ESI Preprints **Not Peer-reviewed**

Extending UTAUT2 with Perceived Risk and Trust: Evidence from Digital Banking Adoption in the Kurdistan Region of Iraq

Mamoun Walid Aridah, PhD in Accounting
Bucharest University of Economic Studies, Bucharest, Romania
Sherzad Ramadhan, PhD in Accounting
Cihan University-Duhok, Duhok, Iraq
Fareeba Ahmed, MSc in Accounting
Bucharest University of Economic Studies, Bucharest, Romania
Hariwan Khorsheed, MSc in Accounting
Cihan University-Duhok, Duhok, Iraq
Shamal Obaied, MSc in Accounting
Cihan University-Duhok, Duhok, Iraq
Amar Aldulaimi, MSc in Accounting
Bucharest University of Economic Studies, Bucharest, Romania

Approved: 08 March 2026
Posted: 10 March 2026

Cite As:
Aridah, M.W., Ramadhan, S., Ahmed, F., Khorsheed, H., Obaied, S. & Aldulaimi, A. (2026). *Extending UTAUT2 with Perceived Risk and Trust: Evidence from Digital Banking Adoption in the Kurdistan Region of Iraq.* ESI Preprints.
https://doi.org/10.19044/esipreprint.3.2026.p1

Abstract

Purpose: This research extends the Unified Theory of Acceptance and Use of Technology (UTAUT2) to investigate the variables affecting the adoption and use of digital banking services. In fragile economic environments, particular attention is paid to the negative impacts of perceived risk and the functions of trust as a direct predictor and modifier of behavioral intention to use digital banking.

Design/methodology/approach: A cross-sectional study was conducted with 360 users of digital banking services in the Kurdistan Region of Iraq. Structural Equation Modeling using SmartPLS 4 was used to evaluate the proposed correlations. Principal structural model evaluations included path coefficients, R^2, Q^2, f^2 effect sizes, and collinearity diagnostics.

The model's predictive efficacy was assessed with PLSpredict, contrasting PLS-SEM with linear regression and naïve standards.

Findings: The findings indicate that performance expectation, effort expectancy, social influence, facilitating conditions, and trust have a large positive impact on behavioral intention; however, perceived risk has a significant negative effect. Behavioral intention is a robust predictor of consumption behavior. Trust favorably affects behavioral intention but does not substantially attenuate the adverse link between perceived risk and behavioral intention. The model exhibits sufficient explanatory power (R^2 = 0.440 for BI; R^2 = 0.409 for UB) and moderate predictive capabilities for essential markers.

Originality/value: This research enhances the digital banking adoption literature by integrating UTAUT2 with perceived risk and trust in a high-risk, undeveloped economic context. It offers empirical insights into the influence of psychological and environmental aspects on user behavior in volatile markets. The results provide actionable insights for financial institutions seeking to develop safe, trust-building digital platforms that reduce risk perception and bolster user confidence.

Keywords: UTAUT2; Perceived Risk; Trust; Digital Banking; Behavioral Intention; Fragile Economies; PLS-SEM; Predictive Analytics

Introduction

The rapid progression of digital technology has profoundly altered the global banking sector, facilitating the rise of digital financial services like mobile banking, electronic wallets, and contactless payments (Mogaji & Nguyen, 2024). Despite these worldwide trends, the adoption rate of digital banking is inconsistent, especially in unstable and emerging nations, attributable to variances in technical infrastructure, institutional trust, and financial literacy (António Porfírio et al., 2024). The Kurdistan Region of Iraq (KRI), an autonomous area administered by the Kurdistan Regional Government (KRG), illustrates this difference. Regardless of the existence of banking infrastructure, the area continues to rely mostly on cash transactions, indicative of widespread financial exclusion in Iraq, where just 19% of individuals own a formal bank account (World Bank, 2023).

Various structural and psychological obstacles persist in hindering the adoption of digital banking in the area. These include restricted financial literacy, absence of user-centric services, diminished institutional trust, and apprehensions about system dependability (Bouteraa et al., 2023; M. Hamakhan, 2020; Pal et al., 2020). In response to these issues, the KRG has implemented measures like the “My Account” scheme, which requires public

employee pay to be put into bank accounts to promote digital adoption, diminish cash reliance, and enhance financial transparency (KRG, 2023).

Digital banking serves as both a technical advancement and a vital facilitator of extensive socio-economic progress, bolstering e-government activities and promoting e-commerce (Barroso & Laborda, 2022; Divya et al., 2024). The transition from rudimentary online services to AI-enhanced, omnichannel platforms has broadened access to financial instruments via cell phones, ATMs, and online portals, resulting in expedited, paperless, and more inclusive financial ecosystems (Kim et al., 2024; Murinde et al., 2022). Innovations including blockchain, open banking APIs, and biometric identification now provide safe and customized financial experiences (Adil et al., 2025; Mahajan & Nanda, 2024). In the meantime, the worldwide interest in Central Bank Digital Currencies (CBDCs) signifies policymakers' endeavors to modernize payment systems and bolster financial resiliency (Wronka, 2023).

However, technology infrastructure alone cannot overcome entrenched societal skepticism. Prolonged violence, corruption, and institutional dysfunction in Iraq and the KRI have substantially diminished trust in the official banking system (Biro, 2024; Modiha, 2025; Muhamad, 2024; Otopah et al., 2024). In April 2025, the Central Bank of Iraq announced that roughly 91.2 trillion IQD (≈ $62 billion) is in circulation outside the banking system, demonstrating a pronounced preference for cash holdings and underscoring ongoing skepticism. Despite being paid public workers in the KRI, the majority of whom acquire their payments via banks, the complete cash withdrawal of earnings is still prevalent (Central Bank of Iraq, 2025; Krishna et al., 2025).

Given these facts, understanding the psychological and behavioral dynamics influencing digital banking adoption is essential. The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) provides a theoretically sound and empirically substantiated framework for analyzing adoption behavior. This research enhances UTAUT2 by including perceived risk as a negative predictor and trust as a direct determinant and moderator, addressing the socio-political complexities of unstable contexts. This conceptual refinement aims to clarify how institutional trust and perceived security significantly influence behavioral intention and usage behavior in a precarious financial environment.

Theoretical Foundations

The implementation of digital banking technologies has been thoroughly analyzed via several behavioral and technical acceptance theories, which underpin the understanding of user intents and technology use. The Theory of Reasoned Action (TRA), introduced by (Fishbein, &

Ajzen, 1975), is one of the oldest and most impactful theories. The Theory of Reasoned Action asserts that behavioral intention is influenced by an individual's attitude towards an action and the impact of subjective standards. This approach presupposes volitional control over behavior, which is not consistently relevant in practical contexts.

To overcome this issue, (Ajzen, 1991) proposed the Theory of Planned Behavior (TPB), which enhances the Theory of Reasoned Action (TRA) by including perceived behavioral control. This supplementary construct measures people' belief in their capacity to execute a certain activity, hence augmenting the model's relevance in circumstances where external limitations may affect actions.

(Davis, 1989) expanded on these cognitive frameworks to create the Technology Acceptance Model (TAM), which focuses on the adoption of information technology. The Technology Adoption Model posits that technology adoption is mostly influenced by two factors: perceived utility and perceived ease of use. Its simplicity and predictive capability have resulted in extensive use in information systems research. Nonetheless, TAM has faced criticism for its inadequate ability to include intricate behavioral and environmental factors.

To address these deficiencies, (Venkatesh et al., 2003) introduced the Unified Theory of Acceptance and Use of Technology (UTAUT). This model synthesizes components from eight previous frameworks, unifying essential factors like performance expectation, effort expectancy, social impact, and enabling environments. (Venkatesh et al., 2012) acknowledged the need to modify the model for consumer-centric contexts by developing UTAUT2, which integrates supplementary constructs hedonic drive, price value, and habit to include a wider spectrum of consumer behaviors.

Theoretical developments have substantially improved the explanatory capacity of adoption models, especially in digital financial services. UTAUT2's versatility and extensibility make it particularly adept at studying user behavior in online and mobile banking environments. Its ability to include mediating and moderating factors allows researchers to investigate intricate interactions among user perceptions, intentions, and actual technology use. Consequently, these models persist in offering a robust theoretical framework for empirical studies on digital banking uptake.

Conceptual Model and Hypotheses Development

Based on the UTAUT2 framework, this study's conceptual model is expanded to include two more constructs: Perceived Risk (PR) and Trust (TR). These additions make the model more relevant to the context of digital banking use. Perform Expectation (PE), Effort Expectation (EE), Social Influence (SI), Facilitating Conditions (FC), Behavioral Intention (BI), and

Use Behavior (UB) are important factors in the model, as illustrated in Figure 1. The study's assumptions are based on the connections between these concepts.

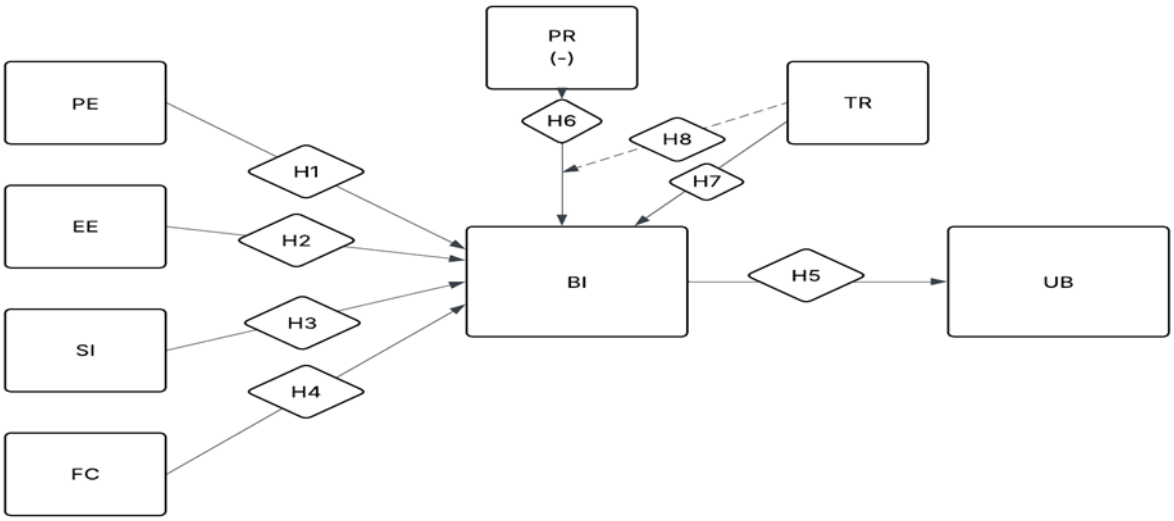

Figure 1: Conceptual Model of Digital Banking Adoption

Association of Digital Banking Intention with Performance Expectancy (PE)

Performance Expectancy (PE) is the extent to which a person perceives that using a certain technology would improve their performance or productivity (Venkatesh et al., 2003). As a fundamental element of the Unified Theory of Acceptance and Use of Technology (UTAUT and UTAUT2), performance expectancy (PE) has been continuously recognized in the literature as a key factor influencing users' behavioral intention to accept technological improvements.

Comprehensive empirical research has shown that when individuals regard a digital banking service, such as mobile banking, internet banking, or e-wallets, as beneficial, efficient, and capable of providing substantial advantages, their intention to adopt and utilize that service markedly increases (Alalwan et al., 2017; Baabdullah et al., 2019; Farzin & Fattahi, 2025; Idrees & Ullah, 2024; Mohd Thas Thaker et al., 2022; Rahman et al., 2020; Raza et al., 2017; Venkatesh et al., 2003; Venkatesh & Zhang, 2010; Zaid Kilani et al., 2023). These results underscore the significance of (PE) in shaping user behavior across various digital financial technology.

Furthermore, similar evidence has been documented in the Kurdistan Region of Iraq. (M. Hamakhan, 2020) found that performance expectation significantly and positively affected customers' propensity to embrace

electronic banking services, hence affirming the relevance of this construct in local contexts.

Considering the consistent empirical evidence in both global and local settings, it is plausible to anticipate that performance expectation would similarly influence user behavior regarding digital banking systems. Consequently, the following hypothesis is posited:

H1: Performance Expectancy positively influences behavioral intention toward digital banking usage.

Association of Effort Expectancy (EE) and Digital Banking Intention

Effort Expectancy (EE), characterized as the level of easiness related to technology use (Venkatesh et al., 2012), (EE) has been extensively recognized in technology acceptance studies as a crucial factor influencing user intention. It conveys consumers' views about the ease and clarity of learning and using a digital technology. The perception of a system as user-friendly enhances its adoption probability, especially among those with constrained time, technical expertise, or self-assurance.

Multiple researches based on the (UTAUT2) paradigm have repeatedly shown that effort expectancy (EE) has a substantial beneficial impact on behavioral intention. Users are more likely to use a digital banking platform when they perceive that it requires less effort (Chand et al., 2025; Herzallah et al., 2025; Linh et al., 2025; Loke et al., 2025; Rayun et al., 2025; Zaid Kilani et al., 2023). The interface's clarity, the system's learnability, and the general user-friendliness enhance the propensity to interact with the technology.

The intensity of this link may fluctuate based on user history or circumstance, although the direction of effect is consistently supported by empirical evidence: ease promotes adoption. Even in research where other factors are more prominent, (EE) is often acknowledged as a contributing element in consumers' decision-making processes. This trend is also applicable in local research (M. Hamakhan, 2020), discovered that effort expectation had a large and beneficial impact on the intention to use electronic banking in the Kurdistan Region of Iraq. The uniform endorsement found in the literature results in the development of the following hypothesis:

H2: Effort Expectancy positively influences behavioral intention toward digital banking usage.

Association of Social Influence (SI) and Digital Banking Intention

Social Influence (SI) is the degree to which individuals' choices are influenced by the views, actions, or anticipations of their peers (Venkatesh et al., 2003). In the realm of digital banking adoption, social influence (SI) is the extent to which perceived social pressure or encouragement affects an individual's inclination to use these services.

Numerous research using the (UTAUT2) paradigm have shown that social influence (SI) significantly impacts behavioral intention. When individuals see that their friends, family, or society anticipate their use of a digital banking platform, they are more inclined to conform to those expectations and cultivate a heightened desire to embrace the technology (Herzallah et al., 2025; Idrees & Ullah, 2024; Linh et al., 2025; Loke et al., 2025). These results indicate that technology adoption is often a social phenomenon, particularly when digital services are nascent or still establishing user trust.

Nonetheless, the impact of (SI) is not uniform across all circumstances. Several research have shown that social influence has no substantial impact on consumers' propensity to embrace digital banking (Alalwan et al., 2017; Merhi et al., 2019; Mohd Thas Thaker et al., 2022). This indicates that for some users, particularly those with previous experience or a strong feeling of self-efficacy, external judgments may have less influence on determining behavioral intentions.

These changes indicate a significant observation: the impact of social influence may be contingent upon circumstance. The phenomenon is particularly pronounced among users who lack familiarity with the technology, belong to collectivist societies, or depend significantly on peer approval. Conversely, in environments where digital banking is already established or where users make autonomous choices, (SI) may diminish in predictive efficacy. Notwithstanding these modifications, the term continues to be theoretically relevant and experimentally validated across several contexts. Consequently, the following hypothesis is posited:

H3: Social Influence positively influences behavioral intention toward digital banking usage.

Association of Facilitating Conditions (FC) and Digital Banking Intention

Facilitating Conditions (FC) denote users' perspectives about the accessibility of resources, infrastructure, and assistance that facilitate the use of a certain technology (Venkatesh et al., 2003). In digital banking settings, financial capability (FC) often include access to internet connection, device

compatibility, technical support, and institutional aid, all of which may influence an individual's confidence in using digital services.

In the (UTAUT) and (UTAUT2) frameworks, facilitating conditions (FC) are primarily regarded as a predictor of actual usage, however, numerous studies have also evidenced its substantial impact on behavioral intention, especially when digital services are novel, intricate, or necessitate environmental support for optimal functionality.

A substantial corpus of recent studies supports this augmented role. FC has been shown to substantially influence user intention in research concerning mobile banking, e-wallets, and digital financial services (Herzallah et al., 2025; Idrees & Ullah, 2024; Linh et al., 2025; Loke et al., 2025). The results indicate that consumers are more likely to use the system when they have confidence in its availability, dependability, and institutional support.

Furthermore, (FC) often enhances constructs such as effort expectation by diminishing perceived obstacles to access. In contexts where consumers exhibit a deficiency in confidence, digital proficiency, or technical assistance, (FC) may significantly impact the desire to adopt. In some models, (FC) is seen to mediate or enhance the effects of other variables, including trust or social influence (Chand et al., 2025; Loke et al., 2025).

Earlier iterations of (UTAUT) prioritized the influence of facilitating conditions (FC) on consumption behavior, however, new findings indicate that (FC) also has a direct and beneficial impact on behavioral intention, especially in developing and underbanked areas, (M. Hamakhan, 2020) revealed that facilitating conditions (FC) strongly influenced the desire to embrace electronic banking services in the Kurdistan Region of Iraq, underscoring its relevance in environments with varying digital infrastructure and user preparedness. In light of this sustained support, the following hypothesis is posited:

H4: Facilitating Conditions positively influence behavioral intention toward digital banking usage

Behavioral Intention (BI) and Use Behavior (UB)

Behavioral Intention (BI) signifies a user's deliberate intention or preparedness to partake in a certain activity, namely, the adoption of digital banking technology. Within the (UTAUT) and UTAUT2 frameworks, behavioral intention (BI) is regarded as the most direct and significant predictor of actual system use (Venkatesh et al., 2003, 2012). It signifies a person's drive to perform, influenced by aspects like perceived utility, user-friendliness, social context, and accessibility of assistance.

In accordance with theory, extensive empirical research substantiates that consumers with more robust behavioral intentions are much more inclined to participate in real digital banking use. Numerous research in mobile banking, FinTech, and e-payment domains corroborate this link (Alalwan et al., 2017; Chand et al., 2025; Herzallah et al., 2025; Idrees & Ullah, 2024). These findings indicate that when consumers articulate a definitive goal to use digital banking services, this intention often manifests as consistent or experimental utilization of such services.

Use Behavior (UB) pertains to the actual implementation of behavior, namely the moment users commence interaction with the system. While business intelligence (BI) is often a robust predictor of user behavior (UB), this correlation is not automatic. The transition from intention to conduct might be influenced by enabling situations, trust, habitual patterns, or perceived obstacles (Chand et al., 2025; Maruping et al., 2017). A user may want to use a banking application but may refrain from doing so owing to inadequate network connection, restricted access, or security apprehensions.

Nevertheless, in UTAUT-based research, the correlation between intention and conduct remains robust. Behavioral intention is often seen as a dependable precursor to use, particularly where structural or contextual limitations are small. Numerous examined research indicate that behavioral intention (BI) strongly predicts usage behavior (UB), hence substantiating the premise that the formation of intention is an essential precursor to real technology use. Informed by the theoretical framework and comprehensive empirical confirmation, the following hypothesis is posited:

H5: Behavioral intention positively influences use behavior in digital banking

Perceived Risk (PR)

According to research by (Lee, 2009; Martins et al., 2014). Digital banking customers' subjective fears of unfavorable outcomes from using technologically-based financial services are known as perceived risk (PR). Rather than being a singular concept, (PR) is multidimensional, typically encompassing financial risk, where users fear monetary loss (Zhao & Khaliq, 2024) (Zhao & Khaliq, 2024), **security and privacy risk, referring to the potential misuse or exposure of personal data** (Chauhan et al., 2019; Hanif & Lallie, 2021), **performance risk, associated with system failure or technical unreliability** (S. Hasan et al., 2023; Kim & Jindabot, 2022) and time risk, which includes concerns about time wasted due to service inefficiencies (Zhao & Khaliq, 2024). All of these factors influence how comfortable people are with using digital platforms, which in turn affects how much they are willing to participate (Appiah & Agblewornu, 2025; Khuc et al., 2025).

In the setting of online banking, several empirical studies have shown that perceived risk significantly inhibits behavioral intention. People are less likely to utilize online financial services when they have strong privacy and financial security concerns, according to research (Lee, 2009; Martins et al., 2014) Newer studies have also confirmed this correlation in a variety of technology contexts. Some studies have shown that certain aspects of public relations (PR) may have a negative impact on user confidence; for example, (Zhao & Khaliq, 2024) found that financial and time-related PR risks significantly lower confidence, while (Appiah & Agblewornu, 2025) found that legal and security-related PR risks are much worse when institutional trust is low. Studies have shown that (PR) acts as a psychological barrier to adoption by reducing intention and suppressing the effect of enabling characteristics like trust and simplicity of use (S. Hasan et al., 2023; Khuc et al., 2025; Namahoot & Jantasri, 2023) in addition to directly reducing intention. In addition, as shown by (Khan & Abideen, 2023) perceived risk acts as a mediator between behavioral intention and actual consumption, highlighting its limiting significance even in the presence of intention. These results, when considered as a whole, support the following hypothesis about the role of perceived risk in preventing the widespread use of digital banking:

H6: Perceived Risk negatively influences Behavioral Intention to use digital banking services.

Trust

An essential component of digital banking adoption, trust acts as a mediator between other elements, most notably perceived risk, and behavioral intention. Users' faith in the safety, dependability, and self-interest of the service's underlying technology and institution is what we mean when we talk about trust in digital settings. With this confidence, users are more likely to interact with platforms that process financial and personal information securely(Gefen et al., 2003; McKnight & Chervany, 2001).

Technical trust pertains to assurance in the system's operation and safety (e.g., encryption, uptime), and institutional trust pertains to views of the financial institution's expertise, honesty, and generosity (Corritore et al., 2003; Pavlou, 2003). These two aspects are usually considered when thinking about trust in online banking. Despite strong impressions of utility and simplicity of use, users are less likely to have positive behavioral intentions when either dimension is poor or nonexistent.

One theory that has been very useful for digital financial services is the one proposed by (Mayer et al., 1995) that trust is based on three things: perceived skill, kindness, and integrity. Integrity means consistently adhering

to stated standards, kindness shows that the organization cherishes its customers, and ability refers to its capability to safely supply digital services. Consumers place a premium on these features in areas where financial institutions have a chickened past or where oversight is weak, such as the Kurdistan Region of Iraq.

Trust is a crucial precursor of behavioral intention, according to empirical studies.In many national settings, trust is shown to be a strong predictor of mobile banking adoption (Merhi et al., 2019) Similarly, among Islamic banking users, a similar impact is shown (Parayil Iqbal et al., 2023) to be true. By demonstrating the mediating function of trust in mobile commerce (Alnoor et al., 2022) provide more support for this. Taken together, these results provide credence to the idea that people are more inclined to act favorably when they trust a brand.

Also, trust acts as a moderator, especially when it comes to how it interacts with risk perception. comes to how it interacts with risk perception. According to research (Kaur & Arora, 2020; Khan & Abideen, 2023). trust may mitigate the detrimental effect of perceived risks on behavioral intention. So, when customers have significant trust, they are more likely to accept digital banking, even when dangers like privacy issues or system instability are present. These changes show that trust is not a constant but rather a contextual factor that influences how users weigh the pros and cons of various options.

To sum up, trust is multi-faceted and ever-changing when it comes to people's propensity to use digital banking services. It modifies risk-intention in addition to directly impacting the formulation of behavioral intention. As a result, we postulate the following hypothesis:

H7: Trust positively influences behavioral intention.

H8: Trust moderates the relationship between perceived risk and behavioral intention, such that the negative effect is weaker when trust is high.

Methodology

This research used a quantitative, cross-sectional approach to investigate the determinants affecting the adoption of digital banking in the Kurdistan Region of Iraq (KRI), specifically in Duhok city. Cross-sectional designs are frequently employed in behavioral and social sciences to examine associations between dimensions assessed at a singular moment in time (Hunziker & Blankenagel, 2024; Levin, 2006; Setia, 2016; Wang & Cheng, 2020). These approaches are especially appropriate for empirical

research using structured surveys to investigate theoretical theories without altering the study setting.

The study model extends the Unified Theory of Acceptance and Use of Technology (UTAUT2) by including Perceived Risk as a negative predictor and Trust as both a direct predictor and a moderating variable of Behavioral Intention.

Data were gathered using a structured online questionnaire, created in Google Forms and disseminated over a three-month duration. To guarantee clarity and cultural congruence, the survey was translated into the Kurdish (Badini) dialect and distributed to two primary groups: academic staff from Cihan University–Duhok and customers of authorized banks in Duhok governorate. A total of 420 questionnaires were disseminated, yielding 360 valid replies that were used into the study. The digital administration of the survey mandated all fields in Google Forms, therefore eliminating missed replies and ensuring a uniform dataset. The gathered replies were extracted in Excel format, cleaned. and systematically categorized for statistical analysis.

Two software packages were used for data processing:

- **SPSS (Version 26) was implemented to provide descriptive statistics for demographic profiling and to conduct pertinent cross-tabulations.**
- SmartPLS (Version 4.1.1) was used to examine the measurement model and the structural model, including hypothesis testing of direct effects.

Due to the incorporation of a moderating variable (Trust × Perceived Risk) and the non-parametric characteristics of Likert-scale data, Partial Least Squares Structural Equation Modeling (PLS-SEM) was used. PLS-SEM is favored in this context because of its appropriateness for small to medium sample sizes, adaptability to data distribution, and capacity to model interaction terms and intricate interactions (Hair et al., 2017; Shmueli et al., 2019). In contrast to covariance-based SEM (CB-SEM), PLS-SEM demonstrates more robustness for exploratory research in the context of ongoing theoretical development (Dash & Paul, 2021; Henseler et al., 2009).

Model assessment was conducted in two primary phases:

1. **The measurement model evaluation evaluated indicator reliability (factor loadings), internal consistency (Cronbach's alpha and composite reliability), convergent validity (average variance extracted), and discriminant validity (HTMT ratios).**

2. **The evaluation of the structural model included the examination of path coefficients, the coefficient of determination (R^2), effect sizes (f^2), and the relevance of moderating effects.**

Bootstrapping was performed using 5,000 resamples to provide reliable standard errors and t-statistics. One-tailed hypothesis testing was used to forecast the direction of the impact (e.g., Perceived Risk is anticipated to adversely affect Behavioral Intention), while two-tailed tests were utilized for moderation and exploratory pathways where the direction of the effect was not explicitly postulated.

Findings

This section defines the study's outcomes, beginning with the demographic profile of the respondents, followed by the results that were derived from the Structural Equation Modeling (SEM) analysis. The study used a two-stage approaches, as encouraged in the PLS-SEM literature, first with the evaluation of the measurement model and then assessing the structural model (Jr. J. F. Hair et al., 2017; Henseler et al., 2009). The measuring model was first evaluated to determine construct reliability, convergent validity, and discriminant validity. The structural model was analyzed to evaluate the proposed relationships and determine the overall performance of the model. The final structural model enhances the original UTAUT2 framework by including Perceived Risk (PR) as a negative predictor of Behavioral Intention (BI) and Trust as both a direct predictor of BI and a moderating variable that affects the intensity of the (PR–BI) link. The model posits that Trust mitigates the adverse influence of Perceived Risk on Behavioral Intention, indicating a buffering effect. This model configuration facilitates a more refined comprehension of the relationship between perceived risk and trust in influencing consumers' willingness to use digital banking services.

Demographic Profile of Participants

A brief overview of the sample's demographics is provided in the table 1, before the structural model findings are presented. These factors include demographics such as age, gender, education level, employment status, and digital banking experience. To guarantee representation, this section gives a general outline of the population.

Table 1: Demographic Profile of Participants

Variable	Category	Frequency	Percentage %
AGE	18–24	74	20.6
	25–34	112	31.1
	35–44	123	34.2
	45–54	21	5.8
	55 and above	30	8.3
GENDER	Male	294	81.7
	Female	66	18.3
EDU	Secondary School	52	14.4
	High School	27	7.5
	Diploma	26	7.2
	Bachelor's degree	92	25.6
	Master's degree	124	34.4
	Doctorate	13	3.6
	Other	26	7.2
EMP	Employed	121	33.6
	Employed Private Sector	173	48.1
	Self-employed	41	11.4
	Unemployed	16	4.4
	Student	9	2.5
BACC	Yes	360	100
	No	0	0
OBO	Yes	294	81.7
	No	66	18.3
HOBS	Daily	67	18.6
	Weekly	65	18.1
	Monthly	228	63.3

EDU: Education Level, EMP: Employment Status. BACC: Do you currently have a bank account? OBO: Do you use mobile or internet banking? HOBS: How often do you use banking services?

The demographics of the 360 participants who took the survey provide important background for understanding the dynamics of behavior related to the adoption of digital banking in Iraq's Kurdistan Region. For a country like Iraq and its region, which is now undergoing digital transformation, it is crucial to validate models like (UTAUT2) by learning about the demographics of digital banking customers and how factors like trust and perceived risk affect their decisions to use these services.

Participants were mostly employed adults in the peak of their careers. A large majority of participants (over 65%) were within the (25-44) age bracket, which is often thought of as the most open to financial technology developments due to its relatively high level of digital fluency. It is common in digital banking research to find underrepresentation of older users (8.3%), although a significant portion of the respondents were between the ages of (18 and 24), showing that there is a generational gap in the use of technology

(Harris et al., 2016). There is a correlation between this age range and the likelihood that people in the middle of their lives may try out or switch to digital financial platforms, especially when these factors convenience, perceived utility, and system trust are significant.

The sample exhibits an obvious gender imbalance, including 81.7% male and just 18.3% female individuals. This obviously reflects the socio-cultural and financial norms of the Kurdistan Region, where males typically have a more dominating role in managing family finances and interacting with official institutions, but it may also partly stem from sampling circumstances. This trend aligns with studies in poor nations indicating that women often encounter obstacles to financial inclusion and digital literacy (R. Hasan et al., 2023). This disparity may affect generalizability and emphasizes the need of developing gender-sensitive approaches in digital banking outreach and education.

The sample had a significant level of educational fulfilment, with over 60% possessing at least a bachelor's or master's degree, while just 14.4% had secondary education or less. This tendency indicates that the sample included an educated, literate demographic adept at comprehending and assessing the dangers and advantages of digital banking systems, a criterion acknowledged as vital in technology adoption study. Education is a recognized precursor of both confidence in digital platforms and the capacity to mitigate perceived risk, making this attribute more pertinent in light of the incorporation of both structures in the expanded model.

Regarding employment, 81.7% of respondents were now engaged in work, whether in the public sector, private sector, or as self-employed individuals. The very low unemployment rate (4.4%) and student status (2.5%) further substantiate the economic engagement and internet accessibility within the sample. Prior research demonstrates a strong correlation between work status and technology use, especially in financial services, where digital banking often complements or substitutes in-person branch visits (Martin & Omrani, 2015). This job profile not only underscores the significance of the study population but also validates the use of a technology-centric paradigm like UTAUT2 in this context.

All respondents indicated ownership of a bank account, demonstrating complete financial inclusion within the sample. This uniformity, albeit constraining some statistical comparisons, was deliberately designed to guarantee that respondents have foundational experience to the financial system. Furthermore, 81.7% indicated the use of mobile or internet banking services, indicating that digital banking is firmly integrated into the financial practices of the majority. This robust adoption provides a significant basis for evaluating behavioral intention and actual use, as delineated within the UTAUT2 paradigm.

The prevalence of financial service use further corroborates this conclusion. A plurality (63.3%) used banking services monthly, presumably correlated with income cycles, whereas roughly 37% interacted with banking systems weekly or daily, indicating a segment of very active users. These users are crucial for studying variation in behavioral intention, as their regular engagement with digital platforms may heighten their sensitivity to variables such as performance expectation, effort expectancy, and notably perceived risk and trust.

The demographic profile indicates a sample that is digitally literate, economically active, and mostly familiar with digital banking, making it an optimal group for testing adoption models.

Measurement Model Evaluation

Evaluating the measuring model is crucial before examining the structural links among the latent constructs. This will guarantee that the constructs utilized in the research are reliable and valid (Hair et al., 2017; Henseler et al., 2015; Sarstedt et al., 2014). Assessing the reliability of individual indicators, internal consistency reliability, convergent validity, and discriminant validity is part of this procedure. In order to get valid and useful results from the structural model, it is necessary to guarantee the measurement model's resilience Reflecting measurement models are usually evaluated for convergent validity in the context of Partial Least Squares Structural Equation Modeling (PLS-SEM) by using outer loadings, composite reliability (CR), and average variance extracted (AVE) (Hair et al., 2021). Fornell Larcker, cross-loadings, and the Heterotrait-Monotrait (HTMT) ratio of correlations are used to evaluate discriminant validity (Henseler et al., 2015; Voorhees et al., 2016).

Improving the overall model fit and enhancing indicator reliability and convergent validity, the assessment method included removing numerous indicators with inadequate outer loadings, meaning they were below the acceptable level of 0.70. In line with conventional SEM wisdom, this procedure aids in the consistent and precise measurement of each construct (Hair et al., 2019; Henseler et al., 2009). Adherence to these standards improves the analysis's rigor and credibility and is in accordance with what the literature suggests as best practices (Shmueli et al., 2019). The reliability coefficients, AVE values, and item loadings, as well as the outcomes of the measurement model assessment, are shown in Table 2.

Table 2: Measurement Model Evaluation: Reliability, Convergent Validity, and Factor Loadings

Latent Variables	Items	FL	Cronbach's alpha	Composite reliability (rho_a)	AVE
PE	PE1	0.849	0.912	0.971	0.736
	PE2	0.848			
	PE3	0.855			
	PE4	0.846			
	PE5	0.890			
EE	EE1	0.767	0.819	0.825	0.579
	EE3	0.733			
	EE5	0.778			
	EE7	0.767			
	EE8	0.760			
FC	FC1	0.766	0.780	0.786	0.531
	FC2	0.700			
	FC5	0.744			
	FC7	0.721			
	FC8	0.713			
PR	PR2	0.712	0.862	0.863	0.547
	PR3	0.768			
	PR4	0.724			
	PR5	0.736			
	PR6	0.746			
	PR7	0.751			
	PR8	0.739			
SI	SI1	0.713	0.868	0.880	0.556
	SI2	0.750			
	SI4	0.776			
	SI5	0.771			
	SI6	0.739			
	SI7	0.723			
	SI8	0.743			
TR	TR4	0.758	0.643	0.643	0.583
	TR6	0.771			
	TR8	0.762			
BI	BI1	0.748	0.869	0.870	0.561
	BI2	0.734			
	BI3	0.726			
	BI4	0.755			
	BI5	0.780			
	BI7	0.743			
	BI8	0.754			
UB	UB1	0.756	0.806	0.807	0.562
	UB2	0.771			
	UB4	0.737			
	UB6	0.730			
	UB8	0.755			

The measuring model was evaluated for validity and reliability across all latent constructs before assessing the structural correlations. Table 2 shows that most outer loadings were higher than the suggested cutoff of 0.70, which indicates good indicator reliability and substantial item-to-construct connections (Hair et al., 2019; Henseler et al., 2015). According to (Hair, 2011; Marcoulides, 2013). certain constructs with consistently high loadings were removed during model refinement in order to improve measurement quality. These items included Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Behavioral Intention (BI).

We used Cronbach's alpha, composite reliability (CR), and (rho_A) to assess the dependability of the internal consistency. With the exception of the Trust (TR) construct, which had a Cronbach's alpha of 0.643, all values above the commonly recognized limit of 0.70, indicating internal consistency (Hair et al., 2017; Henseler et al., 2015), Even if it's a little lower than 0.70, it still passes the acceptable test typically used for exploratory studies and freshly constructed variables. dependability values over 0.80 indicate strong dependability, whereas values between 0.60 and 0.70 are deemed acceptable, especially in early-stage model testing (Hulin et al., 2001)**,** Values exceeding 0.95, however, can be an indication of redundancy instead than dependability.

By demonstrating that each concept explained more than half the variation in its indicators, the convergent validity was supported by composite reliability values over 0.80 and AVE scores above 0.50 across the board (Fornell & Larcker, 1981; Hair et al., 2021). With these findings in hand, we may go on to structural model analysis, which verifies that the measurement model is valid and reliable.

Discriminant Validity

How theoretically and experimentally different one construct is from another in the model is what we mean when we talk about discriminant validity. This method guarantees that the theoretical ideas being assessed are distinct from others by making sure that each latent variable captures events that are not reflected by other conceptions (Hair et al., 2017; Henseler et al., 2015). The Heterotrait-Monotrait (HTMT) ratio of correlations and the Fornell-Larcker criteria are the two main ways that discriminant validity is often evaluated in the context of PLS-SEM. Table 3 displays the HTMT analysis findings, which demonstrate the model's constructs' discriminant validity.

Table 3: Heterotrait–Monotrait Ratio (HTMT) for Discriminant Validity

	BI	EE	FC	PE	PR	SI	Trust	UB	Trust x PR
BI									
EE	0.201								
FC	0.167	0.113							
PE	0.298	0.119	0.121						
PR	0.478	0.119	0.091	0.072					
SI	0.248	0.064	0.060	0.139	0.105				
Trust	0.562	0.070	0.094	0.146	0.118	0.079			
UB	0.761	0.184	0.109	0.267	0.407	0.087	0.513		
Trust x PR	0.099	0.038	0.124	0.054	0.052	0.135	0.181	0.233	

One of the rigorous and generally accepted criteria in PLS-SEM for determining whether constructs are empirically different is the Heterotrait-Monotrait (HTMT) ratio, which was used to evaluate discriminant validity (Henseler et al., 2015; Voorhees et al., 2016). Traditional criteria like the Fornell-Larcker criterion or cross-loadings are not as sensitive as the HTMT method, which compares the average correlations across constructs to the correlations within constructs.

Table 3 above shows that all of the (HTMT) values were significantly lower than the conservative threshold of 0.85 (Henseler et al., 2015), indicating that the constructs had strong discriminant validity. Take, for example, the HTMT values of 0.761 and 0.562, respectively, for Behavioral Intention (BI) and Use Behavior (UB) and Trust, which are much below the threshold. Values as high as 0.478 for PR and BI and 0.562 for Trust and BI did not indicate an issue with the (HTMT). The findings show that each construct represents a distinct part of the conceptual framework, which lends credence to the idea that testing structural models later on will be valid (Franke & Sarstedt, 2019; Hair et al., 2021).

Table 4: Fornell–Larcker Criterion for Discriminant Validity

	BI	EE	FC	PE	PR	SI	Trust	UB
BI	0.749							
EE	0.172	0.761						
FC	0.139	0.052	0.729					
PE	0.285	0.034	0.058	0.858				
PR	-0.416	-0.081	-0.027	-0.035	0.740			
SI	0.223	-0.025	0.030	0.026	-0.080	0.745		
Trust	0.422	0.035	0.004	0.090	-0.087	0.013	0.763	
UB	0.639	0.143	0.056	0.248	-0.342	0.066	0.371	0.750

Discriminant validity among the latent components was further validated by using the Fornell-Larcker criteria in addition to the HTMT evaluation. Each component must have a square root of its Average Variance Extracted (AVE) that is higher than its greatest correlation with all other

components in order to meet this standard (Fornell & Larcker, 1981). To confirm its empirical uniqueness, this makes sure that a concept has more variation with its own indicators than with other constructs.

The results are in Table 4, which shows that every single concept met these criteria. Everything on the diagonal, which stands for the square roots of (AVE), is larger than the off-diagonal values that are located in the same columns and rows. There is a stronger association between AVE and Performance Expectancy (0.858) than with Behavioral Intention (0.285) or Use Behavior (0.248), for instance. Beyond its absolute correlations with other categories like BI (-0.416) and Trust (-0.087), Perceived Risk (PR) has a square root of AVE of 0.740. According to the results, all of the latent variables are sufficiently different, which means that the study meets the Fornell-Larcker criteria for discriminant validity (Cepeda-Carrión et al., 2022; Hair et al., 2017; Henseler et al., 2015).

Structural Model Results

Overview of the Structural Model

After establishing the reliability and validity of the measurement model, the subsequent step in the PLS-SEM analysis is to evaluate the structural model. This phase emphasizes the assessment of the proposed connections among underlying constructs, which in turn helps to ascertain the model's ability to explain and predict outcomes. Figure 2 illustrates the structural model, encompassing all direct and moderating paths.

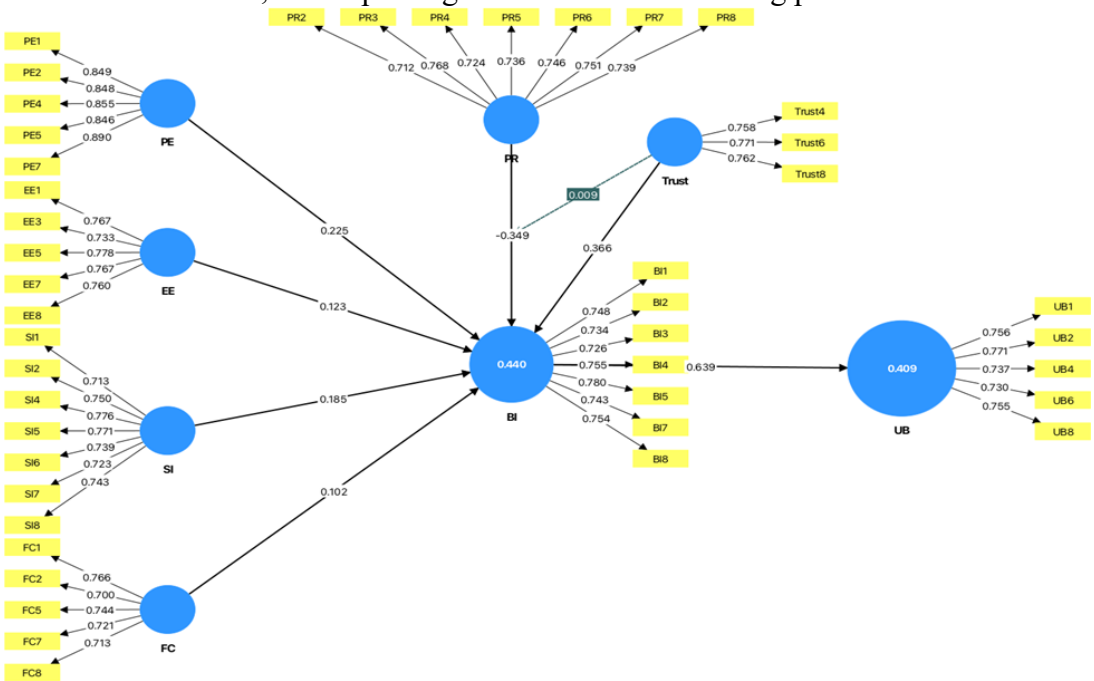

Figure 2: Structural Model with Path Coefficients and R^2 Values (PLS-SEM Results)

Multicollinearity and Variance

According to (Hair et al., 2019; Sarstedt et al., 2014; Shmueli et al., 2019). the main criteria for evaluation include examining multicollinearity using VAIF values, R^2, effect size (f^2), and Q^2. In addition, bootstrapping methods are used to assess the statistical significance and robustness of the route coefficients in order to test the hypotheses. All things considered, these measures provide a comprehensive picture of the model's ability to explain behavioral results and support its theoretical basis.

Table 5: Summary of Final Structural Model Assessment

Endogenous Construct	Predictor Construct	VIF	f^2 Effect Size	R^2	R^2 Adjusted	Q^2
BI	PE	1.015	0.089	0.440	0.429	0.407
	EE	1.013	0.027			
	SI	1.026	0.060			
	FC	1.020	0.018			
	PR → (–)	1.022	0.213			
	TR	1.036	0.231			
	TR× PR	1.054	0.000			
UB	BI	1000	0.691	0.409	0.407	0.248

Table 5 displays the results of the structural model assessment, which computes the interrelationships of latent constructs using significant metrics such as VIF, R^2 and R^2 Adjusted, f^2, and Q^2.The endogenous construct Behavioral Intention (BI) is explained by 44.0% of the variance in the model ($R^2 = 0.440$; Adjusted $R^2 = 0.429$), and the model is highly predictive ($Q^2 = 0.407$) (Hair et al., 2019).

Effect Size (f^2) and Interpretation

Trust and Perceived Risk (PR) serve as significant predictor factors that greatly enhance the understanding of BI, exhibiting modest impact sizes ($f^2 = 0.231$ and $f^2 = 0.213$, respectively). The tendency of users to engage with digital banking services diminishes when they perceive a higher level of risk, as evidenced by the negative correlation of perceived risk with behavioral intention. Effort Expectancy (EE) and Facilitating Conditions (FC) demonstrate smaller contributions ($f^2 < 0.03$), suggesting a limited yet noteworthy influence on (BI). In contrast, Performance Expectancy (PE) and (SI) reveal minor but substantial effects ($f^2 = 0.089$ and 0.060 respectively). In this scenario, the interaction term (Trust × PR) lacks a significant moderating effect, as its influence is negligible ($f^2 = 0.000$).

The model accounts for 40.9% of the variation in Use Behavior (UB), the second endogenous construct, exhibiting a Q^2 of 0.248 and an adjusted R^2 of 0.407, thereby reinforcing its predictive value. The significant direct influence of intention on actual digital banking behavior is evidenced by

previous studies based on the UTAUT and UTAUT2 frameworks (Venkatesh et al., 2003, 2012) with the pathway from behavioral intention (BI) to usage behavior (UB) demonstrating a high effect size ($f^2 = 0.691$).

The VIF values for the predictor constructs are considerably below the established threshold of 5 (Hair et al., 2017), suggesting that multicollinearity is not an issue. The findings confirm that the model fulfills both explanatory and predictive functions, emphasizing the important roles of trust, risk, and intention in shaping digital banking behavior.

Predictive Relevance (Q^2) and Out-of-Sample Prediction

Following the current guidelines for evaluating out-of-sample performance in PLS-SEM, the model's predictive capability was tested using PLSpredict on the two important endogenous constructs Behavioral Intention (BI) and Use Behavior (UB) (Hair et al., 2021; Shmueli et al., 2016, 2019). The model's ability to reliably forecast unknown data is supported by the fact that all indicators of BI and UB had positive Q²_{predict}values, meeting the minimal criterion for predictive relevance (Hair et al., 2019; Sarstedt et al., 2022).

The PLS-SEM model's Mean Absolute Error (MAE) results were compared to those of a linear model (LM) and a naïve benchmark model (IA), alongside Q^2predict. The PLS-SEM model had better performance than both benchmarks, with reduced prediction errors, for all BI indicators and all but one UB indicator (UB6), as shown in Table 6.

Compared to the LM benchmark (0.595) and the IA benchmark (0.667), UB6's PLS-SEM MAE (0.596) was somewhat better (Shmueli et al., 2019), states that a PLS-SEM model is considered to have medium predictive power when most indicators for a specific construct show fewer prediction errors in the model compared to LM. These results provide further evidence that the model is suitable for predictive applications involving digital banking activity, since it seems to have moderate predictive potential for both BI and UB.

Table 6: Q^2 Predict and Prediction Error Metrics for Behavioral Intention (BI) and Use Behavior (UB)

Indicator	Q^2predict	PLS-SEM_MAE	LM_MAE	IA_MAE	PLS < LM?	PLS < IA?
BI1	0.233	0.512	0.543	0.605	Yes	Yes
BI2	0.204	0.513	0.532	0.581	Yes	Yes
BI3	0.196	0.498	0.508	0.570	Yes	Yes
BI4	0.246	0.521	0.554	0.602	Yes	Yes
BI5	0.258	0.512	0.537	0.622	Yes	Yes
BI7	0.214	0.533	0.556	0.601	Yes	Yes
BI8	0.244	0.486	0.524	0.574	Yes	Yes

UB1	0.126	0.586	0.604	0.658	Yes	Yes
UB2	0.136	0.605	0.633	0.673	Yes	Yes
UB4	0.140	0.571	0.595	0.642	Yes	Yes
UB6	0.152	0.596	0.595	0.667	No	Yes
UB8	0.141	0.583	0.593	0.649	Yes	Yes

Hypothesis Testing and Path Coefficients

A structural model assessment was conducted to evaluate the proposed hypotheses, with the results detailed in Table 7. The analysis of path coefficients, t-values, and p-values reveals that seven of the eight hypotheses received support.

Beginning with the factors influencing Behavioral Intention (BI), Performance Expectancy (PE) demonstrated a notable positive impact on BI ($\beta = 0.225$, $t = 5.870$, $p < 0.001$), thereby supporting H1 and affirming that individuals are more likely to embrace digital banking when they believe it improves their financial task performance. The findings indicate that Effort Expectancy (EE) exerted a significant and positive effect on Behavioral Intention (BI) ($\beta = 0.123$, $t = 3.079$, $p = 0.002$), thereby supporting Hypothesis 2 and highlighting the importance of ease of use as a key factor influencing intention. The findings indicate a positive association between Social Influence (SI) and Behavioral Intention (BI) ($\beta = 0.185$, $t = 5.028$, $p < 0.001$), thereby supporting H3. This suggests that the recommendations or opinions of others play a significant role in shaping an individual's intention to utilize digital banking services. In a similar vein, the analysis revealed that Facilitating Conditions (FC) had a positive and statistically significant effect on Behavioral Intention (BI) ($\beta = 0.102$, $t = 2.483$, $p = 0.013$), thereby supporting Hypothesis 4 and underscoring the importance of accessible support and resources in fostering adoption intentions.

The analysis of the influence of Behavioral Intention on actual Use Behavior (UB) revealed a strong and significant path coefficient ($\beta = 0.639$, $t = 21.323$, $p < 0.001$), thereby supporting H5 and aligning with the fundamental principles of behavioral models like UTAUT. The findings indicate that perceived risk had a substantial negative impact on behavioral intention ($\beta = –0.349$, $t = 8.855$, $p < 0.001$), thereby confirming hypothesis H6 and suggesting that an increase in perceived risk leads to a decrease in the intention to adopt digital banking services. Conversely, Trust exhibited a positive and significant effect on BI ($\beta = 0.366$, $t = 9.481$, $p < 0.001$), thereby validating H7 and highlighting the essential function of trust in reducing uncertainty and enhancing usage intentions.

Nevertheless, the proposed moderation effect of Trust on the relationship between Perceived Risk and Behavioral Intention (H8) did not receive support, as the interaction term (Trust × PR → BI) was determined to

be non-significant (β = 0.009, t = 0.252, p = 0.801). This indicates that although trust independently boosts behavioral intention, it does not substantially mitigate or lessen the adverse effects of perceived risk in this scenario.

The findings strongly validate the direct relationships outlined in the research model, consistent with the theoretical underpinnings of the Unified Theory of Acceptance and Use of Technology (UTAUT) and previous empirical investigations (Hair et al., 2017; Venkatesh et al., 2003). The results indicate that trust, perceptions of usability, and concerns about risk are crucial factors influencing behaviors related to the adoption of digital banking.

Table 7: Structural Model Assessment Results and Hypothesis Testing

Hypothesis	Relationship	Path Coefficient (β)	t-Value	p-Value	Supported?
H1	PE -> BI	0.225	5.870	0.000	Yes
H2	EE -> BI	0.123	3.079	0.002	Yes
H3	SI -> BI	0.185	5.028	0.000	Yes
H4	FC -> BI	0.102	2.483	0.013	Yes
H5	BI -> UB	0.639	21.323	0.000	Yes
H6	PR -> BI	-0.349	8.855	0.000	Yes
H7	TR -> BI	0.366	9.481	0.000	Yes
H8	TR x PR -> BI	0.009	0.252	0.801	No

Moderation Analysis

Using the two-stage method suggested in the PLS-SEM literature (Hair et al., 2021), an interaction term (Trust × PR) was generated to assess the moderating influence of Trust on the connection between Perceived Risk (PR) and Behavioral Intention (BI). Based on the data shown in Table 8, it indicates that the interaction term did not have a significant impact on users' desire to utilize digital banking services, showing that Trust does not mitigate the negative effect of Perceived Risk.

Although trust does increase behavioral intention on its own, this result suggests that it does nothing to mitigate the detrimental effects of perceived risk. Previous methodological studies have shown that interaction effects in PLS-SEM often do not approach statistical significance and only account for a minor increase in explained variance. This is especially true in behavioral research including latent variables (Shmueli et al., 2019). So, even though H8 was not supported, evaluating it helps us understand the model's prediction processes more sophisticated.

Table 8: Moderation Analysis Result

Hypothesis	Relationship	Path Coefficient (β)	t-Value	p-Value	Supported?
H8	TR x PR -> BI	0.009	0.252	0.801	No

Discussion

This study examined the factors influencing the adoption of digital banking in a transitional economy, utilizing an extended (UTAUT2) framework that incorporates perceived risk and trust. The empirical findings show a strong correlation with previous theoretical predictions and offer essential insights into user behavior within new digital financial environments.

The results clearly demonstrate the strong positive influence of Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) on Behavioral Intention (BI), effectively validating hypotheses H1-H4. The results align effectively with a substantial body of previous study in the technology adoption field, reinforcing the universality of these constructs across various contexts (Alalwan et al., 2017; Jadil et al., 2021; Oliveira et al., 2014; Venkatesh et al., 2003, 2012). (The strongest influence on (BI) was exerted by (PE), highlighting that perceived utility and system effectiveness play a crucial role in user decision-making within digital banking environments (Lu, 2024; Martins et al., 2014). The contributions of (EE) and (FC) indicate a positive relationship, highlighting that while ease of use and infrastructural support are significant, they are secondary to the perceived performance outcomes (Alkhowaiter, 2020; Shaikh & Karjaluoto, 2019). Social Influence (SI) demonstrated a statistically significant but modest impact on (BI). Previous studies have indicated different magnitudes for this relationship (Abdennebi, 2023; Ly & Ly, 2022; Nasri & Charfeddine, 2012), yet its positive contribution underscores the idea that peer influence and normative expectations significantly shape user intent, especially in collectivist cultures or high-uncertainty environments.

Business Intelligence (BI) demonstrated a significant predictive relationship with Use Behavior (UB), thereby reinforcing H5 and aligning with established theoretical connections in the Theory of Planned Behavior and UTAUT frameworks (Ajzen, 1991; Riffai et al., 2012; Venkatesh et al., 2003). his confirms the key mediating function of intention in the adoption of digital services and highlights the importance of behavioral intention as an indicator of genuine engagement.

Importantly, Perceived Risk (PR) demonstrated a significant negative impact on (BI), with H6 being supported, thereby affirming its obstructive function within digital banking environments (R. Hasan et al., 2023; Lee, 2009; Zhao & Khaliq, 2024). Numerous investigations have underscored the complexity of (PR), encompassing issues related to privacy, security, financial loss, and time wastage, which serve as significant psychological obstacles to the acceptance of technology (Appiah & Agblewornu, 2025; Chauhan et al., 2019; Hanif & Lallie, 2021; Khuc et al., 2025).

Trust has been identified as an essential variable in facilitating business intelligence, thus reinforcing H7. This aligns with the foundational literature on trust, suggesting that trust diminishes perceived uncertainty and encourages risk-taking in online settings (Gefen et al., 2003; McKnight & Chervany, 2001; Pavlou, 2003). In uncertain economic environments like the Kurdistan Region of Iraq (KRI), confidence in digital platforms and institutions is increasingly vital because of infrastructural deficiencies and a historical distrust of formal banking systems (Biro, 2024; Muhamad, 2024; Tariq et al., 2024).

Nonetheless, the proposed moderating effect of trust on the relationship between PR and BI (H8) did not receive support. This finding contrasts with earlier studies (Kaur & Arora, 2020; Merhi et al., 2019), indicating that trust by itself may not be enough to mitigate risk perceptions in contexts characterized by significant institutional fragility or regulatory uncertainty. This nuance highlights a multifaceted interplay among trust, risk, and context, necessitating deeper investigation in subsequent studies.

From a predictive standpoint, the PLSpredict analysis indicated that the model provides moderate predictive capability for both (BI and UB). The Q^2 values exhibited positivity, and the PLS-MAE values were consistently lower than those of the LM and IA benchmarks across nearly all indicators, thereby meeting the criteria set forth by (Hair et al., 2021; Shmueli et al., 2019). This introduces a dimension of practical significance to the model, indicating its importance for decision-makers looking to improve digital banking adoption in similar contexts.

Conclusion

This research sought to investigate the elements that affect the adoption of digital banking services in the Kurdistan Region of Iraq by extending the UTAUT2 model with two tailored constructs: perceived risk and trust. The model was rigorously evaluated using data from 360 valid responses and PLS-SEM analysis, assessing its explanatory and predictive capabilities.

The results highlight the importance of established factors that drive adoption, including performance expectancy, effort expectancy, and social influence. Perceived risk clearly stood out as a major obstacle, whereas trust acted as a powerful facilitator of behavioral intention. Nonetheless, trust did not alleviate the adverse effects of perceived risk, indicating that these two elements function separately within this delicate economic landscape.

This research enhances the understanding of digital adoption by showing that UTAUT2 can be effectively adapted to fragile economies, provided it aligns with the socio-economic context. The findings underscore the critical need for practitioners to implement risk-reduction strategies, such

as enhancing platform security and educating users, alongside fostering trust through transparency and reliable services from financial institutions and digital service providers.

This study provides valuable insights; however, it is constrained by its cross-sectional design and a sample limited to a single region. Future research may benefit from utilizing longitudinal designs or conducting comparative studies across various regions or sectors. Furthermore, examining additional contextual elements like digital literacy, cultural norms, or infrastructure challenges could significantly strengthen the explanatory capacity of adoption models in transitional economies.

Limitations and Future Research

This study provides valuable insights into digital banking adoption in fragile economies, yet it does have several limitations that should be considered. The use of a cross-sectional design limits the capacity to determine causality among the variables under investigation. Future research may utilize longitudinal approaches to track changes over time and enhance the evaluation of causal relationships.

Secondly, the research was confined to the Kurdistan Region of Iraq (KRI), potentially impacting the broader applicability of the findings. Exploring comparative studies across various regions or countries can provide valuable theoretical and practical insights into the adoption of digital banking in fragile and transitional economies.

Additionally, while the model incorporated trust and perceived risk, it overlooked other significant factors, including digital literacy, regulatory confidence, and financial self-efficacy. Future research could delve into these dimensions to cultivate a deeper understanding of user behavior within digital financial services.

Practical Implications

The results present significant insights for policymakers, financial institutions, and technology developers who are looking to boost digital banking adoption in vulnerable economies. To boost user acceptance, focus on enhancing performance, creating a user-friendly design, and building a dependable support system. Mitigating perceived risk is essential; this can be accomplished by fostering transparent communication, providing targeted user education, and establishing strong data protection and privacy measures. Moreover, establishing trust in institutions and technologies should be a key priority, particularly in areas where digital skepticism is widespread. Customizing engagement strategies to resonate with local user perceptions, cultural values, and socio-economic contexts is crucial for achieving sustainable and inclusive digital transformation.

Conflict of Interest: The authors reported no conflict of interest.

Data Availability: All data are included in the content of the paper.

Funding Statement: The authors did not obtain any funding for this research.

Declaration for Human Participants: This study has been approved by Cihan University-Duhok and the principles of the Helsinki Declaration were followed.

AI Statement: No AI software was used in the preparation of this manuscript. All aspects of the research, data collection, analysis, writing, and editing were completed solely by the authors.

References:

1. Abdennebi, H. B. (2023). M-banking adoption from the developing countries perspective: A mediated model. *Digital Business*, *3*(2), 100065. https://doi.org/10.1016/j.digbus.2023.100065
2. Adil, M., Farouk, A., Ali, A., Song, H., & Jin, Z. (2025). Securing Tomorrow of Next-Generation Technologies with Biometrics, State-of-The-Art Techniques, Open Challenges, and Future Research Directions. *Computer Science Review*, *57*, 100750. https://doi.org/10.1016/j.cosrev.2025.100750
3. Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-t
4. Alalwan, A. A., Dwivedi, Y. K., & Rana, N. P. (2017). Factors influencing adoption of mobile banking by Jordanian bank customers: Extending UTAUT2 with trust. *International Journal of Information Management*, *37*(3), 99–110. https://doi.org/10.1016/j.ijinfomgt.2017.01.002
5. Alkhowaiter, W. A. (2020). Digital payment and banking adoption research in Gulf countries: A systematic literature review. *International Journal of Information Management*, *53*, 102102. https://doi.org/10.1016/j.ijinfomgt.2020.102102
6. Alnoor, A., Al-Abrrow, H., Al Halbusi, H., Khaw, K. W., Chew, X., Al-Maatoq, M., & Alharbi, R. K. (2022). Uncovering the antecedents of trust in social commerce: An application of the non-linear artificial neural network approach. *Competitiveness Review: An International Business Journal*, *32*(3), 492–523. https://doi.org/10.1108/cr-04-2021-0051

7. António Porfírio, J., Augusto Felício, J., & Carrilho, T. (2024). Factors affecting digital transformation in banking. *Journal of Business Research*, *171*, 114393. https://doi.org/10.1016/j.jbusres.2023.114393
8. Appiah, T., & Agblewornu, V. V. (2025). The interplay of perceived benefit, perceived risk, and trust in Fintech adoption: Insights from Sub-Saharan Africa. *Heliyon*, *11*(2), e41992. https://doi.org/10.1016/j.heliyon.2025.e41992
9. Baabdullah, A. M., Alalwan, A. A., Rana, N. P., Kizgin, H., & Patil, P. (2019). Consumer use of mobile banking (M-Banking) in Saudi Arabia: Towards an integrated model. *International Journal of Information Management*, *44*, 38–52. https://doi.org/10.1016/j.ijinfomgt.2018.09.002
10. Barroso, M., & Laborda, J. (2022). Digital transformation and the emergence of the Fintech sector: Systematic literature review. *Digital Business*, *2*(2), 100028. https://doi.org/10.1016/j.digbus.2022.100028
11. Biro, R. C. (2024). Political Challenges and Economic Development in the KRI. In *Perspectives on Development in the Middle East and North Africa (MENA) Region* (pp. 113–131). Springer Nature Singapore. https://doi.org/10.1007/978-981-96-0563-7_7
12. Bouteraa, M., Raja Hisham, R. R. I., & Zainol, Z. (2023). Challenges affecting bank consumers' intention to adopt green banking technology in the UAE: A UTAUT-based mixed-methods approach. *Journal of Islamic Marketing*, *14*(10), 2466–2501. https://doi.org/10.1108/jima-02-2022-0039
13. Central Bank of Iraq. (2025). *Currency Outside Banks (Million IQD*. Central Bank of Iraq. https://cbiraq.org/DataValues.aspx?dtFrm=01/31/2004&dtTo=06/06/2025&tmId=156&dtformat=MMM,yyyy
14. Cepeda-Carrión, G., Hair, J. F., Ringle, C. M., Roldán, J. L., & García-Fernández, J. (2022). Guest editorial: Sports management research using partial least squares structural equation modeling (PLS-SEM). *International Journal of Sports Marketing and Sponsorship*, *23*(2), 229–240. https://doi.org/10.1108/ijsms-05-2022-242
15. Chand, A., Liu, D., Zulfiqar, M., Ullah, M. R., & Khan, M. J. (2025). Perceived quality in Fintech services: Expanding UTAUT2 and the Delone and McLean Information System Success Models. *Business Process Management Journal*. https://doi.org/10.1108/bpmj-08-2024-0754
16. Chauhan, V., Yadav, R., & Choudhary, V. (2019). Analyzing the impact of consumer innovativeness and perceived risk in internet

banking adoption: A study of Indian consumers. *International Journal of Bank Marketing*, *37*(1), 323–339. https://doi.org/10.1108/ijbm-02-2018-0028

17. Corritore, C. L., Kracher, B., & Wiedenbeck, S. (2003). On-line trust: Concepts, evolving themes, a model. *International Journal of Human-Computer Studies*, *58*(6), 737–758. https://doi.org/10.1016/s1071-5819(03)00041-7
18. Dash, G., & Paul, J. (2021). CB-SEM vs PLS-SEM methods for research in social sciences and technology forecasting. *Technological Forecasting and Social Change*, *173*, 121092. https://doi.org/10.1016/j.techfore.2021.121092
19. Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, *13*(3), 319. https://doi.org/10.2307/249008
20. Divya, Mathur, Ashish, Mathur, Abhilasha, & Gupta, V. (2024). Fintech Disruption in Traditional Financial Services: Analyzing the Impact of Fintech Startups on Traditional Banking and Financial Institutions. In *Studies in Systems, Decision and Control* (pp. 589–603). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-54379-1_52
21. Farzin, M., & Fattahi, M. (2025). Investigating the adoption of mobile banking and mobile payment services in developing countries. In *Encyclopedia of Monetary Policy, Financial Markets and Banking* (pp. 410–412). Elsevier. https://doi.org/10.1016/b978-0-44-313776-1.00022-2
22. Fishbein, M., & Ajzen, I. (1975). *Belief, Attitude, Intention and Behavior: An Introduction to Theory and Research*. Addison-Wesley.
23. Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, *18*(1), 39. https://doi.org/10.2307/3151312
24. Franke, G., & Sarstedt, M. (2019). Heuristics versus statistics in discriminant validity testing: A comparison of four procedures. *Internet Research*, *29*(3), 430–447. https://doi.org/10.1108/intr-12-2017-0515
25. Gefen, Karahanna, & Straub. (2003). Trust and TAM in Online Shopping: An Integrated Model. *MIS Quarterly*, *27*(1), 51. https://doi.org/10.2307/30036519
26. Hair, J. F. (2011). Multivariate Data Analysis: An Overview. In *International Encyclopedia of Statistical Science* (pp. 904–907). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-04898-2_395

27. Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2–24. https://doi.org/10.1108/ebr-11-2018-0203
28. Hair, Jr. J. F., Astrachan, C. B., Moisescu, O. I., Radomir, L., Sarstedt, M., Vaithilingam, S., & Ringle, C. M. (2021). Executing and interpreting applications of PLS-SEM: Updates for family business researchers. *Journal of Family Business Strategy*, *12*(3), 100392. https://doi.org/10.1016/j.jfbs.2020.100392
29. Hair, Jr. J. F., Matthews, L. M., Matthews, R. L., & Sarstedt, M. (2017). PLS-SEM or CB-SEM: Updated guidelines on which method to use. *International Journal of Multivariate Data Analysis*, *1*(2), 107. https://doi.org/10.1504/ijmda.2017.087624
30. Hair, Jr. Joe. F., Matthews, L. M., Matthews, R. L., & Sarstedt, M. (2017). PLS-SEM or CB-SEM: Updated guidelines on which method to use. *International Journal of Multivariate Data Analysis*, *1*(2), 107. https://doi.org/10.1504/ijmda.2017.087624
31. Hanif, Y., & Lallie, H. S. (2021). Security factors on the intention to use mobile banking applications in the UK older generation (55+). A mixed-method study using modified UTAUT and MTAM - with perceived cyber security, risk, and trust. *Technology in Society*, *67*, 101693. https://doi.org/10.1016/j.techsoc.2021.101693
32. Harris, M., Cox, K. C., Musgrove, C. F., & Ernstberger, K. W. (2016). Consumer preferences for banking technologies by age groups. *International Journal of Bank Marketing*, *34*(4), 587–602. https://doi.org/10.1108/ijbm-04-2015-0056
33. Hasan, R., Ashfaq, M., Parveen, T., & Gunardi, A. (2023). Financial inclusion – does digital financial literacy matter for women entrepreneurs? *International Journal of Social Economics*, *50*(8), 1085–1104. https://doi.org/10.1108/ijse-04-2022-0277
34. Hasan, S., Godhuli, E. R., Rahman, M. S., & Mamun, M. A. A. (2023). The adoption of conversational assistants in the banking industry: Is the perceived risk a moderator? *Heliyon*, *9*(9), e20220. https://doi.org/10.1016/j.heliyon.2023.e20220
35. Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8
36. Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path modeling in international marketing. In *Advances in International Marketing* (pp. 277–319). Emerald Group Publishing Limited. https://doi.org/10.1108/s1474-7979(2009)0000020014

37. Herzallah, F., Abosamaha, A. J., Abu-Siam, Y., Amer, M., Sajjad, U., & Hamid, K. (2025). Determinants of mobile wallet usage among Gen Z: Extending the UTAUT2 model with moderating effects of personal innovativeness and gender. *International Journal of Information Management Data Insights*, *5*(1), 100336. https://doi.org/10.1016/j.jjimei.2025.100336
38. Hulin, C., Netemeyer, R. G., & Cudeck, R. (2001). Can a Reliability Coefficient Be Too High? *Journal of Consumer Psychology*, *19*(55–58). https://doi.org/10.1207/S15327663JCP1001&2_05
39. Hunziker, S., & Blankenagel, M. (2024). Cross-Sectional Research Design. In *Research Design in Business and Management* (pp. 187–199). Springer Fachmedien Wiesbaden. https://doi.org/10.1007/978-3-658-42739-9_10
40. Idrees, M. A., & Ullah, S. (2024). Comparative analysis of FinTech adoption among Islamic and conventional banking users with moderating effect of education level: A UTAUT2 perspective. *Journal of Open Innovation: Technology, Market, and Complexity*, *10*(3), 100343. https://doi.org/10.1016/j.joitmc.2024.100343
41. Jadil, Y., Rana, N. P., & Dwivedi, Y. K. (2021). A meta-analysis of the UTAUT model in the mobile banking literature: The moderating role of sample size and culture. *Journal of Business Research*, *132*, 354–372. https://doi.org/10.1016/j.jbusres.2021.04.052
42. Kaur, S., & Arora, S. (2020). Role of perceived risk in online banking and its impact on behavioral intention: Trust as a moderator. *Journal of Asia Business Studies*, *15*(1), 1–30. https://doi.org/10.1108/jabs-08-2019-0252
43. Khan, W. A., & Abideen, Z. U. (2023). Effects of behavioural intention on usage behaviour of digital wallet: The mediating role of perceived risk and moderating role of perceived service quality and perceived trust. *Future Business Journal*, *9*(1). https://doi.org/10.1186/s43093-023-00242-z
44. Khuc, A. T., Nguyen, P. T. H., Nguyen, M. C., & Le, H. T. (2025). Perceived risks of financial misconduct and fintech in crowdfunding of Vietnamese individual investors. *Emerging Markets Review*, *64*, 101229. https://doi.org/10.1016/j.ememar.2024.101229
45. Kim, L., & Jindabot, T. (2022). Evolution of customer satisfaction in the e-banking service industry. *Innovative Marketing*, *18*(1), 131–141. https://doi.org/10.21511/im.18(1).2022.11
46. Kim, L., Wichianrat, K., & Yeo, S. F. (2024). An integrative framework enhancing perceived e-banking service value: A moderating impact of e-banking experience. *Journal of Open*

Innovation: Technology, Market, and Complexity, *10*(3), 100336. https://doi.org/10.1016/j.joitmc.2024.100336
47. KRG. (2023). *The Kurdistan Regional Government announces the launch of the 'My Account' initiative*. https://www.hawlergov.org/app/ku/node/5446
48. Krishna, B., Krishnan, S., & Sebastian, M. P. (2025). Understanding the process of building institutional trust among digital payment users through national cybersecurity commitment trustworthiness cues: A critical realist perspective. *Information Technology & People*, *38*(2), 714–756. https://doi.org/10.1108/itp-05-2023-0434
49. Lee, M.-C. (2009). Factors influencing the adoption of internet banking: An integration of TAM and TPB with perceived risk and perceived benefit. *Electronic Commerce Research and Applications*, *8*(3), 130–141. https://doi.org/10.1016/j.elerap.2008.11.006
50. Levin, K. A. (2006). Study design III: Cross-sectional studies. *Evidence-Based Dentistry*, *7*(1), 24–25. https://doi.org/10.1038/sj.ebd.6400375
51. Linh, T. T., Huyen, N. T. T., Quynh, N. N., & Doanh, N. K. (2025). Impacts of self-efficacy and herd behavior on farmers' intention to adopt digital payment in the mountainous regions of Northern Vietnam. *Journal of Agribusiness in Developing and Emerging Economies*. https://doi.org/10.1108/jadee-06-2024-0199
52. Loke, Y. J., Chin, P. N., & Lee, H. S. H. (2025). Digital financial services adoption: The role of trust and government intervention as mediators. *Digital Policy, Regulation and Governance*. https://doi.org/10.1108/dprg-02-2024-0028
53. Lu, C.-H. (2024). The moderating role of e-lifestyle on disclosure intention in mobile banking: A privacy calculus perspective. *Electronic Commerce Research and Applications*, *64*, 101374. https://doi.org/10.1016/j.elerap.2024.101374
54. Ly, B., & Ly, R. (2022). Internet banking adoption under Technology Acceptance Model—Evidence from Cambodian users. *Computers in Human Behavior Reports*, *7*, 100224. https://doi.org/10.1016/j.chbr.2022.100224
55. M. Hamakhan, Y. T. (2020). The effect of individual factors on user behaviour and the moderating role of trust: An empirical investigation of consumers' acceptance of electronic banking in the Kurdistan Region of Iraq. *Financial Innovation*, *6*(1). https://doi.org/10.1186/s40854-020-00206-0
56. Mahajan, S., & Nanda, M. (2024). Revolutionizing Banking with Blockchain: Opportunities and Challenges Ahead. In *Blockchain*

Technologies (pp. 287–304). Springer Nature Singapore. https://doi.org/10.1007/978-981-97-1249-6_13
57. Marcoulides, G. A. (2013). *Modern methods for business research*. Psychology Press. https://doi.org/10.4324/9781410604385
58. Martin, L., & Omrani, N. (2015). An assessment of trends in technology use, innovative work practices and employees' attitudes in Europe. *Applied Economics*, *47*(6), 623–638. https://doi.org/10.1080/00036846.2014.978072
59. Martins, C., Oliveira, T., & Popovič, A. (2014). Understanding the Internet banking adoption: A unified theory of acceptance and use of technology and perceived risk application. *International Journal of Information Management*, *34*(1), 1–13. https://doi.org/10.1016/j.ijinfomgt.2013.06.002
60. Maruping, L. M., Bala, H., Venkatesh, V., & Brown, S. A. (2017). Going beyond intention: Integrating behavioral expectation into the unified theory of acceptance and use of technology. *Journal of the Association for Information Science and Technology*, *68*(3), 623–637. https://doi.org/10.1002/asi.23699
61. Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An Integrative Model of Organizational Trust. *The Academy of Management Review*, *20*(3), 709. https://doi.org/10.2307/258792
62. McKnight, D. H., & Chervany, N. L. (2001). What Trust Means in E-Commerce Customer Relationships: An Interdisciplinary Conceptual Typology. *International Journal of Electronic Commerce*, *6*(2), 35–59. https://doi.org/10.1080/10864415.2001.11044235
63. Merhi, M., Hone, K., & Tarhini, A. (2019). A cross-cultural study of the intention to use mobile banking between Lebanese and British consumers: Extending UTAUT2 with security, privacy and trust. *Technology in Society*, *59*, 101151. https://doi.org/10.1016/j.techsoc.2019.101151
64. Modiha, P. (2025). Digital Trust in Banking: Post Graduate Students Perspective. In *Springer Proceedings in Business and Economics* (pp. 1055–1079). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-84885-8_57
65. Mogaji, E., & Nguyen, N. P. (2024). Evaluating the emergence of contactless digital payment technology for transportation. *Technological Forecasting and Social Change*, *203*, 123378. https://doi.org/10.1016/j.techfore.2024.123378
66. Mohd Thas Thaker, H., Mohd Thas Thaker, M. A., Khaliq, A., Allah Pitchay, A., & Iqbal Hussain, H. (2022). Behavioural intention and adoption of internet banking among clients' of Islamic banks in

Malaysia: An analysis using UTAUT2. *Journal of Islamic Marketing*, *13*(5), 1171–1197. https://doi.org/10.1108/jima-11-2019-0228

67. Muhamad, G. M. (2024). Political Economy of State Formation in the Kurdistan Region of Iraq: Challenges and Opportunities. In *Perspectives on Development in the Middle East and North Africa (MENA) Region* (pp. 15–38). Springer Nature Singapore. https://doi.org/10.1007/978-981-97-7725-9_2
68. Murinde, V., Rizopoulos, E., & Zachariadis, M. (2022). The impact of the FinTech revolution on the future of banking: Opportunities and risks. *International Review of Financial Analysis*, *81*, 102103. https://doi.org/10.1016/j.irfa.2022.102103
69. Namahoot, K. S., & Jantasri, V. (2023). Integration of UTAUT model in Thailand cashless payment system adoption: The mediating role of perceived risk and trust. *Journal of Science and Technology Policy Management*, *14*(4), 634–658. https://doi.org/10.1108/jstpm-07-2020-0102
70. Nasri, W., & Charfeddine, L. (2012). Factors affecting the adoption of Internet banking in Tunisia: An integration theory of acceptance model and theory of planned behavior. *The Journal of High Technology Management Research*, *23*(1), 1–14. https://doi.org/10.1016/j.hitech.2012.03.001
71. Oliveira, T., Faria, M., Thomas, M. A., & Popovič, A. (2014). Extending the understanding of mobile banking adoption: When UTAUT meets TTF and ITM. *International Journal of Information Management*, *34*(5), 689–703. https://doi.org/10.1016/j.ijinfomgt.2014.06.004
72. Otopah, A. A., Dogbe, C. S. K., Amofah, O., & Ahlijah, B. (2024). Digital marketing and purchase intention of bank services: The role of trust and engagement. *International Journal of Bank Marketing*, *42*(7), 1920–1945. https://doi.org/10.1108/ijbm-02-2023-0097
73. Pal, A., Herath, T., De', R., & Rao, H. R. (2020). Contextual facilitators and barriers influencing the continued use of mobile payment services in a developing country: Insights from adopters in India. *Information Technology for Development*, *26*(2), 394–420. https://doi.org/10.1080/02681102.2019.1701969
74. Parayil Iqbal, U., Jose, S. M., & Tahir, M. (2023). Integrating trust with extended UTAUT model: A study on Islamic banking customers' m-banking adoption in the Maldives. *Journal of Islamic Marketing*, *14*(7), 1836–1858. https://doi.org/10.1108/jima-01-2022-0030
75. Pavlou, P. A. (2003). Consumer Acceptance of Electronic Commerce: Integrating Trust and Risk with the Technology

Acceptance Model. *International Journal of Electronic Commerce*, *7*(3), 101–134. https://doi.org/10.1080/10864415.2003.11044275

76. Rahman, M., Ismail, I., & Bahri, S. (2020). Analysing consumer adoption of cashless payment in Malaysia. *Digital Business*, *1*(1), 100004. https://doi.org/10.1016/j.digbus.2021.100004
77. Rayun, S. M. N., Salam, M. A., Islam, W., Firmansyah, E. A., & Kalinaki, K. (2025). Unraveling the dynamics of mobile wallets in promoting cashless tourism in Bangladesh: Implementation of UTAUT2 model. *Journal of Hospitality and Tourism Technology*. https://doi.org/10.1108/jhtt-04-2024-0222
78. Raza, S. A., Umer, A., & Shah, N. (2017). New determinants of ease of use and perceived usefulness for mobile banking adoption. *International Journal of Electronic Customer Relationship Management*, *11*(1), 44. https://doi.org/10.1504/ijecrm.2017.086751
79. Riffai, M. M. M. A., Grant, K., & Edgar, D. (2012). Big TAM in Oman: Exploring the promise of on-line banking, its adoption by customers and the challenges of banking in Oman. *International Journal of Information Management*, *32*(3), 239–250. https://doi.org/10.1016/j.ijinfomgt.2011.11.007
80. Sarstedt, M., Ringle, C. M., & Hair, J. F. (2022). Partial Least Squares Structural Equation Modeling. In *Handbook of Market Research* (pp. 587–632). Springer International Publishing. https://doi.org/10.1007/978-3-319-57413-4_15
81. Sarstedt, M., Ringle, C. M., Smith, D., Reams, R., & Hair, J. F. (2014). Partial least squares structural equation modeling (PLS-SEM): A useful tool for family business researchers. *Journal of Family Business Strategy*, *5*(1), 105–115. https://doi.org/10.1016/j.jfbs.2014.01.002
82. Setia, M. (2016). Methodology series module 3: Cross-sectional studies. *Indian Journal of Dermatology*, *61*(3), 261. https://doi.org/10.4103/0019-5154.182410
83. Shaikh, A. A., & Karjaluoto, H. (2019). *Marketing and mobile financial services: A global perspective on digital banking consumer behaviour*. Routledge.
84. Shmueli, G., Ray, S., Velasquez Estrada, J. M., & Chatla, S. B. (2016). The elephant in the room: Predictive performance of PLS models. *Journal of Business Research*, *69*(10), 4552–4564. https://doi.org/10.1016/j.jbusres.2016.03.049
85. Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J.-H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict. *European*

Journal of Marketing, *53*(11), 2322–2347. https://doi.org/10.1108/ejm-02-2019-0189

86. Tariq, M., Maryam, S. Z., & Shaheen, W. A. (2024). Cognitive factors and actual usage of Fintech innovation: Exploring the UTAUT framework for digital banking. *Heliyon*, *10*(15), e35582. https://doi.org/10.1016/j.heliyon.2024.e35582
87. Venkatesh, Morris, Davis, & Davis. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly*, *27*(3), 425. https://doi.org/10.2307/30036540
88. Venkatesh, Thong, & Xu. (2012). Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. *MIS Quarterly*, *36*(1), 157. https://doi.org/10.2307/41410412
89. Venkatesh, V., & Zhang, X. (2010). Unified Theory of Acceptance and Use of Technology: U.S. Vs. China. *Journal of Global Information Technology Management*, *13*(1), 5–27. https://doi.org/10.1080/1097198x.2010.10856507
90. Voorhees, C. M., Brady, M. K., Calantone, R., & Ramirez, E. (2016). Discriminant validity testing in marketing: An analysis, causes for concern, and proposed remedies. *Journal of the Academy of Marketing Science*, *44*(1), 119–134. https://doi.org/10.1007/s11747-015-0455-4
91. Wang, X., & Cheng, Z. (2020). Cross-Sectional Studies. *Chest*, *158*(1), S65–S71. https://doi.org/10.1016/j.chest.2020.03.012
92. World Bank. (2023). *Iraq Economic Monitor, Spring/Summer 2023 – Reemerging pressures: Iraq's recovery at risk (With a special focus on financial intermediation in Iraq)*. World Bank. http://hdl.handle.net/10986/40103
93. Wronka, C. (2023). Central bank digital currencies (CBDCs) and their potential impact on traditional banking and monetary policy: An initial analysis. *Digital Finance*, *5*(3–4), 613–641. https://doi.org/10.1007/s42521-023-00090-0
94. Zaid Kilani, A. A.-H., Kakeesh, D. F., Al-Weshah, G. A., & Al-Debei, M. M. (2023). Consumer post-adoption of e-wallet: An extended UTAUT2 perspective with trust. *Journal of Open Innovation: Technology, Market, and Complexity*, *9*(3), 100113. https://doi.org/10.1016/j.joitmc.2023.100113
95. Zhao, H., & Khaliq, N. (2024). In quest of perceived risk determinants affecting intention to use fintech: Moderating effects of situational factors. *Technological Forecasting and Social Change*, *207*, 123599. https://doi.org/10.1016/j.techfore.2024.123599