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Extending C-TAM-TPB: Dual-level Moderation of Perceived Web Security and Age in Digital Banking

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Abstract

This study examines the intention to adopt digital banking in Saudi Arabia by integrating the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB). It includes Perceived Web Security (PWS) and Age as moderators, addressing trust and security perceptions across user segments in emerging markets. Data were collected from 353 digital banking users in Saudi Arabia using a cross-sectional quantitative design. The model was tested via Partial Least Squares Structural Equation Modeling (PLS-SEM), assessing measurement validity, path significance, moderation, and mediation effects. Predictive accuracy was evaluated with in-sample (R^2) and out-of-sample (Q^2, PLS-Predict) indicators. The results confirmed the significance of core TAM variables—Perceived Ease of Use (PEU), Perceived Usefulness (PU), and Attitude Toward Use (ATU)—on Behavioral Intention (BI). Attitude was a strong predictor of BI, but Subjective Norms (SN) and Perceived Behavioral Control (PBC) were not significant. PWS moderated the ATU–BI relationship, enhancing intention under high security perception, but Age's dual-moderation effect was unsupported. Sequential mediation analysis validated that PEU and PU influence BI indirectly via ATU. This study enhances digital adoption research through a validated dual-level moderation model combining security perception and age. It refines TAM-TPB integration and offers practical insights for creating secure, user-centered digital banking systems tailored to specific cultures.

Keywords:

Digital Banking Adoption;
TAM; TPB; PWS; PLS-SEM;
Behavioral Intention;
Moderation; Mediation;
Saudi Arabia;
Fintech User Behavior.

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1- Introduction

Billions of dollars have been invested in the realm of digital banking, yet a significant number of users still hesitate to fully engage with these innovative platforms [1, 2]. Why is this the case? The technology is undeniably present—secure, fast, and smart—but issues surrounding trust, differing generational attitudes, and perceived risks continue to overshadow the potential advantages [3, 4]. It is a paradox that banks are acutely aware that while growth in infrastructure and technological advancements is occurring at an impressive rate, it does not necessarily translate into an increase in user behavior and engagement with these banking solutions [5, 6].

Digital banking (DB), which represents the digital extension of traditional financial services, has undergone a remarkable evolution in recent years. This transformation has led to the introduction of seamless access options that cater to users through various channels, including mobile apps, online portals, and even increasingly popular AI-driven customer service systems [7]. Despite its promising potential and the significant global investments made in this sector, the returns on investment have remained surprisingly modest [8, 9]. Many banks continue to grapple with issues stemming from low customer engagement levels, even as they pour substantial resources into enhancing the user

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experience and enhancing cybersecurity measures [10]. The challenge facing these institutions extends beyond mere technological hurdles; it delves deeply into behavioral aspects. Consumers evaluate factors such as ease of use, utility, and trust differently on the basis of their individual identities and situational contexts [11]. Understanding these varied perceptions is crucial for banks aiming to enhance their digital offerings and improve customer satisfaction.

1-1- Digital Transformation and Saudi Arabia's Strategic Push

These variations in responses to digital technologies are even more evident in Saudi Arabia. The Kingdom is vigorously pursuing a bold and ambitious digital transformation agenda under its Vision 2030 initiative [12]. This extensive nationwide transformation aims to diversify the economy and modernize services across various sectors, including the banking and financial industries [13]. The Saudi Central Bank has actively promoted fintech development through comprehensive regulatory reforms and the establishment of sandbox environments, which serve to encourage innovation in digital financial services and create a more dynamic financial ecosystem [14, 15].

The widespread adoption of mobile devices among the population, combined with the urgent necessity driven by the pandemic, has dramatically accelerated the movement toward digital-first banking models [16-18]. Government initiatives to reduce cash reliance and enhance digital access have accelerated the shift to digital banking [19, 20], but it is important to note that this growth is not evenly distributed across all demographic groups. Older users continue to express substantial concerns regarding the data security and privacy issues associated with digital banking [21, 22]. In contrast, younger users generally adopt these new technologies more quickly; however, they may often prioritize convenience and speed over caution and security. These nuanced differences in user behavior and technology acceptance often go unnoticed and unaddressed in standard models of technology adoption and acceptance [22, 23], while these behaviors reveal a spectrum of trust and risk perceptions across generations.

Over the past two decades, extensive frameworks such as the Technology Acceptance Model (TAM), its extended version TAM2, and the Theory of Planned Behavior (TPB) have provided valuable lenses for comprehensively understanding user behavior toward digital tools [24, 25]. These theoretical models have played a significant role in isolating key predictors that influence technology adoption, including perceived usefulness (PU), ease of use (PEU), subjective norms (SNs), and behavioral control. However, it is important to note that most applications of these established models tend to focus narrowly on individual variables rather than considering the potential interactive effects between them. Additionally, they are predominantly used more for the confirmation of existing theories than for the in-depth exploration of user behavior dynamics [26, 27].

1-2- Gaps in the Literature and Study Objective

Recent studies have increasingly highlighted the importance of developing richer and more context-sensitive models that consider not only psychological factors but also demographic moderators [28, 29]. Unlike prior research by [30-32], which focused on perceived ease of use and usefulness in Western contexts, this study incorporates perceived web security and age as culturally relevant moderators. These variables, which directly impact user experiences, may significantly influence how users interpret their digital banking experiences. However, these crucial variables are rarely studied in conjunction with each other and even less frequently within non-Western settings, including countries such as Saudi Arabia, as previously noted in the literature [33, 34]. This underscores the need for a more comprehensive approach to understanding user interactions in diverse cultural contexts.

To address this identified gap comprehensively, the current study significantly extends the C-TAM-TPB framework by introducing the concepts of perceived web security (PWS) and age as dual-level moderators. We thoroughly explore how these specific factors interact with important constructs such as perceived usefulness (PU), perceived ease of use (PEU), subjective norms (SNs), and overall attitudes to influence the behavioral intention to adopt digital banking solutions. The model methodically synthesizes key constructs drawn from the Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB), perceived risk theory, and various integrative adoption models. This robust framework is rigorously tested using primary quantitative data that have been meticulously collected from banking users in Saudi Arabia.

This paper contributes to the literature in three keyways: (1) by advancing a dual-moderation model for understanding digital banking behavior, (2) by offering empirical evidence from an emerging fintech leader in the Middle East, and (3) by providing actionable insights for banks seeking to align their digital strategies with user psychology. The goal is not just to understand adoption but also to understand why adoption sometimes stalls, despite every technological advantage [35, 36].

The structure of this article is as follows. Section 2 reviews the theoretical foundations and hypothesis development. Section 3 outlines the research methodology. Section 4 presents the results. Section 5 offers a discussion of the findings, and Section 6 concludes with practical implications and suggestions for future research.

2- Theoretical Background and Hypothesis Development

The Technology Acceptance Model (TAM) developed by Davis in 1989 and the Theory of Planned Behavior (TPB) introduced by Ajzen in 1991 have both been extensively applied to analyze technology adoption behaviors [37, 38]. TAM focuses mainly on users' perceptions of technology, specifically highlighting two key factors, namely, perceived usefulness (PU) and perceived ease of use (PEU), which serve as fundamental influences on the adoption process. In contrast, [39, 40], the TPB takes a broader approach by integrating psychological and social factors, including attitudes toward use (ATU), subjective norms, and perceived behavioral control, to forecast behavioral intentions regarding the use of technology. Although each framework on its own is strong, the integration of the TAM and TPB provides a more holistic perspective on technology adoption [41, 42]. This is especially relevant in contexts such as digital banking, where technology-related perceptions interact with psychological and social factors [43].

2-1- Technology Acceptance Model (TAM)

Perceived usefulness (PU), a fundamental component of the technology acceptance model (TAM), is characterized as the extent to which a person believes that utilizing a specific system will improve their task efficiency [44]. Initially, PEU influences perceived usefulness (PU), and individuals who perceive a system as easy to navigate are more inclined to view it as useful [45, 46]. Researchers consistently show that perceived ease of use positively influences attitudes toward use and perceived usefulness (PU) [47-49]. In addition to the influence of perceived ease of use (PEU), perceived usefulness plays a crucial role in determining attitudes toward use [40, 50].

Hence, the following hypotheses are proposed:

- ***H1: Perceived ease of use (PEU) positively influences perceived usefulness (PU).***
- ***H2: Perceived ease of use (PEU) positively influences attitudes toward use (ATU).***
- ***H3: Perceived usefulness (PU) positively influences ATU.***
- ***H4: Perceived usefulness (PU) positively influences the behavioral intention to use digital banking services.***

2-1-1- Mediation logic and drive

PU has a significant influence on behavioral intention within the realm of digital services [51, 52]. Perceived ease of use (PEU), which refers to the extent to which a person believes that using technology will require minimal effort, has an indirect effect on behavioral intention [53]. Both PU and ATU subsequently serve as mediators in the relationship leading to behavioral intention [53]. When users recognize digital banking services as advantageous for overseeing their financial tasks, they cultivate positive attitudes toward embracing these services [54, 55]. These positive attitudes subsequently bolster their behavioral intention to adopt the service [56, 57].

- ***H10: Perceived ease of use positively influences attitudes toward use through the mediation of perceived usefulness.***
- ***H11: Perceived usefulness positively influences the behavioral intention to use digital banking services through attitudes toward use.***
- ***H12: Perceived ease of use positively influences the behavioral intention to use digital banking services through the sequential mediation of perceived usefulness and attitudes toward use.***

2-2- Theory of Planned Behavior (TPB)

occurred in the early 1990s when banks started considering the internet from an automated self-service standpoint. E-banking includes all modern, remote banking systems conducted via computers with direct online access to the information stored in the bank’s mainframe [58]. They are expected to provide customers with all banking services available in branches, and these services must be described as perfect with an impeccable security system [59]. In this vein, researchers have recently focused on mobile banking. According to some research, a bank is internet banking compatible if it provides

2-2-1-Attitudes Toward Digital Banking and Behavioral Intentions

According to the TPB framework, it is expected that the behavioral intention (BI) is influenced by three main factors: the attitude toward the behavior (AT), the subjective norm (SN), and perceived behavioral control (PBC) [60].

Attitude pertains to the extent to which an individual holds a positive or negative evaluation toward engaging in a specific behavior [61]. The realm of digital banking encompasses the consumer's perception of the advantages, innovation, and logical reasoning behind the use of digital banking services [62, 63]. Previous studies have shown that individuals who view attitudes as advantageous and prudent are much more inclined to develop intentions to participate in such behavior [64, 65]. Positive attitudes toward digital banking can stem from perceived benefits such as saving time, increased convenience, and effective financial management [66].

Thus, the following is expected:

- ***H5: Attitudes toward the use of digital banking positively influence the behavioral intention to use digital banking services.***

2-2-2- Subjective Norms and Behavioral Intention

Subjective norms relate to how an individual perceives the social pressures surrounding the decision to engage in or abstain from a specific behavior [67]. In regard to digital banking, these subjective norms include perceived endorsements or anticipated expectations from significant reference groups, including relatives, peers, and wider societal influences [68].

In collectivistic societies such as Saudi Arabia, social influences are crucial in determining the acceptance of financial technology [69]. When influential peers support digital banking, individuals tend to develop more robust behavioral intentions [70, 71]. Additionally, normative pressure from reliable social networks can diminish the uncertainty and perceived risks linked to digital financial services [72].

Therefore, the following hypothesis is proposed:

- ***H6: Subjective norms positively influence the behavioral intention to use digital banking services.***

2-2-3- Perceived Behavioral Control and Behavioral Intention

Perceived behavioral control (PBC) refers to how individuals view the ease or difficulty of engaging in certain behaviors, considering both internal factors (such as skills and self-assurance) and external obstacles (such as accessibility and costs) [60, 73]. In the realm of digital banking, PBC indicates the level of consumers' self-reliance in utilizing technology and their ability to handle financial activities via digital platforms [74].

In alignment with the theory of planned behavior (TPB), an increased sense of perceived control increases the probability that a person will form an intention to engage in a specific behavior [60, 75]. Studies within the realm of digital finance indicate that individuals who believe that they can effectively maneuver through digital banking platforms are more likely to express an intention to adopt them) [7, 76, 77]). A strong sense of confidence in handling both technical and financial components notably reduces perceived complexity and promotes a greater intention to act [78].

Thus, the following is hypothesized:

- ***H7: Perceived behavioral control positively influences the behavioral intention to use digital banking services.***

2-3- Perceived Web Security and its Moderating Role

The evolution of digital banking services has increased concerns surrounding data privacy, cybersecurity, and transaction security [79]. In settings where financial transactions take place online, the way in which consumers perceive security, particularly perceived web security (PWS), plays a crucial role in influencing their behavioral responses [80, 81]. PWS refers to the extent to which users feel confident that an online service can safeguard sensitive financial and personal data from unauthorized access [82]. In digital banking, the trustworthiness of online platform security is vital for minimizing perceived risk and motivating users to conduct financial transactions [83]. While consumers may view digital banking positively as useful, efficient, or innovative, their ultimate decision to adopt such services is significantly influenced by their confidence in the platforms' ability to safeguard against various threats [84, 85]. Specifically, it is anticipated that perceived web security will act as a moderating factor in the connection between ATU and BI [86, 87]. When users perceive the online environment to be secure, the beneficial impact of their attitudes on their intentions is enhanced [88]. However, if consumers harbor concerns regarding the security of digital banking platforms, even positive attitudes may not effectively convert into genuine intentions to use these services [89].

This moderate effect is especially significant in the financial services sector, where the repercussions of security breaches can be dire (such as identity theft, financial loss, and fraud) [90]. Owing to the considerable risks at play, perceived web security serves as a confidence booster—enhancing the impact of positive attitudes when security beliefs are strong yet diminishing this connection when security beliefs are weak [83]. Recent empirical studies have

substantiated the crucial role of security perceptions, where [91] reported that perceived security significantly moderates the relationship between trust and mobile banking adoption in South Korea, [92] reported that security perceptions directly influence e-commerce intentions and moderate the impact of trust, and [93] reported that, in Middle Eastern markets, perceived web security is among the strongest predictors of online banking usage, especially for new or hesitant users.

Thus, in this study, the following hypotheses are proposed:

- ***H8: Perceived web security positively moderates the relationship between attitudes toward the use of digital banking services and the behavioral intention to use digital banking services.***

2-4- Dual-level Moderation of Perceived Web Security and Age

The concept of dual-level moderation regarding perceived web security and age reveals how demographic factors shape user interactions with digital banking platforms. Grounded in the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB), this approach illustrates that security perceptions vary with age [94, 95], where Age influences how users respond to security cues, with older adults potentially relying more on security assurance when forming behavioral intentions (see Figure 1). Research shows that older adults often rely more heavily on trust and perceived security when adopting digital banking, whereas younger users may be more sceptical despite their technological fluency [96]. This age differential invites investigations into how it moderates the link between perceived security and engagement intentions [97, 98]. Such insights hold importance for service providers aiming to customize security assurances and marketing approaches for different age groups.

Thus,

- ***H9: Age moderates the moderating effect of perceived web security (PWS) on the relationship between ATU and BI to use digital banking services***

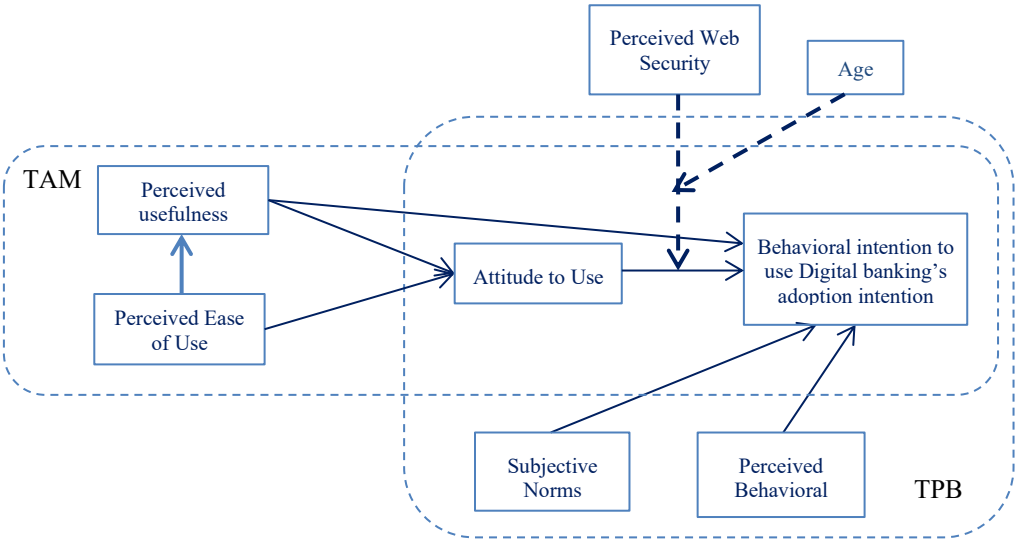

Figure 1. Conceptual model

3- Research Methodology

This research employs a comprehensive approach to examine the factors influencing the use of digital banking services in Saudi Arabia. It integrates elements from both the [99] Technology Acceptance Model (TAM) and the [100] Theory of Planned Behavior (TPB) while also incorporating perceived web security (PWS) as a moderate influence. The methodology comprises several essential components:

Research Design & Collection: This research uses a quantitative, cross-sectional approach to collect information from digital banking users at a single point in time. This cross-sectional technique provides a detailed snapshot that highlights the behavioral intentions of consumers concerning the use of digital banking across different demographic groups within Saudi Arabia. To ensure that the participants were well informed, they received comprehensive information about the study's objectives, guarantees of confidentiality, and terms related to voluntary participation. Consent was secured by making it clear that, by completing the questionnaire, the participants agreed to take part in the study. The survey was conducted over a span of two months, allowing for extensive outreach across multiple cities throughout Saudi Arabia.

Population and Sampling: A convenience sampling method was employed to engage various demographics, leveraging a multitude of online channels and banking communities for outreach. However, efforts have been made to encompass a broad spectrum of diversity concerning gender, age, education, and income. In total, 353 valid responses were collected, exceeding the minimum sample size requirements determined by G*Power software [101], for achieving a medium effect size ($f^2 = 0.15$), $\alpha = 0.05$, and power $(1–\beta) = 0.95$, which required at least 129 respondents.

Measurement Instrumentation: The revised questionnaire items were meticulously developed on the basis of previous research to evaluate the constructs outlined in the conceptual framework. These constructs included several key components, such as Behavioral Intention (BI), Attitude Toward Use (ATU), Perceived Usefulness (PU), Perceived Ease of Use (PEOU), and Perceived Web Security (PWS), which were adapted from [102], and Perceived Behavioral Control (PBC) and Subjective Norms (SN), which were adapted from [103]. Each item was assessed via a five-point Likert scale, with responses ranging from 1, which signifies "Strongly Disagree," to 5, which represents "Strongly Agree." Ultimately, 24 items were utilized to measure respondents' perceptions regarding the critical dimensions of the research effectively.

Hypothesis Development: The hypotheses of the study were crafted after a thorough examination of the existing body of literature that focuses on how individuals adopt technology and their perceptions of security within digital contexts. These hypotheses suggest that there are direct influences from attitudes, subjective norms, perceived behavioral control, and perceived usefulness on the intention to adopt technology. Additionally, there is an indirect influence from perceived usefulness and perceived ease of use. Additionally, it is proposed that perceived web security plays a moderating role in the relationship between attitude and behavioral intention.

4- Data Analysis and Results

The data collected underwent a thorough analysis utilizing partial least squares structural equation modeling (PLS-SEM) version 4 [104]. The decision to employ PLS-SEM was influenced by its proven ability to explore complex models that incorporate multiple constructs and relationships, particularly when working with moderate sample sizes and datasets that deviate from normal distribution patterns [105]. The analytical procedure was meticulously structured into a two-step sequence following [106]; it commenced with an evaluation of the measurement model, focusing on reliability and validity [107, 108], followed by the estimation of the structural model and the testing of hypotheses. Furthermore, a moderation analysis was performed to explore the influence of perceived web security (PWS) as a moderating variable on the relationship between attitude and behavioral intention. Hypothesis development was also addressed during this process.

4-1- Common Method Bias (CMB)

We commenced our evaluation of full collinearity to investigate the presence of common method bias [109], given that the data were sourced from a singular entity, in accordance with the methodologies outlined by [110, 111]. The methodology employed involves regressing all variables onto a shared variable. A variance inflation factor (VIF) threshold of less than 3.3 signifies the absence of bias stemming from single-source data [107, 112]. The results of this assessment, as presented in Table 1, revealed that the VIF was indeed below the 3.3 mark, thereby indicating that no bias was present in the data collected.

Table 1. Full Collinearity Testing

Construct	BI	ATU	AGE	PBC	PEU	PU	PWS	SN
VIF	2.287	1.010	1.012	1.045	2.588	1.992	1.999	2.352

Note: ATU Attitude, PBC= Perceived behavioral Control, PU= Perceived usefulness, PEU= Perceived ease of use, PWS = Perceived Web security, and SN = subjective Norms.

4-2- Step 1: Assessment of the Measurement Model

First, to evaluate indicator reliability, convergent validity, and internal consistency reliability, in accordance with the criteria established by Hair et al. [107] and Darsono et al. [112], indicator reliability was assessed via outer loadings with an accepted threshold of ≥ 0.5, whereas convergent validity was analyzed through the average variance extracted (AVE) with a minimum acceptable value of ≥ 0.5. Additionally, internal consistency was evaluated via composite reliability (CR) with a threshold acceptance of ≥ (0.708, 0.5, and 0.7), in accordance with the criteria established by Hair et al. [107] and Darsono et al. [112]. The data presented in Table 2 reveal that every item loading surpassed the suggested benchmark of 0.708, which indicates a high level of indicator reliability. Moreover, the average variance extracted (AVE) values for each construct were greater than the acceptable minimum of 0.50, thereby validating the convergent validity at the construct level. In addition, all the constructs displayed composite reliability values that exceeded the 0.70 threshold, reflecting a strong level of internal consistency reliability.

Table 2. Measurement model assessment

Variable	Item	Loading	CR	AVE
Behavioral Intention	Using digital banking services for my financial transactions is something I plan to do	0.862	0.904	0.759
	I intend to use digital banking services for my financial needs.	0.89		
	I see myself regularly using digital banking services for managing my finances	0.861		
Attitude	Using digital banking is a good idea	0.858	0.879	0.707
	It is an innovative idea to use digital banking.	0.846		
	In my view, using digital banking is a wise idea	0.818		
Perceived Behavioral Control	I am confident I can adopt digital banking services if I have access to the necessary technology, such as a smartphone or reliable internet	0.838	0.906	0.708
	I will adopt digital banking services if banks provide adequate training or tutorials to help users understand how to use them.	0.878		
	I feel capable of adopting digital banking services if they align with my financial situation, such as low or no associated fees.	0.837		
	I am more likely to adopt digital banking services if I have consistent access to promotions or offers that encourage their use	0.811		
Perceived ease of use	I can quickly become proficient in using digital banking services with little assistance	0.832	0.879	0.708
	The design and interface of digital banking services are clear and easy to navigate.	0.815		
	Using digital banking services is straightforward and requires minimal effort	0.876		
Perceived usefulness	Overall, using digital banking services is advantageous for meeting my financial needs.	0.843	0.915	0.729
	Digital banking services make it easier for me to manage my financial activities.	0.853		
	I find digital banking services to be highly beneficial for my financial management.	0.847		
	Using digital banking services helps me complete my tasks more efficiently.	0.872		
Perceived Web Security	I feel confident sharing sensitive information while using digital banking services."	0.763	0.882	0.715
	Digital banking services provide a secure platform for managing personal and financial information.	0.880		
	Overall, I find digital banking services to offer a safe environment for financial transactions and data sharing.	0.889		
Subjective Norms	My family believes I should adopt digital banking services for managing my financial needs	0.778	0.881	0.649
	Most people whose opinions I value think I should use digital banking services.	0.805		
	The people in my life whose views I respect would approve of my decision to use digital banking services.	0.861		
	My friends can influence me to adopt digital banking services.	0.777		

Next, discriminant validity was ensured by employing the Fornell & Larcker [113] criterion, as indicated in Table 3. The average variance extracted (AVE) was confirmed to exceed the highest squared correlations with any other construct, thus validating the distinctiveness of the constructs involved.

Table 3. Discriminant validity

Construct	ATU	Age	BI	PBC	PEU	PU	PWS	SN
ATU	0.841							
Age	0.049	1						
BI	0.753	0.024	0.871					
PBC	0.698	0.014	0.726	0.841				
PEU	0.743	0.031	0.768	0.717	0.841			
PU	0.759	0.065	0.772	0.798	0.802	0.854		
PWS	0.624	-0.039	0.625	0.697	0.751	0.723	0.846	
SN	0.643	0.045	0.643	0.76	0.691	0.744	0.69	0.806

4-3-Step 2: Assessment of the Structural Model

4-3-1- Path Coefficients

The path coefficients were evaluated via a bootstrapping method with an extensive sample size of 10,000, as noted by Memon et al. [108]. This comprehensive assessment encompassed an in-depth exploration of direct effects, alongside indirect effects that involve mediation, and considered the examination of moderation effects. On the basis of Hahn and Ang [114] that p values are not enough to test the hypothesis by themselves, the analysis included a detailed presentation of path coefficients, standard errors, t values, and p values for the structural model, in line with the recommendations of Hair et al. [107] and Becker et al. [115].

Direct effects (H1–H7)

The results validated the foundational TAM relationships. **Perceived ease of use (PEU)** had a strong and significant influence on both **perceived usefulness (PU)** ($\beta = 0.743$, $t = 19.061$, $p < 0.001$) and **attitude toward use (ATU)** ($\beta = 0.367$, $t = 6.564$, $p < 0.001$), supporting H1 and H2, respectively. Similarly, **PU** was found to significantly influence both **ATU** ($\beta = 0.457$, $t = 6.799$, $p < 0.001$; H3) and **behavioral intention (BI)** ($\beta = 0.325$, $t = 5.294$, $p < 0.001$; H4), confirming its central role in digital banking adoption. **ATU**, in turn, had a significant positive effect on BI ($\beta = 0.343$, $t = 6.104$, $p < 0.001$), lending support to H5.

In contrast, the TPB-based predictors **subjective forms (SNs) and perceived behavioral control (PBC)** did not significantly affect behavioral intention. The coefficients for SN ($\beta = 0.043$, $p = 0.195$) and PBC ($\beta = 0.089$, $p = 0.123$) were both statistically insignificant, resulting in no support for H6 and H7. This may reflect the specific cultural or contextual dynamics of the study sample, where individual utility and trust concerns outweigh perceived social pressure or control (Table 4 and 5).

Moderation effects (H8–H9)

The study found support for H8, which posited that **perceived web security (PWS)** moderates the relationship between **attitudes toward use and behavioral intentions**. The interaction effect was statistically significant ($\beta = 0.140$, $t = 2.215$, $p = 0.027$), indicating that higher perceptions of security strengthen the influence of favorable attitudes on adoption intentions. This effect is visualized in **Figure 2**, where the slope representing the ATU–BI relationship is steeper under conditions of high perceived security and flatter when perceived security is low.

However, H9, which proposed a **dual-level moderation** involving **Age and PWS**, was not supported. The three-way interaction (Age × PWS × ATU → BI) yielded a nonsignificant result ($\beta = -0.007$, $t = 0.275$, $p = 0.783$), suggesting that while perceived security is a critical contextual factor, age does not significantly alter its moderating effect.

Indirect effects (H10–H12)

The model also provided evidence for several indirect pathways. **H10** tested the total indirect effect of **PEU on ATU through PU**, which was statistically significant ($\beta = 0.414$, $t = 4.690$, $p < 0.001$), indicating that PU partially mediates the relationship between PEU and ATU. **H11** examined whether **PU influences BI via ATU**, and this path was also supported ($\beta = 0.143$, $t = 3.706$, $p < 0.001$), showing that usefulness affects behavior not only directly but also indirectly through attitudinal change (Figure 3).

Finally, **H12**, which tested **sequential mediation** from **PEU → PU → ATU → BI**, was supported ($\beta = 0.45$, $t = 5.458$, $p < 0.001$). This confirms that the impact of ease of use on intention is not only direct but also indirectly channeled through both perceived value and positive attitude formation.

Table 4. Structural model assessment: Hypothesis testing (direct relationships)

	Relationship	β	Std Dev.	t value	p value	BCI [LL, UL]	f^2	Result
H1	PU → ATU	0.457	0.068	6.729	p<.001	[0.322, 0.587]	0.2	Supported
H2	PEU → PU	0.802	0.032	24.794	p<.001	[0.726, 0.855]	1.806	Supported
H3	PEU → ATU	0.377	0.067	5.644	p<.001	[0.245, 0.505]	0.135	supported
H4	PU → BI	0.273	0.088	3.207	0.001	[0.114, 0.457]	0.059	Supported
H5	ATU → BI	0.311	0.073	4.239	p<.001	[0.165, 0.451]	0.116	Supported
H6	SN → BI	0.041	0.067	0.578	0.563	[-0.093, 0.169]	0.002	Not Supported
H7	PBC → BI	0.185	0.086	2.074	0.038	[0.009, 0.344]	0.029	Supported
H8	PWS × ATU → BI	-0.061	0.02	3.083	0.002	[-0.101, -0.023]	0.027	Supported
H9	Age × PWS × ATU → BI	-0.007	0.019	0.275	0.783	[-0.046, 0.029]	0	Not Supported

Table 5. Structural model assessment: hypothesis testing (indirect relationships)

	Total effect (Direct with Indirect)						Specific Indirect effect					
	Total effect	**STd. Beta**	**Std Dev.**	**t value**	**P-values**	**PCI [LL, UL]**	**STd. Beta**	**Std Dev.**	**t value**	**P-values**	**PCI [LL, UL]**	**Effect**
H10	PEU → ATU	0.743	0.039	19.061	p<.001	[0.655, 0.81]	0.366	0.058	6.38	p<.001	[0.259, 0.482]	PEU → PU → ATU
H11	PU → BI	0.414	0.091	4.69	p<.001	[0.25, 0.603]	0.141	0.038	3.744	p<.001	[0.077, 0.227]	PU → ATU → BI
H12	PEU → BI	0.45	0.084	5.458	p<.001	[0.294, 0.619]	0.219	0.072	3.136	0.002	[0.09, 0.373]	PEU → PU → BI
							0.118	0.038	3.092	0.002	[0.054, 0.201]	PEU → ATU → BI
							0.113	0.031	3.706	p<.001	[0.062, 0.183]	PEU → PU → ATU → BI

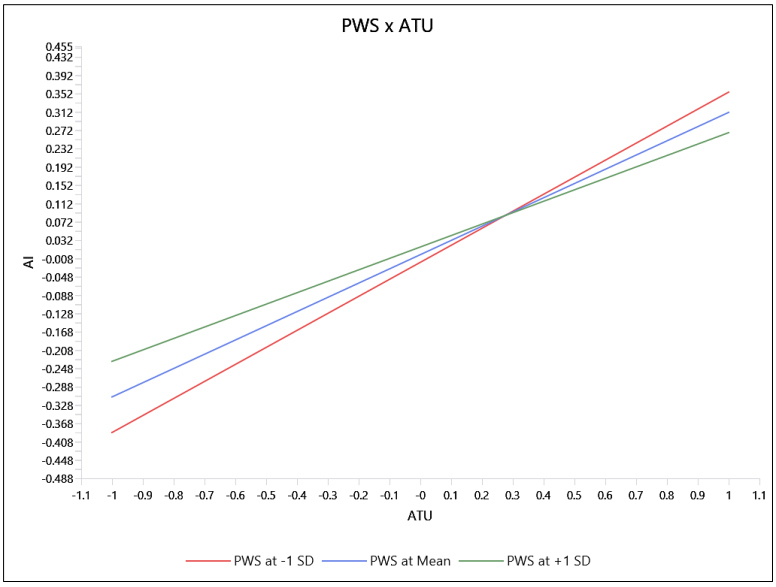

Figure 2. Moderating effect of the PWS on the ATU→BI relationship

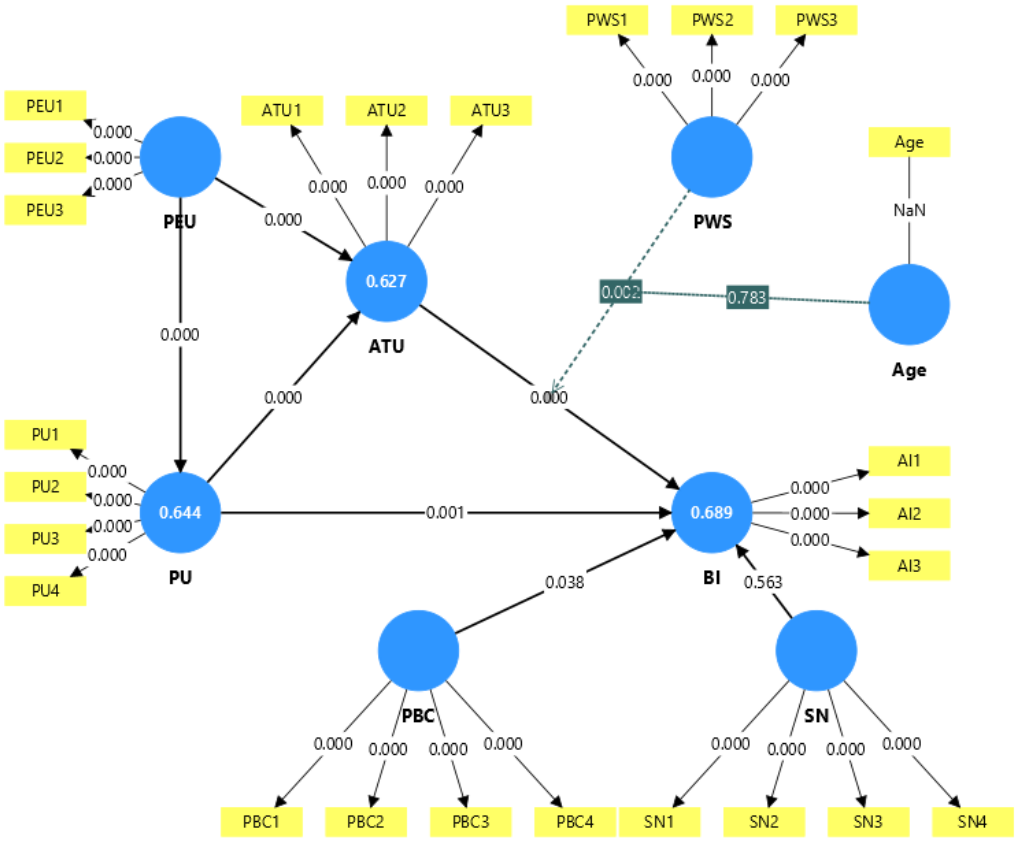

Figure 3. Integrated C-TAM-TPB Structural Model with R² Values and Moderation Effects (PWS and Age)

4-3-2- Testing Coefficient of Determination, Effect Sizes, and Predictive Performance

To assess the model's explanatory and predictive capacity, both in-sample and out-of-sample performance measures were employed [116]. This included evaluation of the **R² (coefficient of determination)**, **f² (effect sizes)**, and **Q² (predictive relevance)** values, as well as the results from **PLS-Predict** analysis.

First In-Sample Predictive Accuracy (R² and f²)

The coefficient of determination (R^2) indicates the proportion of variance explained by the independent variables in the endogenous constructs [117]. As shown in Table 6, **Behavioral Intention (BI)** had the highest R^2 value at **0.689**, followed by **Attitude Toward Use (ATU)** at **0.627** and **Perceived Usefulness (PU)** at **0.644**. According to Cohen's (1988) benchmarks, these values represent **substantial explanatory power**. Next, we calculated the effect size to provide a deeper understanding of the distinct roles played by individual predictors in the R^2 of the dependent variables.

According to Daly & Cohen [118] and Cohen [119], the effect size is weak, medium, and strong at 0.02, 0.15, and 0.35, respectively. As shown in Table 7, **PU → BI** had a moderate effect size (**f^2 = 0.06109**), whereas **PBC → BI** had a small but notable effect (**f^2 = 0.02894**). Conversely, **SN → BI** had a minimal impact (**f^2 = 0.00322**), and **PEU → BI** reported **no additional effect (f^2 = 0)**, likely because its influence was fully mediated through PU and ATU.

Table 6. Predictive relevance

	Q^2 predict	R-square
BI	0.619	0.689
ATU	0.549	0.627
PU	0.64	0.644

Table 7. Effect size

	f^2
PEU → BI	0
PU → BI	0.06109
SN → BI	0.00322
PBC → BI	0.02894

Out-of-Sample Predictive Performance (Q^2 and PLS-Predict)

To evaluate the model's predictive relevance, **Stone–Geisser's Q^2** values were obtained through blindfolding procedures. All the Q^2 values were above zero (Table 8), indicating **predictive relevance** for the key endogenous constructs [120]: **BI = 0.619**, **ATU = 0.549**, and **PU = 0.640** (see Table 6). These results confirm that the model demonstrates strong out-of-sample predictive ability [116] and performs well in explaining future observations, particularly for behavioral intentions. Further out-of-sample validation was conducted via 10-fold **PLS-Predict** (Table 8) to check for predictive relevance as per [116]. The root mean square error (RMSE) values for the BI indicators were compared between the PLS model and a linear regression benchmark (LM). The PLS-RMSE values were lower or comparable across all three BI items:

- **BI1**: PLS-RMSE = 0.607 vs. LM-RMSE = 0.602 (ΔRMSE = 0.005);
- **BI2**: PLS-RMSE = 0.612 vs. LM-RMSE = 0.622 (ΔRMSE = -0.010);
- **BI3**: PLS-RMSE = 0.634 vs. LM-RMSE = 0.645 (ΔRMSE = -0.011).

Table 8. PLS-Predict

Item	Q^2predict	PLS-RMSE	LM_RMSE	ΔRMSE
BI1	0.513	0.607	0.602	0.005
BI2	0.445	0.612	0.622	-0.01
BI3	0.445	0.634	0.645	-0.011

These results show that the **PLS method consistently outperforms or matches the linear model**, supporting the robustness of the proposed model in predicting digital banking behavior. The **negative ΔRMSE** values for BI2 and BI3 further confirm the superior predictive power of the PLS path model.

5- Discussion

The results largely support the Technology Acceptance Model (TAM) constructs, confirming prior studies such as Davis [38, 45, 46], which emphasize the importance of usability and usefulness in influencing technology adoption. PEU was found to significantly influence both PU and ATU, affirming the well-documented pathway where ease of use builds positive attitudes through a perception of value [44, 45]. PU's strong impact on both ATU and BI further validates the TAM structure in the Saudi banking context. Similar to the findings of [50-53], this suggests that even in culturally diverse settings, usefulness remains a universal predictor of digital engagement. In regard to attitudes (ATU) influencing behavioral intentions (BIs), the study aligns closely with [55-57], who confirmed ATU's central role across fintech and mobile banking environments. These supported hypotheses (H1–H5) show strong coherence with international findings, reinforcing the robustness of the TAM. In contrast, the TPB constructs—Subjective Norms (SN) and Perceived Behavioral Control (PBC)—did not significantly affect BI (H6, H7). This diverges from [67, 69, 71], who observed positive effects of SN in collectivist cultures. One explanation may lie in shifting cultural norms within Saudi Arabia, where digital decision-making may be becoming more individualized, particularly among younger populations. Additionally, although PBC was supported in [60, 73, 74], the sample may have included digitally confident users who did not perceive control as a barrier. A major contribution of this study is the confirmation of perceived web security (PWS) as a key moderator (H8). Echoing the findings of [79, 80, 91, 93], the results confirm that when users perceive a

platform as secure, their favorable attitude is more likely to lead to intention. In digital banking, this type of trust bridge is essential. However, the dual moderation effect with age (H9) was not supported, diverging from studies such as [94-96]. These earlier works suggested that older users would be more sensitive to security risks. A possible explanation is the widespread national digital literacy campaigns that may have minimized generational gaps, at least in terms of perceived web trust. Finally, the mediation paths (H10–H12) were all supported, reflecting previous findings by [53-55]. This strengthens the argument that TAM variables function best as a chain of influence, where usability leads to usefulness, which builds attitudes and ultimately results in intentions.

6- Conclusion

This study contributes to the understanding of digital banking adoption by empirically validating an extended TAM-TPB framework in the Saudi Arabian context. The model confirmed the dominance of usability, usefulness, and trust (PWS) as the strongest predictors of behavioral intention. These findings are consistent with major technology adoption literature and highlight the importance of focusing on the user experience in digital transformation initiatives. While traditional TPB elements such as subjective norms and perceived control do not hold in this context, the significant influence of perceived web security underscores the evolving nature of digital trust. The unsupported dual moderation by age challenges conventional assumptions about demographic influence, suggesting that security awareness may now be universally distributed across age groups. Practical implications suggest that banks should invest not only in digital interfaces but also in transparent and visible trust cues such as secure logins, verified platforms, and real-time fraud protection. Theoretical contributions include validating an integrated TAM-TPB model with layered moderation and proposing that behavioral intentions are best understood through both rational evaluation (TAM) and contextual risk perceptions (PWS).

6-1- Research Theoretical Implications

This study provides several theoretical contributions to the literature on technology acceptance and digital banking behavior:

- This research **extends the TAM and TPB** by incorporating perceived web security (PWS) as a moderator and examining dual moderation with age. This finding shows that traditional frameworks are enhanced by adding trust-based and demographic factors, particularly in fintech settings.
- **Clarification of the TPB Limits:** The lack of significance of subjective norms (SNs) and perceived behavioral control (PBC) raises questions about the applicability of the TPB in high-tech sectors such as digital banking, indicating that attitudes and perceived value may outweigh social pressures.
- The findings **confirm that technology adoption** follows a cognitive-emotional sequence (PEU → PU → ATU → BI), supporting the need to view perceptions as accumulating into intention over time.

6-2- Practical Implications

- **Prioritize User-Friendly Design:** Banks and fintech should simplify digital interfaces. Usability boosts perceived usefulness and enhances adoption.
- **Perceived security** can be enhanced by making features such as two-factor authentication and digital certificates visible and understandable to users, with a focus on safety education in UX design.
- **Individual attitudes and perceived benefits in marketing** rather than social norms should be targeted. Personalized onboarding may be more effective than group promotions.
- **Avoiding Age-Based Stereotyping:** Age does not significantly moderate behavior regarding security perceptions, so assumptions about generational adoption should be rethought. Fintech solutions should be designed with universal trust elements.

6-3- Limitations and Future Research Directions

While this study makes significant contributions, several limitations should be acknowledged:

1. **Cross-Sectional Design:** Data collected at one time limit the inference of causality and the observation of changes. Future research should consider a longitudinal approach to better capture behavioral evolution.
2. **Self-reported data** can introduce bias, especially regarding perceived control or security. Actual usage behaviors, such as login frequency and transaction volume, should be monitored when feasible.
3. **The sample focuses** on users in Saudi Arabia, limiting generalizability. While it is a fintech leader in the Middle East, cultural and infrastructural differences exist. Future studies could analyze comparisons across Gulf or MENA regions.
4. **The limited moderators** tested included only the PWS and age. Future research may examine digital literacy, institutional trust, or gender-based digital comfort.
5. The study examined digital banking broadly. Future work could analyze specific technology types (e.g., mobile apps vs. internet banking) to determine whether adoption patterns vary by delivery channel.

7- Declarations

7-1- Data Availability Statement

The data presented in this study are available on request from the corresponding author.

7-2- Funding

The author received no financial support for the research, authorship, and/or publication of this article.

7-3- Acknowledgements

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7-4- Institutional Review Board Statement

Not applicable.

7-5- Informed Consent Statement

All participants provided informed consent at the beginning of the questionnaire. This study gathered information exclusively from bank customers in Saudi Arabia. The participants received detailed information about the research goals before participating. Participation was voluntary, and respondents completed the questionnaire only after reviewing the information addressing concerns about digital banking. Informed consent is critical to ensure that participants understand the study's objectives.

7-6- Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the author.

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