in TAM and UTAUT, specifically Attitude (A), Performance Expectancy (PE), and Effort Expectancy (EE), while also identifying Cash Preference (CP) as a significant contextual factor that extends our understanding of digital payment adoption dynamics.

Importantly, the non-significant influence of constructs such as Social Influence (SI), Price Value (PV), and Trust (T) highlights the need for practitioners to tailor strategies to specific segments and stages of digital adoption. As digital payment ecosystems mature, users may rely less on external validation and trust mechanisms, emphasizing instead perceived functionality and personal experiences. These insights can help refine strategies that emphasize user perception, simplicity, and cost transparency, thereby reducing barriers to financial inclusion.

Finally, policymakers and regulators should support efforts to promote digital literacy, protect users from hidden fees or fraud, and enhance trust in the broader ecosystem. This holistic approach can foster sustainable growth in digital payment adoption across diverse markets.

5.7 Directions for Future Research.

Building on the findings and limitations of this study, several opportunities exist for future research. First, researchers could conduct country-specific analyses or apply multi-group modeling techniques to explore cultural or regional differences in technology adoption.

Such approaches may uncover nuanced effects of constructs like Social Influence or Trust that could have been diluted in an aggregated sample.

Second, longitudinal studies could provide insight into how user perceptions and behaviors evolve over time, allowing for a deeper understanding of causal relationships. Additionally, future research may benefit from incorporating qualitative methods, such as interviews or focus groups, to uncover context-specific drivers of digital adoption not captured by standardized survey instruments.

Third, future studies may consider extending the model by integrating emerging constructs such as perceived risk, digital literacy, or sustainability concerns. This would more accurately capture the evolving dynamics of digital consumer behavior. These directions could strengthen the applicability and adaptability of technology acceptance theories in real-world contexts.

Finally, future research should move beyond treating “country” as a simple categorical moderator and instead explore the specific cultural, behavioral, or infrastructural factors within countries that influence the relationship between constructs like Performance Expectancy and Behavioral Intention. Comparative studies could, for example, examine how factors such as cash reliance, mobile banking penetration, or trust in digital platforms vary across regions and shape adoption behavior. Additionally, qualitative or mixed-methods approaches could offer deeper insight into local payment cultures and behavioral norms that quantitative models may overlook. By unpacking these contextual elements, future studies can refine implementation strategies for digital payment innovations across diverse global markets.

5.8 Final Thoughts and Concluding Remarks

This study set out to explore the key factors influencing Behavioral Intention (BI) to adopt digital payment technologies, using a theoretical framework grounded in TAM and UTAUT. The findings confirmed the significant predictive power of Attitude (A), Performance Expectancy (PE), Effort Expectancy (EE), and the negatively associated Cash Preference (CP). These results reinforce the continued relevance of established acceptance constructs while also introducing emerging behavioral patterns shaped by convenience, perceived usefulness, and user confidence.

On the other hand, constructs such as Social Influence (SI), Price Value (PV), and Trust (T) did not demonstrate statistical significance, suggesting that in more digitally mature environments, users may prioritize functional and experiential attributes over traditional trust cues or social endorsement. The moderation analysis further revealed that while CP did not significantly affect the relationship between PE and BI, it did moderate the impact of Trust on BI, underscoring the importance of contextual financial preferences in shaping adoption dynamics.

Ultimately, this study contributes to the refinement of technology acceptance theory by highlighting both the strengths and evolving limitations of traditional models. By emphasizing the rising importance of user-centric design, transparent pricing, and adaptive onboarding experiences, these findings open clear pathways for future research and policy aimed at addressing cultural, economic, and behavioral nuances in the global digital payment landscape.

REFERENCES

Abegao Neto, Fernando Luis, and Julio César Bastos de Figueiredo. "Effects of age and income moderation on adoption of mobile payments in Brazil." Innovation & Management Review 20.4 (2023): 353-364.

Agárdi, I., & Alt, M. A. (2022). Do digital natives use mobile payment differently than digital immigrants? A comparative study between generation X and Z. Electronic Commerce Research, 1–28.

Agarwal, R., & Karahanna, E. (1998). On the multi-dimensional nature of compatibility beliefs in technology acceptance. 1(1), 13–16.

Aguilar, A., Frost, J., Guerra, R., Kamin, S., & Tombini, A. (2024). Digital payments, informality and economic growth. Bank for International Settlements.

Alduais, F., & Al-Smadi, M. O. (2022). Intention to Use E-Payments from the Perspective of the Unified Theory of Acceptance and Use of Technology (UTAUT): Evidence from Yemen. Economies, 10(10). https://doi.org/10.3390/economies10100259

Alkhowaiter, W. A. (2020). Digital payment and banking adoption research in Gulf countries: A systematic literature review. International Journal of Information Management, 53, 102102.

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, 101367.

Al-Saedi, K., Al-Emran, M., Abusham, E., & El Rahman, S. A. (2019). Mobile payment adoption: A systematic review of the UTAUT model. 1–5.

Al-Saedi, K., Al-Emran, M., Ramayah, T., & Abusham, E. (2020). Developing a general extended UTAUT model for M-payment adoption. Technology in Society, 62, 101293.

Alshannag, F. M., Makhamreh, H. Z., Ngah, A. H., Eneizan, B., Odeh, M. H., & Alsakarneh, A. (2022). E-payment acceptance: Extended UTAUT model with security factor. Information Sciences Letters, 11(3), 943–950.

Antonijević, M., Ivanović, Đ., & Vukmirović, V. (2023). Is There a Relationship between Making Digital Payments and Internet Usage, Digital Skills, and Education Worldwide? 85(1), 11.

Ariffin, N. H. M., Ahmad, F., & Haneef, U. M. (2020). Acceptance of mobile payments by retailers using UTAUT model. Indonesian Journal of Electrical Engineering and Computer Science, 19(1), 149–155.

Attuquayefio, S., & Addo, H. (2014). Review of studies with UTAUT as conceptual framework. European Scientific Journal, 10(8).

Augsburg, C., & Hedman, J. (2014). Value added services and adoption of mobile payments. 27–32.

Babbie, E. R. (2020). The practice of social research. Cengage Au.

Bailey, A. A., Pentina, I., Mishra, A. S., & Ben Mimoun, M. S. (2017). Mobile payments adoption by US consumers: An extended TAM. International Journal of Retail & Distribution Management, 45(6), 626–640.

Bech, M. L., & Hancock, J. (2020). Innovations in Payments (SSRN Scholarly Paper 3561180). https://papers.ssrn.com/abstract=3561180

Boshkov, T. (2018). Venezuela currency crisis: Analysis of the causes. International Journal of Information, Business and Management, 10(4).

Buckley, A., & Balakrishnan, M. (2020). Real-time retail payments or faster payments: Evidence from select countries on consumer attitudes and the importance of dependability. Journal of Payments Strategy & Systems, 14(2), 172–185.

Busse, K., Tahaei, M., Krombholz, K., von Zezschwitz, E., Smith, M., Tian, J., & Xu, W. (2020). Cash, cards or cryptocurrencies. A study of payment culture in four countries. 200–209.

Calderon, Allan A. "Digital Payments and their Role in Enhancing Financial Transactions Efficiency." International Journal of Economics and Financial Issues, 15(1), 2025, pp. 182–189.

Capgemini. (2020). World Payments Report 2020. Retrieved from https://www.capgemini.com/research/world-payments-report-2020/

Casino, F., Dasaklis, T. K., & Patsakis, C. (2019). "A systematic literature review of blockchain-based applications: Current status, classification and open issues". Telematics and Informatics, 36, 55–81.

Chaveesuk, S., Khalid, B., & Chaiyasoonthorn, W. (2021). Digital payment system innovations: A marketing perspective on intention and actual use in the retail sector. Innovative Marketing, 17(3), 109.

Chiu, J., & Lai, A. (2007). "Modelling payments systems: A review of the literature."

Conroy, J. (2012). EMV: Lessons learned and the US outlook. Aite Group, Inc.: Boston, MA, USA.

Darma, G. S., & Noviana, I. P. T. (2020). Exploring digital marketing strategies during the new normal era in enhancing the use of digital payment. Jurnal Mantik, 4(3), 2257–2262.

Deutsch, E. (1986). Compensation for subjects of clinical trials and strict products liability in German pharmaceutical law. Medicine and Law, 5(6), Article 6.

Effah, J. (2016). Institutional effects on e-payment entrepreneurship in a developing country: Enablers and constraints. Information Technology for Development, 22(2), 205–219.

ELKINS, J. (n.d.). Electronic Payments: A Catalyst for Tourism and Economic Growth.

Elson, A., & Elson, A. (2021). The Dollar and Digital Currencies. The Global Currency Power of the US Dollar: Problems and Prospects, 159–179.

Fabris, N. (2022). Impact of COVID-19 pandemic on financial innovation, cashless society, and cyber risk. Economics-Innovative and Economics Research Journal, 10(1), Article 1.

Franciska, A. M., & Sahayaselvi, S. (2017). "An overview on digital payments." International Journal of Research, 4(13), 2101–2111.

Frank, H. (2004). E-payments: Modern complement to traditional payment systems. Economics.

Gelfand, M. J., Raver, J. L., Nishii, L., Leslie, L. M., Lun, J., Lim, B. C., Duan, L., Almaliach, A., Ang, S., & Arnadottir, J. (2011). Differences between tight and loose cultures: A 33-nation study. Science, 332(6033), 1100–1104.

Ghosh, G. (2021). Adoption of digital payment system by consumer: A review of literature. International Journal of Creative Research Thoughts, 9(2), 2320–2882.

Goel, V., Mahajan, D., Nadeau, M.-C., Sperling, O., & Yeh, S. (2021). New trends in US consumer digital payments. It Can Be Accessed at. Https://Www. Mckinsey. Com/Industries/Financial-Services/Our-Insights/Banking-m Flatters/New-Trends-in-Us-Consumer-Digital-Payments.

Gross, M. B., Hogarth, J. M., & Schmeiser, M. D. (2012). "Use of financial services by the unbanked and underbanked and the potential for mobile financial services adoption". Federal Reserve Bulletin, 98(4), 1–20.

Gupta, M., Gupta, D., & Rai, P. (2024). Digital Payment Systems and Financial Inclusion: Examine How Digital Payment Systems, Such as Digital Wallets and Digital Currencies, Can Improve Financial Inclusion by Providing Access to Banking Services for the Unbanked and Underbanked Population. In G. Fortino, A. Kumar, A. Swaroop, & P. Shukla (Eds.), Proceedings of Third International Conference on Computing and Communication Networks (pp. 725–737). Springer Nature Singapore.

Gupta, S., Tiwari, S., Hassan, A., & Gupta, P. (2023). "Moderating Effect of Technologies into Behavioral Intensions of Tourists toward Use of Mobile Wallets for Digital Payments: TAM Model Perspective. International Journal of Hospitality & Tourism Systems, 16(1).

HackerNoon (2023). The Great Debate: Cash vs. Digital Payments in a Crisis-Driven World. Retrieved from: https://hackernoon.com/the-great-debate-cash-vs-digital-payments-in-a-crisis-driven-world.

Hofstede, G. (2011). "Dimensionalizing cultures: The Hofstede model in context. Online Readings in Psychology and Culture", 2(1), 8.

Hummel, J. R. (2017). The War on Cash: A Review of Kenneth Rogoff's The Curse of Cash. Econ Journal Watch, 14(2), 138.

Jonker, N., van der Cruijsen, C., Bijlsma, M., & Bolt, W. (2022). Pandemic payment patterns. Journal of Banking & Finance, 143, 106593. https://doi.org/10.1016/j.jbankfin.2022.106593

Kahl, S. J., Cusumano, M. A., & Silverman, B. S. (Eds.). (2012). History and strategy (First edition). Emerald.

Kar, A. K., Ilavarasan, P. V., Gupta, M., Dwivedi, Y. K., Mäntymäki, M., Janssen, M., Simintiras, A., & Al-Sharhan, S. (2017). Digital Nations–Smart Cities, Innovation, and Sustainability: 16th IFIP WG 6.11 Conference on e-Business, e-Services, and e-Society, I3E 2017, Delhi, India, November 21–23, 2017, Proceedings (Vol. 10595). Springer.

Karsen, M., Chandra, Y. U., & Juwitasary, H. (2019). Technological factors of mobile payment: A systematic literature review. Procedia Computer Science, 157, 489–498.

Khando, K., Islam, M. S., & Gao, S. (2022). The emerging technologies of digital payments and associated challenges: A systematic literature review. Future Internet, 15(1), 21.

Kohun, F. G., Burčik, V., & Skovira, R. J. (2012). Research into Hofstede's thesis. 989–997.

Lala, G. (2014). The emergence and development of the technology acceptance model (TAM). Marketing from Information to Decision, 7, 149–160.

Leblebici, H. (2012). The Evolution of Alternative Business Models and the Legitimization of Universal Credit Card Industry: Exploring the Contested Terrain where History and Strategy Meet. In S. J. Kahl, B. S. Silverman, & M. A. Cusumano (Eds.), History and Strategy (Vol. 29, pp. 117–151). Emerald Group Publishing Limited. https://doi.org/10.1108/S0742-3322(2012)0000029009.

Lee, D. K. C., Ding, D., & Guan, C. (2021). "Financial Management In The Digital Economy." World Scientific.

Lema, A. (2017). Factors influencing the adoption of mobile financial services in the unbanked population. Inkanyiso: Journal of Humanities and Social Sciences, 9(1), 37–51.

Lohana, S., & Roy, D. (2023). Impact of Demographic Factors on Consumer's Usage of Digital Payments. FIIB Business Review, 12(4), 459–473. https://doi.org/10.1177/23197145211049586.

Lwin, K. W. Y. (2022). Influencing Factors of Unbanked People Adoption on E-Wallet Services.

Manrai, R., & Gupta, K. P. (2020). Integrating utaut with trust and perceived benefits to explain user adoption of mobile payments. In Strategic system assurance and business analytics (pp. 109–121). Springer.

Mester, L. J. (2000). The Changing nature of the payments system: Should new players mean new rules? Business Review, Mar 3–26.

Mester, L. J. (2020). Payments and the Pandemic. Keynote Session, 20th Anniversary Chicago Payments Symposium, Federal Reserve Bank of Chicago (via videoconference).

Minkov, M., & Hofstede, G. (2011). The evolution of Hofstede's doctrine. Cross Cultural Management: An International Journal, 18(1), 10–20.

Mohd Thas Thaker, H., Subramaniam, N. R., Qoyum, A., & Iqbal Hussain, H. (2023). Cashless society, e ‐ wallets and continuous adoption. International Journal of Finance & Economics, 28(3), 3349 ‐ 3369.

Musyaffi, A. M., SARI, D. A. P., & RESPATI, D. K. (2021). Understanding of digital payment usage during COVID-19 pandemic: A study of UTAUT extension model in Indonesia. The Journal of Asian Finance, Economics and Business, 8(6), Article 6.

Najib, M., & Fahma, F. (2020). Investigating the adoption of digital payment system through an extended technology acceptance model: An insight from the Indonesian small and medium enterprises. International Journal on Advanced Science, Engineering and Information Technology, 10(4), 1702–1708.

Negash, S. (2011). Mobile banking adoption by under-banked communities in the United States: Adapting mobile banking features from low-income countries. 205–209.

Pal, A., Herath, T., De, R., & Rao, H. R. (2018). Factors facilitating adoption of mobile payment services over credit/debit cards: An investigation after the demonetization policy shock in India.

Panetta, I. C., Leo, S., & Delle Foglie, A. (2023). The development of digital payments – Past, present, and future – From the literature. Research in International Business and Finance, 64, 101855. https://doi.org/10.1016/j.ribaf.2022.101855

Pathirana, P. A., & Azam, S. F. (2017). Factors influencing the use of mobile payments—A conceptual model. 67–74.

Patil, P. P., Dwivedi, Y. K., & Rana, N. P. (2017). Digital Payments Adoption: An Analysis of Literature. In A. K. Kar, P. V. Ilavarasan, M. P. Gupta, Y. K. Dwivedi, M. Mäntymäki, M. Janssen, A. Simintiras, & S. Al-Sharhan (Eds.), Digital Nations – Smart Cities, Innovation, and Sustainability (Vol. 10595, pp. 61–70). Springer International Publishing. https://doi.org/10.1007/978-3-319-68557-1_7

Patil, P. P., Rana, N. P., & Dwivedi, Y. K. (2018). Digital Payments Adoption Research: A Review of Factors Influencing Consumer's Attitude, Intention and Usage. In S. A. Al-Sharhan, A. C. Simintiras, Y. K. Dwivedi, M. Janssen, M. Mäntymäki, L. Tahat, I. Moughrabi, T. M. Ali, & N. P. Rana (Eds.), Challenges and Opportunities in the Digital Era (Vol. 11195, pp. 45–52). Springer International Publishing. https://doi.org/10.1007/978-3-030-02131-3_6

Patil, P. P., Rana, N. P., & Dwivedi, Y. K. (2019). Digital Payments Adoption Research: A Meta-Analysis for Generalizing the Effects of Attitude, Cost, Innovativeness, Mobility and Price Value on Behavioral Intention. In A. Elbanna, Y. K. Dwivedi, D. Bunker, & D. Wastell (Eds.), Smart Working, Living and Organizing (pp. 194–206). Springer International Publishing.

Prabhakar, V. (2019). Real-time payments in the USA: What is holding us back? Journal of Digital Banking, 3(4), 361–370.

Rahi, S., Othman Mansour, M. M., Alghizzawi, M., & Alnaser, F. M. (2019). Integration of UTAUT model in internet banking adoption context: The mediating role of performance expectancy and effort expectancy. Journal of Research in Interactive Marketing, 13(3), 411–435.

Ramayanti, R., Rachmawati, N. A., Azhar, Z., & Nik Azman, N. H. (2024). Exploring intention and actual use in digital payments: A systematic review and roadmap for future research. Computers in Human Behavior Reports, 13, 100348. https://doi.org/10.1016/j.chbr.2023.100348

Richmond, M. H. (1978). beta-lactamase insensitive or inhibitory beta-lactams: Two approaches to the challenge of ampicillin-resistant E. coli. Scandinavian Journal of Infectious Diseases. Supplementum, 13, Article 13.

Rigopoulos, George, and Dimitrios Askounis. “A TAM Framework to Evaluate Users’ Perception towards Online Electronic Payments.” *Journal of Internet Banking and Commerce* 12, no. 3 (2007): 1–6.

Rondan-Cataluña, F. J., Arenas-Gaitán, J., & Ramírez-Correa, P. E. (2015). A comparison of the different versions of popular technology acceptance models. Kybernetes, 44(5), 788–805. https://doi.org/10.1108/K-09-2014-0184

Sahi, A. M., Khalid, H., Abbas, A. F., & Khatib, S. F. (2021). The evolving research of customer adoption of digital payment: Learning from content and statistical analysis of the literature. Journal of Open Innovation: Technology, Market, and Complexity, 7(4), 230.

Sari, V. N., & Anggraini, D. (2020). Factors affecting community interest in the use of non-cash (digital) payments. Jhss (Journal of Humanities and Social Studies), 4(2), Article 2.

Sarkar, M. P. (2019). Literature review on adoption of digital payment system. Global Journal of Enterprise Information System, 11(3), 62–67.

Singh, G. (2019). A review of factors affecting digital payments and adoption behavior for mobile e-wallets. International Journal of Research in Management & Business Studies, 6(4), 89–96.

Sivathanu, Brijesh. "Adoption of digital payment systems in the era of demonetization in India: An empirical study." Journal of Science and Technology Policy Management 10.1 (2019): 143-171.

Slade, E. L., Dwivedi, Y. K., Piercy, N. C., & Williams, M. D. (2015). Modeling consumers’ adoption intentions of remote mobile payments in the United Kingdom: Extending UTAUT with innovativeness, risk, and trust. Psychology & Marketing, 32(8), 860–873.

Staykova, K. S., & Damsgaard, J. (2015). The race to dominate the mobile payments platform: Entry and expansion strategies. Electronic Commerce Research and Applications, 14(5), Article 5.

Stone-Romero, E. F., Alvarez, K., & Thompson, L. F. (2009). The construct validity of conceptual and operational definitions of contextual performance and related constructs. Emerging Trends in Human Resource Management Theory and Research, 19(2), 104–116. https://doi.org/10.1016/j.hrmr.2008.10.003

Takyi, A., & Gyaase, P. O. (2012). Enhancing security of online payments: A conceptual model for a robust e-payment protocol for e-commerce. 232–239.

Thakur, R., & Srivastava, M. (2014). Adoption readiness, personal innovativeness, perceived risk and usage intention across customer groups for mobile payment services in India. Internet Research, 24(3), 369–392. https://doi.org/10.1108/IntR-12-2012-0244

Tobbin, P. (2012). The Adoption of' Transformational Mobile Banking 'by the Unbanked: An Exploratory Field Study. Communications & Strategies, 86, 103–120.

Toh, Y. L., & Tran, T. (2020). How the COVID-19 pandemic may reshape the digital payments landscape. Payments System Research Briefing, 1–10.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. MIS Quarterly, 27(3), 425–478. JSTOR. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. MIS Quarterly, 157–178.

Vinitha, K., & Vasantha, S. (2017). Factors Influencing Consumer's Intention to Adopt Digital Payment-Conceptual Model. Indian Journal of Public Health Research & Development, 8(3).

Vinitha, K., & Vasantha, S. (2020). Determinants of customer intention to use digital payment systems. Journal of Advanced Research in Dynamical and Control Systems, 12(2), Article 2.

Wenting, L. (2021). Digital Payments. Financial Management in The Digital Economy, 6, 105.

Wu, Z., & Liu, Y. (2023). Exploring country differences in the adoption of mobile payment service: The surprising robustness of the UTAUT2 model. International Journal of Bank Marketing, 41(2), 237–268.

Yang, C.-C., Yang, S.-Y., & Chang, Y.-C. (2023). Predicting older adults' mobile payment adoption: An extended TAM model. International Journal of Environmental Research and Public Health, 20(2), 1391.

Yaokumah, W., Kumah, P., & Okai, E. S. A. (2017). Demographic influences on e-payment services. International Journal of E-Business Research (IJEBR), 13(1), 44–65.

Yüksek, G., Lew, A. A., Othman, N., Coşkun, İ. O., & Karagöz, D. (2019). Heritage tourism beyond borders and civilizations. 11th Tourism Outlook Conference, Eskisehir, Turkey, 2-5 October 2018.

APPENDIX

Cover Letter and Instructions for Informed Pilot Participants

Dear Informed Pilot Participant,

Thank you so much for your willingness to provide your insights regarding the **"** ***Country socio economic landscape as moderating factor on the rise, adoption and usage of Digital Payments: USA, Canada, UK, and Australia*"** study.

Introduction

This quantitative research study is focused on the country moderating effects of the rise, adoption and usage of Digital Payments in the US, Canada, UK and Australia. There is an ongoing debate about adoption of digital payments and usage around the world. Several studies are focused on consumer behavior towards new technologies, using well known theoretical anchors, such as TAM and UTAUT. The digital payment research has also been focused on specific digital payment options (e.g. Mobile Payments) along with specific country use cases, the powerful catalyzing effect of external shocks such as COVID, as well within the idea of the imminent evolution to a "cashless society", thesis with significant support, but also opposition in the academic world.

Additionally, the topic becomes even more critical when there is also research focused on the digital payments impact in terms of financial inclusion and the overall economy. The reality is that there are still unanswered questions not only related to the country landscape effect, but also in terms of moving from adoption to day-to-day usage. For example, the same digital payments option (e.g. e-commerce, electronic wallet, Real Time Payments), may be aggressively offered in different countries, to a significant volume of clients by their financial institution, technology giants (Apple, Google), as well as fintech (Revolut, Stripe), but the usage behavior is not necessarily the same worldwide.

This study is expected to provide additional insight into this ongoing research. The target population is 100 current or perspective consumers in four (4) different countries, using an online survey administered by Qualtrics, as well as comparing them to existing secondary country payments data.

About your Participation

In this study, you are asked to join other expert panel members to critique a draft of the survey instrument intended to be used for data collection in this study. We greatly appreciate your interest in sharing your expertise in survey design by assisting in developing the survey instrument.

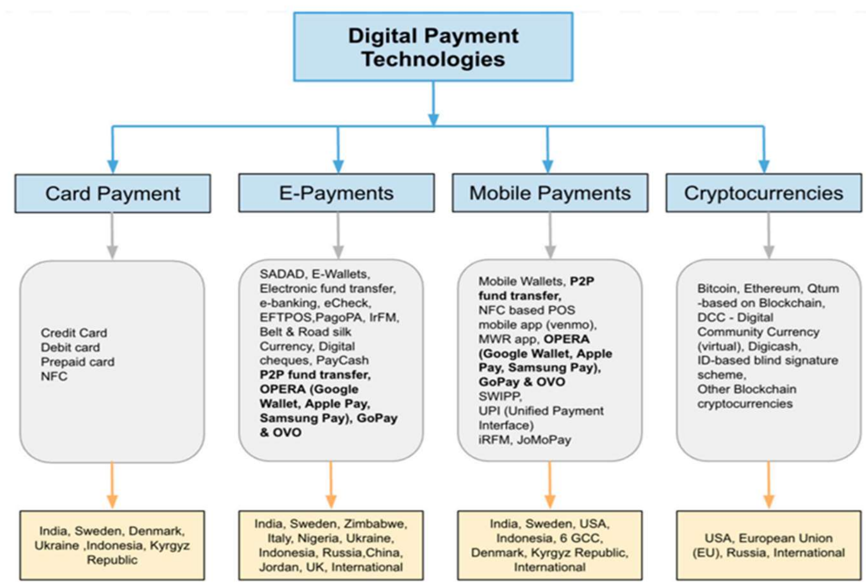
To guide you in this task, please find below an overview of key elements of this study and specific directions for your tasks.

Please direct any questions regarding this study or the instructions provided herein to: Fidel Chacon | Email: fchac001@fiu.edu

Study Overview

This research proposal focuses on gaining further knowledge of the drivers of adoption and usage behavior of new technologies, innovation, and digitalization of payments in different markets, given their specific socio-economic landscape, cultural and market dynamics. The research will be focused on the US, Canada, The UK, and Australia. This work is aimed at contributing additional findings in terms of measuring the key digital payment intention, usage, and adoption related variables by country, providing additional contributions for the ongoing debate around innovation and digitalization of payments. The country's socio-economic profile will be analyzed as the mediator of usage and adoption variables, as well as using secondary data for comparison and contextualization.

As a definition, Digital payments, also called electronic payments, is the transfer of value (goods, services, funds) from one payment account to another using a digital device or channel (Khando et al., 2022). Digital payments can be partially digital, primarily digital, or fully digital. For this study, we will use the following categorization of digital payments driven by the number of papers found by (Khando et al., 2022) as follows: 1) Card Payments (Credit/debit/prepaid cards) 2) E-payments (Fast funds, digital wallets), 3) Mobile Payments (P2P funds transfer, mobile apps) 4) Cryptocurrencies (bitcoin, DCC).

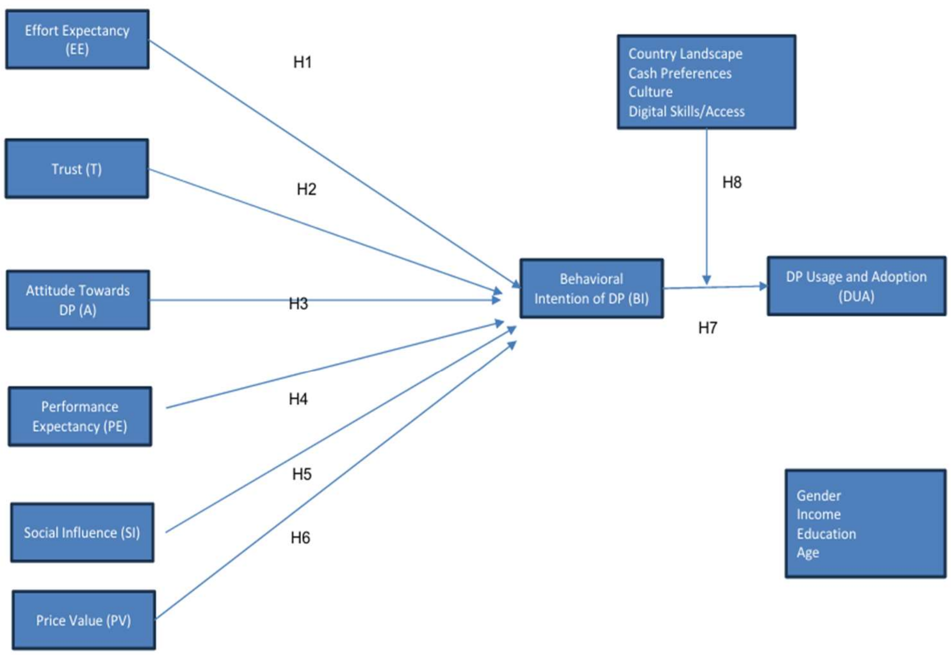


Summary of Constructs

Construct	**Definition**
Performance Expectancy	What are the benefit expectations for adoption? "*the degree to which using a technology will provide benefits to consumers in performing certain activities*"(Venkatesh et al., 2012)
Effort Expectancy	Determined by the existing capabilities in the country to use an additional service, as well as habit. "*The degree of ease related to consumers' use of technology. also known as perceived ease of use in the TAM model, is one of the important predictors of behavioral intention to use* "(Venkatesh et al., 2012)
Behavioral Intention	The combination of factors that will contribute to consumers willing to adopt this technology. "*a person's intentions to perform a variety of behaviors*" (Thakur & Srivastava, 2014)
Use Behavior	Adoption, initial attempts to do transactions, not necessarily a significative volume. Learning curve. Customer registered for the service; the question is if the issue will be consistent day to day. Questions will show differentiation between strong users vs. just limited transaction type users. The actual frequency of using digital payments (Venkatesh et al., 2012)
Social Influence	The community information received about digital payment options, such as family, friends, social media as a potential driver for adoption and usage. "*Social influence consists of two factors: (1) consumers' beliefs about people they consider important (e.g. family members or close friends) to influence their behavior; (2) the motivation to consult important others about their attitude towards new technologies.*"(Venkatesh et al., 2012)
Attitude	Determined by expectation of ease, satisfaction and effort, conditioned as well as habits, as well as a collectivist or individualist society (Kohun et al., 2012).
Price Value	The consumer's perception of the value obtained from the digital payment offering. "*consumers' cognitive tradeoff between the perceived benefits of the applications and the monetary cost for using them*" (Venkatesh et al., 2012)

Usage behavior and cash preferences	Determined by the consumer's perception of the need of cash for day-to-day transactions, regional requirements (e.g. services that can only be paid in cash).

Measurement Model



Research Context

The initial phase of this study will consist of a survey questionnaire to be applied to digital payments current and potential users in four (4) different countries (US, Canada, UK, and Australia). Then it will include analysis of payments related to public secondary data for the target countries.

The Qualtrics survey platform will host the survey which respondents will complete online. Then after the informed and regular pilot process, the final version of the survey will be distributed using Cloud Research to respondents in the US, Canada, UK, and Australia.

The responses and data will be analyzed using SPSS and the SmartPLS software. Validity and reliability tests will be conducted to ensure the instrument measures what it is intended to measure and produces consistent results.

Instructions for Review of Survey

You have been selected as a distinguished member of a small, exclusive group of DBA candidates from Florida International University - Cohort 5.6 and 5.7 with academic research experience.

Your contribution to this study is significant, and I am privileged to have you on board. You will provide valuable insights that will help fine-tune the survey instrument for data collection. Your expertise in survey design is highly regarded, and your input will play an integral role in ensuring the success of this study.

As a reviewer, you are requested to review and evaluate the survey instrument. Specifically, we are asking you to assess each question and the overall flow of the survey and provide feedback on your evaluation directly on the survey instrument.

We ask for all suggestions to improve the overall survey instrument. You will receive the survey instrument listing each item. Read each question/statement and consider if there are potential issues when providing your feedback and suggestions on whether the information is:

Criteria for Evaluation:

ID	Criteria:	Definitions:
1	Clear and understandable?	Is the question or statement phrased clearly and easy to understand?
2	Targeted to contributors in an organization?	Is the question relevant and appropriate for the survey respondents?
3	Measuring the variable of interest?	Does the question accurately measure the construct or variable it is intended to assess?
4	Double-barreled?	Does the question ask about two or more issues at once, making it difficult to answer?
5	Leading?	Does the question suggest a particular answer or influence the respondent's answer?
6	Loaded?	Does the question contain assumptions or emotionally charged language that could bias the response?
7	Confusing?	Is the question difficult to understand due to complex wording or structure?
8	Ambiguous?	Is the question vague or open to multiple interpretations?

9	Easy to understand and answer?	Is the question straightforward, making it easy for respondents to provide an accurate answer?

Thank you once again for your valuable participation.

Regards,

FCh

Country socio economic landscape as moderating factor on the rise, adoption and usage of Digital Payments: US, Canada, UK, and Australia

Qualifiers	Items	Qualifiers
Country of residence		What country do you primarily reside in: United States, United Kingdom, Canada, Australia, Brazil, Mexico, Other
Household finances		Are you personally responsible for making purchasing or payment decisions in your household or for yourself?
Age		What is your age group? Under 18, 18-25, 26-34, 35-44, 45-54, 55-64, 65 and older
Definitions	**Items**	**Preliminary questions/all participants**
Key terms definition (presented before the questions)		Which of the following are banking services as defined in this study? Select all that apply: A mortgage, a car loan, a tax accountant , credit score monitoring, a checking account
Key terms definition (presented before the questions)		Which of the following are digital payments as defined in this study? Select all that apply: giving cash to a car valet attendant, an online credit card payment, a transfer of bitcoin, a check sent for an utility payment, sending money to a friend using a peer-to-peer mobile application
Preliminary Questions	**Items**	**Preliminary questions/all participants**
Digital Banking		For banking services, in what way(s) do you typically interact with your bank? Select all that apply. : I visit the branch or call customer service, I access their website on a computer, I use banking applications on my mobile phone,
Education		What's your highest education level achieved? Some high school, no diploma, High school diploma or equivalent, some college, no degree; associate (2 year) dregree, Bachelor's (4 years) degree, Master's degree, Doctorate degree, Trade school, Apprenticeship, Prefer not to say
Income		What's your annual income? Less than 20k USD or equivalent, 20-45 K USD or equivalent, 45-75K or equivalent, 75-100K USD or equivalent, greater than 100K or equivalent
Gender		What's your gender? Male , Female, Other, Prefer not to answer
Digital Payments expertise		Have you used digital payment products in the last six (6) months? Y/N
Banked population		Are you a banking services user? Y/N.
Digital Payments expertise		How comfortable are you with digital payments? Extremely comfortable, moderately comfortable, slightly comfortable, neither comfortable nor uncomfortable, slightly uncomfortable, moderately uncomfortable, extremely uncomfortable
Type of Community		How would you define your community in terms of population area?? Rural area, small city/town, suburb near a large city, major city, none of the above
CONTROL VARIABLE	**Items**	**Variable Definition / Scale / Questions**
PERFORMANCE EXPECTANCY	PE	**On scale from 1-7, where 1=Strongly Disagree; 2=Disagree; 3=Somewhat Disagree; 4=Neither Agree or Disagree;5= Somewhat Agree; 6=Agree;7=Strongly Agree** **Answer the following statements:**
	PE1	Digital Payments help me to accomplish my day to day transactions faster.
	PE2	Digital Payments increase the efficiency with which I am performing regular payments
	PE3	Digital payments increase the efficiency with which I am managing my personal finances
	PE4	I find that digital payments are useful for me to accomplish my financial goals.
	PE5	Digital Payments improves the overall quality of making or receiving payments
CONTROL VARIABLE	**Items**	**Variable Definition / Scale / Questions**
EFFORT EXPECTANCY	EE	**On scale from 1-7, where 1=Strongly Disagree; 2=Disagree; 3=Somewhat Disagree; 4=Neither Agree or Disagree;5= Somewhat Agree; 6=Agree;7=Strongly Agree** **Answer the following statements:**
	EE1	I understand how to use digital payments
	EE2	I am skilled in using digital payments
	EE3	It is easy for me to learn how to use digital payments, the currently available options as well as newest offered in my community/market
	EE4	It is easy for me to navigate through different digital payment options and successfully transact the way I want (e.g. sending a peer to peer payment, an electronic commerce transaction, mobile payment apps)
CONTROL VARIABLE	**Items**	**Variable Definition / Scale / Questions**
PRICE VALUE	PV	**On scale from 1-7, where 1=Strongly Disagree; 2=Disagree; 3=Somewhat Disagree; 4=Neither Agree or Disagree;5= Somewhat Agree; 6=Agree;7=Strongly Agree** **Answer the following statements:** **In your organization...**
	PV1	Overall, the transaction cost of digital payment options is reasonable given the value I receive
	PV2	Other alternatives available to me for making payments have a higher price/transaction cost in comparison to digital payment options.
	PV3	I reduce/eliminate commissions using digital payment options to send/receive money to/from family members abroad
	PV4	I will continue using digital payments as long as the benefit I receive exceeds the total cost to use it , financial and others (E.g. time, efficiency, effort)
CONTROL VARIABLE	**Items**	**Variable Definition / Scale / Questions**
SOCIAL INFLUENCE	SI	**On scale from 1-7, where 1=Strongly Disagree; 2=Disagree; 3=Somewhat Disagree; 4=Neither Agree or Disagree;5= Somewhat Agree; 6=Agree;7=Strongly Agree** **Answer the following statements:**
	SI1	My family and friends think I should use digital payments
	SI2	My school/work colleagues recommend the use of digital payments for day to day transactions
	SI3	My bank (s) and other business I transact with encourage and support the use of digital payments
	SI4	The digital payments commercials in regular media (tv/news sites)are appealing and instructive
CONTROL VARIABLE	**Items**	**Variable Definition / Scale / Questions**
ATTITUDE TOWARDS PRODUCTS	ATP	**On scale from 1-7, where 1=Strongly Disagree; 2=Disagree; 3=Somewhat Disagree; 4=Neither Agree or Disagree;5= Somewhat Agree; 6=Agree;7=Strongly Agree** **Answer the following statements.**
	ATP1	Overall, I have had a positive use experience using digital payments
	ATP2	The reputation of the company offering digital payments is important to me.
	ATP3	The customer service provided by my digital payment providers meets my expectations.
	ATP4	The availability of transacting using digital payments keeps increasing at places (physical/virtual, domestic/abroad) I regularly interact with
CONTROL VARIABLE	**Items**	**Variable Definition / Scale / Questions**
USAGE BEHAVIOR AND CASH PREFERENCES	UB	**On scale from 1-7, where 1=Strongly Disagree; 2=Disagree; 3=Somewhat Disagree; 4=Neutral; Somewhat Agree; 5=Agree; 6=Strongly Agree** **Answer the following statements.**
	CASH1	There is a significant reliance on cash use for regular transactions in my community
	USE1	The domestic payment networks in my community (e.g. Interac, Lynx, STAR, Venmo, CHAPS, FPS, AusPayNet, AfterPay) are extremely reliable for day-to-day transactions and I don't need to carry that much cash with me.
	CASH2	I need to have cash with me at all times for regular transactions
	USE2	Most of the merchants/service provides I regularly transact with take digital payments
	USE3	There are services/goods that I can only pay using non-digital methods (checks or cash)
	CASH3	Even when digital payments are available, I often choose to pay with cash
	CASH4	I prefer using cash over digital payment methods for most of my purchases
	CASH5	Using cash feels safer and more secure than using cards or mobile payments
	CASH6	I rarely use cash in my daily transactions
	CASH7	I regularly keep a significant amount of cash available in the case of emergencies or unexpected situations.
CONTROL VARIABLE	**Items**	**Variable Definition / Scale / Questions**
TRUST	TR	**On scale from 1-7, where 1=Strongly Disagree; 2=Disagree; 3=Somewhat Disagree; 4=Neither Agree or Disagree;5= Somewhat Agree; 6=Agree;7=Strongly Agree** **Answer the following statements:**
	TR1	I am confident when using digital payment options for regular payments
	TR2	I believe that applications on mobile devices used for digital payments are the future of payments
	TR3	I embrace the use of applications on mobile devices for digital payment.
	TR4	I believe that the institutions I have accounts with will inform me about any unusual digital payment transactions witn my account
	TR5	I trust digital payments offerings more than other options (e.g. cash, checks)
	TR6	Overall, I find digital payment options secure and safe
CONTROL VARIABLE	**Items**	**Variable Definition / Scale / Questions**
BEHAVIORAL INTENTION	BI	**On scale from 1-7, where 1=Strongly Disagree; 2=Disagree; 3=Somewhat Disagree; 4=Neither Agree or Disagree;5= Somewhat Agree; 6=Agree;7=Strongly Agree** **Answer the following statements:**
	BI1	I intend to keep using digital payments offerings in the future, including learning about new options in the marketplace.
	BI2	I am willing to use the different payment options offered in my country/community, for domestic use only as well as international, such as Interac, Lynx, STAR, Venmo, CHAPS, FPS, AusPayNet, AfterPay, or international: Visa, MC, PayPal.
	BI3	When possible, I am open to change some of my cash payments to digital methods
	BI4	I intend to keep learning and using new technologies with payment applications as soon as they become available in my community

FLORIDA INTERNATIONAL UNIVERSITY

INFORMATIONAL LETTER

Country Socio Economic landscape as moderating factors on the rise and adoption of Digital Payments

You are invited to participate in a research study conducted by Fidel E. Chacon from the Florida International University (FIU) College of Business. The purpose of this study is to explore the factors influencing the adoption and use of digital payments across different countries.

Your participation in this study is voluntary. You may choose not to participate or to withdraw at any time without penalty. The survey does not collect personal identifiers such as your name, date of birth, or contact information. All responses will remain confidential and will be used solely for academic purposes.

If you have any questions about the purpose, procedures, or other issues relating to this research, you may contact Fidel Chacon at FIU Business School at 305-205-4504 or via email at fchac001@fiu.edu.

If you would like to talk with someone about your rights as a participant in this research study, or about ethical issues with this research, you may contact the FIU Office of Research Integrity by phone at 305-348-2494 or by email at ori@fiu.edu.

By clicking on the 'consent to participate' button below (in the actual survey form), you are providing your informed consent to participate in this study.

RIGHT TO DECLINE OR WITHDRAW

Your participation in this study is voluntary. You are free to participate in the study or withdraw your consent at any time during the study. You will not lose any benefits if you decide not to participate or if you quit participating in the study early. The investigator reserves the right to remove you without your consent at such a time that he/she feels it is in the best interest.

FIU | Research & Economic Development
FLORIDA INTERNATIONAL UNIVERSITY

MEMORANDUM

To:	Dr. Amin Shoja
CC:	Fidel Chacon
From:	Carrie Bassols, BA, IRB Coordinator ceb
Date:	June 6, 2024
Proposal Title:	"C56 - CHACON - Country socio economic landscape as moderating factor on the rise and adoption of Digital Payments: US, Canada, UK, and Australia"

The Florida International University Office of Research Integrity has reviewed your research study for the use of human subjects and deemed it Exempt via the **Exempt Review** process.

IRB Protocol Exemption #:	IRB-24-0287	**IRB Exemption Date:**	06/06/24
TOPAZ Reference #:	114316		

As a requirement of IRB Exemption you are required to:

1) Submit an IRB Exempt Amendment Form for all proposed additions or changes in the procedures involving human subjects. All additions and changes must be reviewed and approved prior to implementation.
2) Promptly submit an IRB Exempt Event Report Form for every serious or unusual or unanticipated adverse event, problems with the rights or welfare of the human subjects, and/or deviations from the approved protocol.
1) Submit an IRB Exempt Project Completion Report Form when the study is finished or discontinued.

Special Conditions: N/A

For further information, you may visit the IRB website at http://research.fiu.edu/irb.

Case Processing Summary

		N	%
Cases	Valid	190	99.5
	Excluded[a]	1	.5
	Total	191	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
.864	.874	5

Item Statistics

	Mean	Std. Deviation	N
PE1_num	6.5368	.67941	190
PE2_num	6.4421	.75894	190
PE3_num	6.2632	.86325	190
PE4_num	6.6684	.56395	190
PE5_num	6.4211	.72124	190

Inter-Item Correlation Matrix

	PE1_num	PE2_num	PE3_num	PE4_num	PE5_num
PE1_num	1.000	.666	.462	.688	.638
PE2_num	.666	1.000	.548	.629	.518
PE3_num	.462	.548	1.000	.495	.543
PE4_num	.688	.629	.495	1.000	.631
PE5_num	.638	.518	.543	.631	1.000

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.891	.894	5

Item Statistics

	Mean	Std. Deviation	N
EE1_num	6.5211	.58832	190
EE2_num	6.1947	.78273	190
EE3_num	6.3684	.70602	190
EE4_num	6.4737	.66416	190
EE5_num	6.4737	.63149	190

Inter-Item Correlation Matrix

	EE1_num	EE2_num	EE3_num	EE4_num	EE5_num
EE1_num	1.000	.675	.631	.570	.600
EE2_num	.675	1.000	.655	.575	.583
EE3_num	.631	.655	1.000	.687	.639
EE4_num	.570	.575	.687	1.000	.661
EE5_num	.600	.583	.639	.661	1.000

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.726	.728	5

Item Statistics

	Mean	Std. Deviation	N
SI1_num	5.8105	.93486	190
SI2_num	4.8474	1.34631	190
SI3_num	3.0842	1.61122	190
SI4_num	4.6316	1.64302	190
SI5_num	3.5211	1.61576	190

Inter-Item Correlation Matrix

	SI1_num	SI2_num	SI3_num	SI4_num	SI5_num
SI1_num	1.000	.490	.091	.381	.150
SI2_num	.490	1.000	.238	.372	.445
SI3_num	.091	.238	1.000	.364	.558
SI4_num	.381	.372	.364	1.000	.394
SI5_num	.150	.445	.558	.394	1.000

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.865	.876	5

Item Statistics

	Mean	Std. Deviation	N
PV1_num	4.5526	1.54812	190
PV2_num	5.4421	1.06125	190
PV3_num	5.2316	1.29265	190
PV4_num	5.6737	1.04848	190
PV5_num	5.7316	1.12525	190

Inter-Item Correlation Matrix

	PV1_num	PV2_num	PV3_num	PV4_num	PV5_num
PV1_num	1.000	.646	.539	.389	.529
PV2_num	.646	1.000	.623	.592	.649
PV3_num	.539	.623	1.000	.552	.690
PV4_num	.389	.592	.552	1.000	.652
PV5_num	.529	.649	.690	.652	1.000

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.899	.901	5

Item Statistics

	Mean	Std. Deviation	N
A1_num	6.1211	.85516	190
A2_num	6.2053	.83252	190
A3_num	6.1053	.88460	190
A4_num	6.5474	.60454	190
A5_num	6.3526	.80137	190

Inter-Item Correlation Matrix

	A1_num	A2_num	A3_num	A4_num	A5_num
A1_num	1.000	.716	.794	.567	.594
A2_num	.716	1.000	.768	.596	.589
A3_num	.794	.768	1.000	.624	.574
A4_num	.567	.596	.624	1.000	.637
A5_num	.594	.589	.574	.637	1.000

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.828	.835	6

Item Statistics

	Mean	Std. Deviation	N
CP1_num	2.7737	1.54178	190
CP2_num	2.9316	1.75498	190
CP3_num	4.3053	1.79696	190
CP4_num	2.5632	1.54773	190
CP5_num	2.2158	1.46232	190
CP6_num	4.6895	1.84115	190

Inter-Item Correlation Matrix

	CP1_num	CP2_num	CP3_num	CP4_num	CP5_num	CP6_num
CP1_num	1.000	.530	.384	.617	.524	.238
CP2_num	.530	1.000	.335	.616	.692	.576
CP3_num	.384	.335	1.000	.379	.319	.360
CP4_num	.617	.616	.379	1.000	.659	.260
CP5_num	.524	.692	.319	.659	1.000	.371
CP6_num	.238	.576	.360	.260	.371	1.000

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.919	.921	5

Item Statistics

	Mean	Std. Deviation	N
T1_num	5.3947	1.18052	190
T2_num	5.2737	1.36426	190
T3_num	4.6211	1.49198	190
T4_num	4.9105	1.37529	190
T5_num	5.4684	1.21130	190

Inter-Item Correlation Matrix

	T1_num	T2_num	T3_num	T4_num	T5_num
T1_num	1.000	.862	.653	.667	.714
T2_num	.862	1.000	.670	.684	.703
T3_num	.653	.670	1.000	.829	.573
T4_num	.667	.684	.829	1.000	.648
T5_num	.714	.703	.573	.648	1.000

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.891	.896	5

Item Statistics

	Mean	Std. Deviation	N
BI1_num	6.5211	.65633	190
BI2_num	6.4263	.72180	190
BI3_num	6.2474	.86488	190
BI4_num	6.1947	.99681	190
BI5_num	6.2579	.96050	190

Inter-Item Correlation Matrix

	BI1_num	BI2_num	BI3_num	BI4_num	BI5_num
BI1_num	1.000	.735	.545	.580	.591
BI2_num	.735	1.000	.568	.656	.650
BI3_num	.545	.568	1.000	.545	.572
BI4_num	.580	.656	.545	1.000	.887
BI5_num	.591	.650	.572	.887	1.000

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.884
Bartlett's Test of Sphericity	Approx. Chi-Square	4395.514
	df	630
	Sig.	<.001

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.806[a]	.650	.639	.42634	.650	56.694	6	183	<.001

a. Predictors: (Constant), REGR factor score 8 for analysis 1, REGR factor score 4 for analysis 1, REGR factor score 5 for analysis 1, REGR factor score 2 for analysis 1, REGR factor score 3 for analysis 1, REGR factor score 6 for analysis 1

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	95.0% Confidence Interval for B Lower Bound	95.0% Confidence Interval for B Upper Bound
1	(Constant)	6.329	.031		204.637	<.001	6.268	6.390
	REGR factor score 2 for analysis 1	.107	.040	.150	2.656	.009	.027	.186
	REGR factor score 3 for analysis 1	.185	.041	.261	4.539	<.001	.105	.266
	REGR factor score 4 for analysis 1	.024	.037	.034	.646	.519	-.049	.097
	REGR factor score 5 for analysis 1	-.131	.033	-.184	-3.945	<.001	-.196	-.065
	REGR factor score 6 for analysis 1	.309	.042	.436	7.425	<.001	.227	.391
	REGR factor score 8 for analysis 1	.063	.031	.088	1.993	.048	.001	.125

a. Dependent Variable: BI_num

Coefficient Correlations[a]

Model			REGR factor score 8 for analysis 1	REGR factor score 4 for analysis 1	REGR factor score 5 for analysis 1	REGR factor score 2 for analysis 1	REGR factor score 3 for analysis 1	REGR factor score 6 for analysis 1
1	Correlations	REGR factor score 8 for analysis 1	1.000	-.060	-.123	.011	-.001	.062
		REGR factor score 4 for analysis 1	-.060	1.000	.040	-.038	-.105	-.395
		REGR factor score 5 for analysis 1	-.123	.040	1.000	.138	.080	.072
		REGR factor score 2 for analysis 1	.011	-.038	.138	1.000	-.407	-.225
		REGR factor score 3 for analysis 1	-.001	-.105	.080	-.407	1.000	-.254
		REGR factor score 6 for analysis 1	.062	-.395	.072	-.225	-.254	1.000
	Covariances	REGR factor score 8 for analysis 1	.001	-7.018E-5	.000	1.356E-5	-6.449E-7	8.139E-5
		REGR factor score 4 for analysis 1	-7.018E-5	.001	4.914E-5	-5.628E-5	.000	-.001
		REGR factor score 5 for analysis 1	.000	4.914E-5	.001	.000	.000	9.915E-5
		REGR factor score 2 for analysis 1	1.356E-5	-5.628E-5	.000	.002	-.001	.000
		REGR factor score 3 for analysis 1	-6.449E-7	.000	.000	-.001	.002	.000
		REGR factor score 6 for analysis 1	8.139E-5	-.001	9.915E-5	.000	.000	.002

a. Dependent Variable: BI_num

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	T_num, CP_num, SI_num, PE_numb, PV_num, EE_numb, A_num[b]	.	Enter

a. Dependent Variable: BI_num

b. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.811[a]	.658	.644	.42300

a. Predictors: (Constant), T_num, CP_num, SI_num, PE_numb, PV_num, EE_numb, A_num

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	62.530	7	8.933	49.925	<.001[b]
	Residual	32.565	182	.179		
	Total	95.095	189			

a. Dependent Variable: BI_num

b. Predictors: (Constant), T_num, CP_num, SI_num, PE_numb, PV_num, EE_numb, A_num

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	VIF
1	(Constant)	.625	.437		1.430	.154		
	PE_numb	.208	.074	.171	2.797	.006	.503	1.989
	EE_numb	.253	.090	.165	2.827	.005	.555	1.801
	SI_num	.043	.032	.060	1.327	.186	.913	1.095
	PV_num	.031	.041	.043	.756	.450	.585	1.708
	A_num	.512	.077	.488	6.672	<.001	.352	2.844
	CP_num	-.089	.027	-.154	-3.371	<.001	.904	1.106
	T_num	-.039	.031	-.064	-1.271	.205	.753	1.329

a. Dependent Variable: BI_num

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions (Constant)	PE_numb	EE_numb	SI_num	PV_num	A_num	CP_num	T_num
1	1	7.767	1.000	.00	.00	.00	.00	.00	.00	.00	.00
	2	.131	7.690	.00	.00	.00	.01	.01	.00	.73	.01
	3	.040	13.858	.00	.00	.00	.87	.02	.00	.00	.16
	4	.033	15.432	.01	.01	.01	.11	.00	.00	.03	.67
	5	.018	20.569	.02	.01	.02	.00	.81	.00	.05	.11
	6	.004	43.414	.65	.06	.00	.00	.12	.35	.15	.01
	7	.003	49.085	.10	.37	.87	.01	.01	.01	.03	.00
	8	.003	53.062	.22	.55	.09	.00	.03	.63	.01	.05

a. Dependent Variable: BI_num

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.811[a]	.658	.644	.42300	.658	49.925	7	182	<.001

a. Predictors: (Constant), T_num, CP_num, SI_num, PE_numb, PV_num, EE_numb, A_num

Coefficients[a]

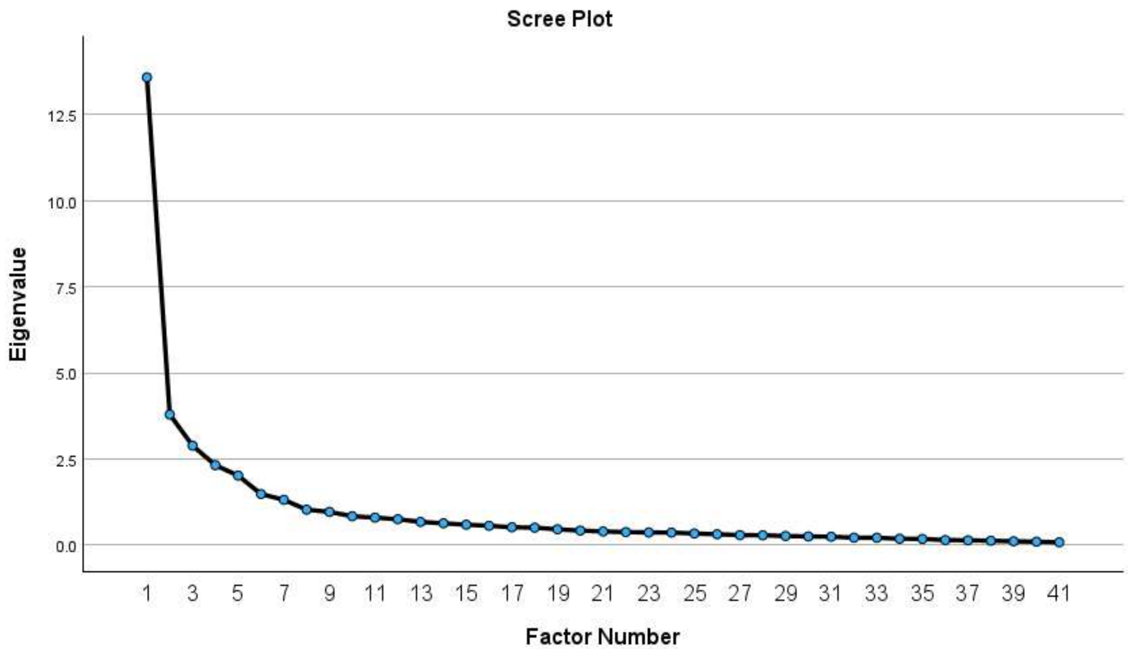
		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
Model		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	.625	.437		1.430	.154	-.237	1.487					
	PE_numb	.208	.074	.171	2.797	.006	.061	.355	.638	.203	.121	.503	1.989
	EE_numb	.253	.090	.165	2.827	.005	.076	.430	.614	.205	.123	.555	1.801
	SI_num	.043	.032	.060	1.327	.186	-.021	.106	.252	.098	.058	.913	1.095
	PV_num	.031	.041	.043	.756	.450	-.049	.111	.492	.056	.033	.585	1.708
	A_num	.512	.077	.488	6.672	<.001	.360	.663	.758	.443	.289	.352	2.844
	CP_num	-.089	.027	-.154	-3.371	<.001	-.142	-.037	-.380	-.242	-.146	.904	1.106
	T_num	-.039	.031	-.064	-1.271	.205	-.100	.022	.275	-.094	-.055	.753	1.329

a. Dependent Variable: BI_num

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
Model		B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1	(Constant)	.625	.437		1.430	.154		
	PE_numb	.208	.074	.171	2.797	.006	.503	1.989
	EE_numb	.253	.090	.165	2.827	.005	.555	1.801
	SI_num	.043	.032	.060	1.327	.186	.913	1.095
	PV_num	.031	.041	.043	.756	.450	.585	1.708
	A_num	.512	.077	.488	6.672	<.001	.352	2.844
	CP_num	-.089	.027	-.154	-3.371	<.001	.904	1.106
	T_num	-.039	.031	-.064	-1.271	.205	.753	1.329

a. Dependent Variable: BI_num


Scree Plot
Eigenvalue
12.5
10.0
7.5
5.0
2.5
0.0
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41
Factor Number

Factor Matrix[a]

	Factor 1	2	3	4	5	6	7	8
PE1_num	.669							
PE2_num	.630							
PE3_num	.529							
PE4_num	.678							
PE5_num	.648							
EE1_num	.600							
EE2_num	.619							
EE3_num	.626							
EE4_num	.637							
EE5_num	.674							
SI1_num	.441							
SI2_num								
SI3_num				.454				
SI4_num				.584				
SI5_num				.645				
PV1_num								
PV2_num	.582				-.404			
PV3_num	.592							
PV4_num	.637							
PV5_num	.676				-.455			
A1_num	.768							
A2_num	.768							
A3_num	.807							
A4_num	.745							
A5_num	.696							
CP1_num			.516					
CP2_num			.672					
CP3_num			.429					
CP4_num			.556					
CP5_num	-.460		.554					
CP6_num			.529					
T1_num	.480	.611						
T2_num	.456	.636						
T3_num		.721						
T4_num	.428	.701						
T5_num	.508	.521						
BI1_num	.769							
BI2_num	.748							
BI3_num	.633							
BI4_num	.718							
BI5_num	.717							

Extraction Method: Principal Axis Factoring.

a. 8 factors extracted. 7 iterations required.

Appendix Table A1. Demographic Characteristics by Country

Country	Variable	Category	n (%)
United States	Gender	Male	25 (50.0%)
United States	Gender	Female	23 (46.0%)
United States	Gender	Other	1 (2.0%)
United States	Gender	Prefer not to say	1 (2.0%)
United States	Age	26-34	17 (34.0%)
United States	Age	35-44	14 (28.0%)
United States	Age	45-54	11 (22.0%)
United States	Age	18-25	3 (6.0%)
United States	Age	65-+	3 (6.0%)
United States	Age	55-64	2 (4.0%)
United States	Education	Bachelor's (4-year) degree	22 (44.0%)
United States	Education	Master's degree	9 (18.0%)
United States	Education	Some college, no degree	8 (16.0%)

United States	Education	High school diploma or equivalent	7 (14.0%)
United States	Education	Doctorate degree	2 (4.0%)
United States	Education	Associate (2-year) degree	2 (4.0%)
United States	Income	At least $20,000, but less than $45,000, USD or equivalent	13 (26.0%)
United States	Income	$100,000 or more, USD or equivalent	13 (26.0%)
United States	Income	At least $45,000, but less than $75,000, USD or equivalent	11 (22.0%)
United States	Income	Less than $20,000, USD or equivalent	9 (18.0%)
United States	Income	At least $75,000, but less than $100,000, USD or equivalent	4 (8.0%)
United States	Geographic Area	Suburb near a large city	17 (34.0%)
United States	Geographic Area	Small City/town	15 (30.0%)

United States	Geographic Area	Major city	13 (26.0%)
United States	Geographic Area	Rural Area	5 (10.0%)

Canada	Gender	Male	31 (66.0%)
Canada	Gender	Female	16 (34.0%)
Canada	Age	26-34	19 (40.4%)
Canada	Age	35-44	13 (27.7%)
Canada	Age	18-25	7 (14.9%)
Canada	Age	55-64	4 (8.5%)
Canada	Age	65-+	2 (4.3%)
Canada	Age	45-54	2 (4.3%)
Canada	Education	Bachelor's (4-year) degree	14 (29.8%)
Canada	Education	Some college, no degree	14 (29.8%)
Canada	Education	High school diploma or equivalent	6 (12.8%)
Canada	Education	Master's degree	5 (10.6%)

Canada	Education	Trade school	3 (6.4%)
Canada	Education	Associate (2-year) degree	2 (4.3%)
Canada	Education	Doctorate degree	2 (4.3%)
Canada	Education	Some high school, no diploma	1 (2.1%)
Canada	Income	At least $45,000, but less than $75,000, USD or equivalent	13 (27.7%)
Canada	Income	At least $20,000, but less than $45,000, USD or equivalent	12 (25.5%)
Canada	Income	Less than $20,000, USD or equivalent	9 (19.1%)
Canada	Income	At least $75,000, but less than $100,000, USD or equivalent	9 (19.1%)
Canada	Income	$100,000 or more, USD or equivalent	4 (8.5%)
Canada	Geographic Area	Major city	26 (55.3%)

Canada	Geographic Area	Suburb near a large city	9 (19.1%)
Canada	Geographic Area	Small City/town	8 (17.0%)
Canada	Geographic Area	Rural Area	4 (8.5%)

Australia	Gender	Female	27 (54.0%)
Australia	Gender	Male	23 (46.0%)
Australia	Age	35-44	15 (30.0%)
Australia	Age	45-54	12 (24.0%)
Australia	Age	18-25	9 (18.0%)
Australia	Age	55-64	7 (14.0%)
Australia	Age	26-34	7 (14.0%)
Australia	Education	Bachelor's (4-year) degree	21 (42.0%)
Australia	Education	Master's degree	11 (22.0%)
Australia	Education	Some college, no degree	6 (12.0%)
Australia	Education	Doctorate degree	4 (8.0%)

Australia	Education	Some high school, no diploma	3 (6.0%)
Australia	Education	Trade school	3 (6.0%)
Australia	Education	High school diploma or equivalent	1 (2.0%)
Australia	Education	Associate (2-year) degree	1 (2.0%)
Australia	Income	At least $45,000, but less than $75,000, USD or equivalent	15 (30.0%)
Australia	Income	At least $20,000, but less than $45,000, USD or equivalent	12 (24.0%)
Australia	Income	At least $75,000, but less than $100,000, USD or equivalent	11 (22.0%)
Australia	Income	Less than $20,000, USD or equivalent	6 (12.0%)
Australia	Income	$100,000 or more, USD or equivalent	6 (12.0%)
Australia	Geographic Area	Suburb near a large city	19 (38.0%)

Australia	Geographic Area	Major city	17 (34.0%)
Australia	Geographic Area	Rural Area	8 (16.0%)
Australia	Geographic Area	Small City/town	6 (12.0%)

United Kingdom	Gender	Female	22 (51.2%)
United Kingdom	Gender	Male	20 (46.5%)
United Kingdom	Gender	Prefer not to say	1 (2.3%)
United Kingdom	Age	26-34	15 (34.9%)
United Kingdom	Age	35-44	12 (27.9%)
United Kingdom	Age	45-54	9 (20.9%)
United Kingdom	Age	55-64	5 (11.6%)
United Kingdom	Age	18-25	2 (4.7%)
United Kingdom	Education	Bachelor's (4-year) degree	20 (46.5%)
United Kingdom	Education	Some college, no degree	9 (20.9%)
United Kingdom	Education	Master's degree	6 (14.0%)

United Kingdom	Education	High school diploma or equivalent	4 (9.3%)
United Kingdom	Education	Doctorate degree	2 (4.7%)
United Kingdom	Education	Apprenticeship	2 (4.7%)
United Kingdom	Income	At least $20,000, but less than $45,000, USD or equivalent	19 (44.2%)
United Kingdom	Income	At least $75,000, but less than $100,000, USD or equivalent	8 (18.6%)
United Kingdom	Income	At least $45,000, but less than $75,000, USD or equivalent	7 (16.3%)
United Kingdom	Income	Less than $20,000, USD or equivalent	7 (16.3%)
United Kingdom	Income	$100,000 or more, USD or equivalent	2 (4.7%)
United Kingdom	Geographic Area	Small City/town	19 (44.2%)
United Kingdom	Geographic Area	Major city	12 (27.9%)
United Kingdom	Geographic Area	Suburb near a large city	8 (18.6%)

United Kingdom	Geographic Area	Rural Area	4 (9.3%)

VITA

FIDEL E. CHACON

1987-1993	B.Sc. Economics Universidad Central de Venezuela Caracas, Venezuela
2001-2003	M.A. International Business Florida International University Miami, Florida
2022-2025	Doctorate of Business Administration (DBA) Florida International University Miami, Florida