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Artificial Intelligent Applications in Enabled Banking Services: The Next Frontier of Customer Engagement in the Era of ChatGPT

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Abstract

The recent global changes in Information and Communications Technology (ICT), have demonstrated a tremendous range of technological use cases including the use of Artificial Intelligent (AI) applications (apps) for financial services. In light of the latest developments of generative AI tools such as ChatGPT, this study develops an innovative research model used for the prediction of the most significant factors influencing consumers' willingness to accept and willingness to buy generative AI banking apps, under the theory of the Value-based Adoption Model (VAM). The authors have conducted an online survey of Greek consumers of AI banking apps using Structural Equation Modeling (SEM) to determine which variables enhance customers' perceived value performing significant influence on AI banking apps adoption and willingness to purchase. This research found that trust and happiness are the most significant variables impacting the intention to use and buy conversational AI banking apps. The most likely outcome is the mediating role of consumers' perceived value in willingness to accept and pay using AI banking apps. The conclusions and implications for marketing can help financial institutions augment the accuracy of the audit and advisory services, enhancing customer satisfaction and engagement and increasing bank competitiveness.

Keywords

Artificial Intelligent Banking Applications, Value-Based Adoption Model, Willingness to Accept, Willingness to Pay

1. Introduction

The rapid diffusion of generative AI tools such as chatbots, like ChatGPT, created by the integration of deep learning and language models based on the

Generative Pre-training Transformer (GPT) architecture, consists of emerging technology set to change the landscape of conversation agents (Thorp, 2023). In light of the latest developments, a new field of research delineates the necessity of specific knowledge concerning this massive revolution of AI apps in services. It is a fact that past developments in robotics and current achievements in AI and big data increasingly allow the banking industry to introduce AI financial apps engaging customers in semi-customized service experiences. Numerous banks have created their own AI service apps providing assistance to customers fulfilling their financial tasks, largely moving from cash to digital transactions, enhancing the perceived value of the experience. Judging by the financial data provided by Statista (Statista.com, 2017), the global digital payments sector has evolved tremendously over the past few years valued over $3 trillion in 2017, $4.7 trillion over the following two years, and $6.6 trillion by 2021. It is a fact that the global e-market is expected to reach $12.55 trillion from 2021 to 2027 (Magoutas et al., 2022).

In Greece, commercial banks are expanding their client base by using digital marketing to reach citizens who previously did not use banking services. Observing the growing importance of AI app evolution financial institutions have continually been applying the new technological achievements into business enhancing customer service efficiency. Since the Covid-19 pandemic has prompted more clients to turn to digital banking for financial services due to the curfews and branch closures, Greek commercial banks have expanded their client base by using digital marketing. Positive emotions significantly influence customers to pay for products or services and accept the use of AI apps in businesses, according to consumer research (Pal et al., 2023). In addition, researchers have identified that although banking companies and customers have all beneficiaries transformed (Stocchi et al., 2021) from using mobile apps completing their daily tasks, perceived risk affects negatively customer satisfaction and customer experience (Kar, 2020), implying that as perceived sacrifices increase, consumers are less likely to accept the use of technology. On the contrary, perceived value is a significant driver enhancing not only the customer experience (Mbama et al. 2018), but it also impacts on customers satisfaction (Sukendia et al., 2021).

Many scholars have researched online banking services over the last 13 years. We have selected a few of the most recent studies which highlight the importance of AI in banking services and the crucial role of AI assistant chatbots (Rahman et al., 2021), the effectiveness of banking applications, and the efficacies of AI-based financial mechanisms (Priya & Sharma, 2023), the e-service quality of internet banking and the relationship with customer satisfaction (Singh, 2019), the role of AI in aligning financial services through a single AI-centric channel (Kaneria, 2022), and the role of AI in personalized banking services (Paul et al., 2021). While significant contributions have been made to the literature of banking services, none of them has explained which are the drivers that impact the intention to use and buy conversational AI banking apps based on the model for adopting technology based on value. In order to define the most significant factors influencing consumers' willingness to accept and willingness to buy generative AI banking apps, this study empirically examines consumers interaction with Greek commercial banks AI apps from the Value-based Adoption Model (VAM) perspective (Kim & Malhotra, 2007). Since none of the previous studies has examined the WTA, and WTP using banking apps, through the lenses of the value maximization perspective, the present study fills this gap. The study reveals that since in AI environment the main factors describing the Perceived Benefits (PB) are Happiness (HAP) and Perceived Immersion (PIM), while Trust (TST) and Perceived Security (PS) represent the Perceived Sacrifices (PES) of the reconstructed VAM model. The proposed framework investigates the reflected relationships between the independent factors with the WTA and the WTP using AI banking apps, further examining if consumers' PV mediates the relationship between PB, PES and acceptance and purchase intention of banking apps.

The article is organized as follows. The introduction is followed by the literature review. The next section focuses on the hypotheses development and the conceptual model. This is followed by the methodology used. The results of the study are presented after that, while the discussion of the findings follows subsequently. The conclusions, implications, and limitations are contained in the last section.

2. Literature Review

2.1. Banking Apps

AI banking apps could be defined as the special software applications that can be downloaded on devices like smartphones or tablets from the mobile applications' stores like App Store for Apple ios software, or Google Play functioning with android software respectively. More specifically, AI banking apps are developed to satisfy the most relevant customer needs (Bradley & Stewart, 2003). Some of the benefits using banking apps are e-services available to customers, including balance info, remote payments, and real-time transfer tracking (Salihu & Metin, 2017). Using this electronic customer interface benefits banks by reducing labor costs, minimizing consumer wait times, and increasing profits. However, software breakdowns, maintenance problems, and internet security issues prevent new customers from trusting AI banking apps (Glikson & Woolley, 2020).

2.2. The Value-Adoption Model

The model for adopting AI technology based on the value proposes that people choose behavior with the highest payoff by comparing benefits with sacrifices (Vishwakarma et al., 2020). According to the Cognitive Evaluation Theory, both extrinsic and intrinsic motivations of consumers can influence their perceived value (PV) and behavioral intention. We decided not to examine the well-known Technology Adoption Model (TAM) framework, since it has been extensively used in previous researches to explain how employees use traditional technologies. Since individuals adopt new generative AI technology for work and personal use, the value function is defined over perceived gain or loss relative to a reference point. The VAM framework is a highly utilized tool in research, among others, in virtual reality (Vishwakarma et al., 2020), social media (Chung & Koo, 2015), and augmented reality (Luo et al., 2020). It has been thoroughly tested and has proven to be exceptionally efficient in modeling consumer acceptance (Sohn & Kwon, 2020; Kim et al., 2021).

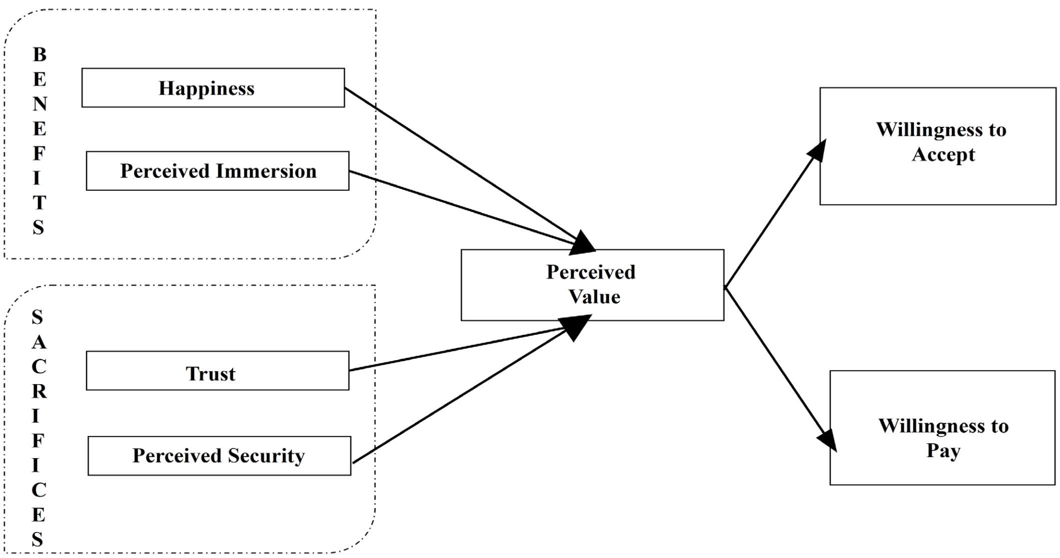
The proposed framework presents a multistep decision-making process that takes into account the value-oriented relationship between Benefits-PV-WTA, Benefits-PV-WTP, Sacrifices-PV-WTA, and Sacrifices-PV-WTP. Thus, the acceptance of using and paying for generative AI banking apps is connected with factors that positively impact the PB and the PES.

3. Hypotheses and Conceptual Framework

The study proposes an augmented research framework of perceived value based on PB and PES of the VAM (**Figure 1**). By adopting the theory of consumer choice and decision-making from economics and marketing research, this study extends the VAM and explains customers' AI banking apps adoption from the value maximization perspective, which illustrates a major organizational challenge (Slater & Wilbur, 1997).

3.1. Measuring the Effect of Perceived Benefits

The advantages brought by using AI banking apps are described as PB. We



(Source: Figure created by the authors with input taken from the hypothesis framework).

Figure 1. The conceptual model.

examine two different motives for adopting the AI banking app technology: Happiness (HAP) and Perceived Immersion (PIM). Since HAP is an important sub-dimension of PB (Venkatesh et al., 2012) there are many studies supporting that HAP has a positive impact on WTA. When individuals experience higher levels of HAP, they appear to be more open-minded and willing to accept new ideas (Middlewood et al., 2016). According to Hu et al. (2021) inner incentives describe the HAP of using new ICT achievements providing evidence to foretell consumers' technology use in the market. Since researchers (Helliwell et al., 2020) found a positive relationship between HAP and acceptance of change it is hypothesized that HAP has a positive impact on WTA the use of AI banking apps (H1a), HAP has a positive impact on PV using AI banking apps (H1b) and HAP has a positive impact on WTP (H1c).

H1a. Happiness positively affects Willingness to accept.

H1b. Happiness positively affects Perceived value.

H1c. Happiness positively affects Willingness to pay.

Immersion is the neurologic state in which a person is attentive to an experience and it resonates emotionally (Zak, 2022). Sung et al. (2021) also supported that consumers' emotional states influence the behavioral intentions of a potential consumer. Individuals perceiving high levels of immersion in a virtual environment are more likely to get engaged with novel concepts (Slater, 1997). Since more research is needed to establish a determinative relationship, we hypothesize that PIM positively impacts WTA's use of AI banking apps (H2a). Hypothesis H2b illustrates that PIM has a positive impact on PV using AI banking apps and H2c suggests that PIM has a positive impact on WTP.

H2a. Perceived Immersion positively affects Willingness to accept.

H2b. Perceived Immersion positively affects Perceived value.

H2c. Perceived Immersion positively affects Willingness to pay.

3.2. Measuring the Effect of Perceived Sacrifices

Regarding the impact of factors contributing to PES of AI banking apps use we then focus on consumer Trust (TST) and Perceived Security (PS). Whereas consumers may suffer a leak of personal data while using AI apps, there is a hidden risk created by the lack of TST becoming one of the main reasons why consumers avoid using the new technology (Keen, 1999). TST is an essential substance for effective relationships in marketing (Sekhon et al., 2014). Consumers who initially use a new technological product are more likely to continue its use and trust it (Wang & Siau, 2022). Thus, it is hypothesized that TST has a positive impact on WTA the use of AI banking apps (H3a), TST has a positive impact on PV to use AI banking apps (H3b), and TST has a positive impact on WTP (H3c).

H3a. Trust positively affects Willingness to accept.

H3b. Trust positively affects Perceived value.

H3c. Trust positively affects Willingness to pay.

PS refers to the risk of experiencing abuse of personal billing information, related to mobile transactions (Ooi & Tan, 2016). Hence, this is one basic reason why PS is considered to be a fundamental factor of PES while adopting new technological achievements. It is then hypothesized that PS has a positive impact on WTA the use of AI banking apps (H4a), PS has a positive impact on PV to use AI banking apps (H4b) and PS has a positive impact on WTP (H4c).

H4a. Perceived security positively affects Willingness to accept.

H4b. Perceived security positively affects Perceived value.

H4c. Perceived security positively affects Willingness to pay.

3.3. Exploring the Relationship between Perceived Value, Acceptance, and Purchase Intention

Several studies also establish that PV positively affects usage acceptance and purchase intention as a desirable customer behavior (Rust & Huang, 2012). However, PV was found to be one of the most important predictors in the adoption of virtual reality (Vishwakarma et al., 2020). Based on the VAM, the PV is measured when we count the benefits and the sacrifices compared to the final result (Bradley & Stewart, 2003). Hence, it is hypothesized that PV is likely to lead in WTA (H5) and WTP (H6).

H5. Perceived value positively affects Willingness to accept.

H6. Perceived value positively affects Willingness to pay.

Since previous researchers (Sohn & Kwon, 2020) tested the VAM they assumed that PV is a significant predictor in innovative ICT achievements' adoption. Thus, we hypothesize that the PV mediates the relationship between all indicators and the WTA (H5a-H5d) and that the PV mediates the relationship between all indicators and the WTP (H6a-H6d).

H5a. Perceived value mediates the relationship between Happiness and Willingness to accept.

H5b. Perceived value mediates the relationship between Perceived Immersion and Willingness to accept.

H5c. Perceived value mediates the relationship between Trust and Willingness to accept.

H5d. Perceived value mediates the relationship between Perceived security and Willingness to accept.

H6a. Perceived value mediates the relationship between Happiness and Willingness to pay.

H6b. Perceived value mediates the relationship between Perceived Immersion and Willingness to pay.

H6c. Perceived value mediates the relationship between Trust and Willingness to pay.

H6d. Perceived value mediates the relationship between Perceived security and Willingness to pay.

4. Methodology

4.1. Data Collection and Pre-Testing

The items for all the constructs were extracted from previously validated studies, such as that on HAP (Van Boven & Gilovich, 2003), PIM (Jennett et al., 2008), TST (Gefen, Karahanna, & Straub, 2003), PS (Luarn & Lin, 2005), (Parasuraman et al., 2005), (Schierz et al., 2010), and PV (Sirdeshmukh et al., 2002), WTA (Lu et al., 2019), (Venkatesh, Thong, & Xu, 2012), and finally WTP (Laroche et al., 2003). Five-point Likert scales were used to assess all constructs. All the items were slightly modified to suit the AI banking apps context. Then, the questionnaire was pretested by circulating a survey to 33 AI banking app users via an online questionnaire instrument using Qualtrics. Two screening questions were asked to confirm that the respondents had downloaded the AI app of their basic bank account on their device and were capable of participating in the research. The final section concluded by asking questions about demographic information, level of education, and income (**Table 1**). The questionnaire was then finalized following its latter structure. We distributed 550 questionnaires in four months and received 506 responses. Of these responses, 98 were excluded from the data analysis because they contained unengaged responses and missing information. Therefore, the sample size used in this study consisted of 408 respondents (response rate of 74%) is ideal since it complies with the Cochran formula (Cochran, 1977), as shown in Equations (1) and (2), representing all the targeted population.

$$n_0 = \frac{z^2 pq}{e^2} \tag{1}$$

z = z-value

p = population

$q = 1 - p$

e = adequate sample error

$$n = \frac{(1.96)^2 (0.5)(0.5)}{(0.05)^2} = 384.16 \tag{2}$$

4.2. Data Analysis and Common Method Bias

The present research used IBM SPSS Statistics version 28.0 to analyze the demographics and the common method bias. The research used the PLS-SEM technique to analyze the data and the hypotheses proposed in the model through the Smart PLS software version 4.0.9.2 (Hair et al., 2017). Method bias, a significant concern in behavioral studies, emerges when fluctuations in responses are prompted by the measurement tool itself rather than the genuine inclinations of the participants that the tool aims to uncover. To tackle this matter, our initial step involved incorporating a segment within the questionnaire elucidating the absolute confidentiality of the answers, emphasizing the absence of inherently

Table 1. Demographic characteristics.

Items	Frequency (N = 408)	%
Gender		
Male	216	53%
Female	192	47%
Age		
Younger than 18 years	0	0%
19 - 30	86	21%
31 - 40	151	37%
41 - 50	118	29%
51 - 60	33	8%
61 - 70	12	3%
Over 70 years	8	2%
Education		
High School	20	5%
Vocational Diploma	20	5%
University Degree	258	63%
Master's Degree	98	24%
PhD	12	3%
Income		
Less than 1.000 euros	45	11%
1.001 - 1.800 euros	188	46%
1.801 - 2.500 euros	16	4%
2.501 - 3.200 euros	4	1%
More than 3.200 euros	8	2%
Prefer not to answer	147	36%
I have downloaded the AI application of my bank account		
Yes	408	100%
Favorite ICT device		
Mobile phone	298	73%
Tablet	16	4%
PC	86	21%
Smartwatch	8	2%

correct or incorrect responses. Moreover, participants were instructed to maintain a neutral and truthful stance while completing the survey. Subsequently, we employed Harman's single-factor technique as a secondary measure. The Variance Extracted using one factor is 8.806%, less than 50%, confirming that no factor accounted for the majority of the covariance between the measures, indicating no common method bias in this study (Podsakoff et al., 2003).

5. Results

5.1. Descriptive Data Analysis

Regarding descriptive analysis, for HAP, the mean value of 3.57 and the standard deviation (STD) of ±1.099 show that average respondents fell in agreement with statements with variation (2.47 to 4.66), respectively. The mean value for the immersion is 3.55, and the standard deviation is ±1.110, showing that this deviation ranges from 2.44 to 4.66. This suggests that agreed statements were observed. Considering the mean value of TST = 3.58 and the STD of ±1.125 that average participants replied with variation between 2.45 to 4.7. As for the mean value of PS = 3.53, the standard deviation of ±1.089 demonstrates the deviation ranging from 2.44 to 4.61. Regarding the PV, the mean value of 3.55 shows that, on average, they went for positively agreed with the statements. Also, the standard deviation of ±1.105 shows that it ranges from 2.44 to 4.65, while the mean value of WTA = 3.5, STD ± 1.154 demonstrates the deviation ranging from 2.34 to 4.65. Lastly, for WTP, the mean value of 3.53 and the STD of ±1.17 show that average respondents fell in agreement with statements with variation (2.36 to 4.7), displayed in **Table 2**.

5.2. Assessment of Measurement Model

The measurement model was designed to measure item reliability, internal consistency of the reliability of the constructs, convergent validity, and discriminant validity (Fornell & Larcker, 1981). We verified the scales' reliability and convergent validity by employing the normal criteria: item reliability of the measures by using factor loading (>0.704), Cronbach's alpha, and the Composite Reliability (CR) of the constructs (>0.7), and the Average Variance Extracted (AVE) (>0.5). The latent item loadings ranged from 0.717 to 0.834, showing statistical

Table 2. Descriptive statistics.

Constructs	Mean	STD	Skewness	Kurtosis
HAP	3.57	1.099	−0.647	−0.173
PIM	3.55	1.110	−0.617	−0.238
TST	3.58	1.125	−0.646	−0.226
PS	3.53	1.089	−0.592	−0.221
PV	3.55	1.105	−0.637	−0.208
WTA	3.50	1.154	−0.616	−0.311
WTP	3.53	1.17	−0.62	−0.33

significance. Cronbach's alpha ranged from 0.704 to 0.834, and CR ranged from 0.834 to 0.888, confirming their reliability. Moreover, AVE ranged from 0.557 to 0.652, above the threshold level of 0.50, which indicates that there is convergent validity of the variables included in the model. Table 3 represents all these values.

For discriminant validity, we applied two methods. First, we applied the Fornell and Larcker method, as shown in Table 4, where the values on the diagonal representing the square root of the AVE are: HAP = 0.8075, PIM = 0.778, PS =

Table 3. Reliability and validity analysis.

Construct	Items	Loading > 0.704	Alpha > 0.7	CR > 0.7	AVE > 0.5
HAP	HAP_1	0.834	0.733	0.849	0.652
	HAP_2	0.778			
	HAP_3	0.809			
PIM	PIM_1	0.764	0.782	0.859	0.605
	PIM_2	0.763			
	PIM_3	0.767			
	PIM_4	0.815			
PS	PS_1	0.759	0.704	0.834	0.626
	PS_2	0.793			
	PS_3	0.821			
PV	PV_1	0.791	0.724	0.844	0.644
	PV_2	0.83			
	PV_3	0.786			
TST	TST_1	0.741	0.801	0.863	0.557
	TST_2	0.759			
	TST_3	0.719			
	TST_4	0.757			
	TST_5	0.754			
WTA	WTA_1	0.765	0.849	0.888	0.57
	WTA_2	0.767			
	WTA_3	0.762			
	WTA_4	0.756			
	WTA_5	0.763			
	WTA_6	0.717			
WTP	WTP_1	0.811	0.732	0.848	0.65
	WTP_2	0.814			
	WTP_3	0.794			

0.7912, PV = 0.8025, TST = 0.7463, WTA = 0.755, and WTP = 0.8062, indicating discriminant validity in our research (Fornell & Larcker, 1981).

Table 5 shows the results of the second method, Heterotrait-Monotrait (HTMT) which was also applied to evaluate discriminant validity. According to Henseler et al. (2015) HTMT values lower than 0.85 indicating discriminant validity, by measuring the ability of a set of measures to distinguish between different constructs.

5.3. Assessment of the Structural Model

Then the structural model was carried out to test the direct and the indirect effect. Figure 2 shows the structural model of the research. To test the hypotheses, the statistical bootstrap technique was applied with the recommended 5000 sample size.

The hypotheses H1a-H1c, as shown in Table 6, are being supported since the standardized β regression weights are significant and positive (β = 0.146, 0.179, and 0.141 i.e., WTA, PV, and WTP) which means that the inner impulse of HAP appears to be one the most significant factors of AI technology acceptance (Kim & Malhotra, 2007). The results outlined that the hypotheses H2a-H2c, named

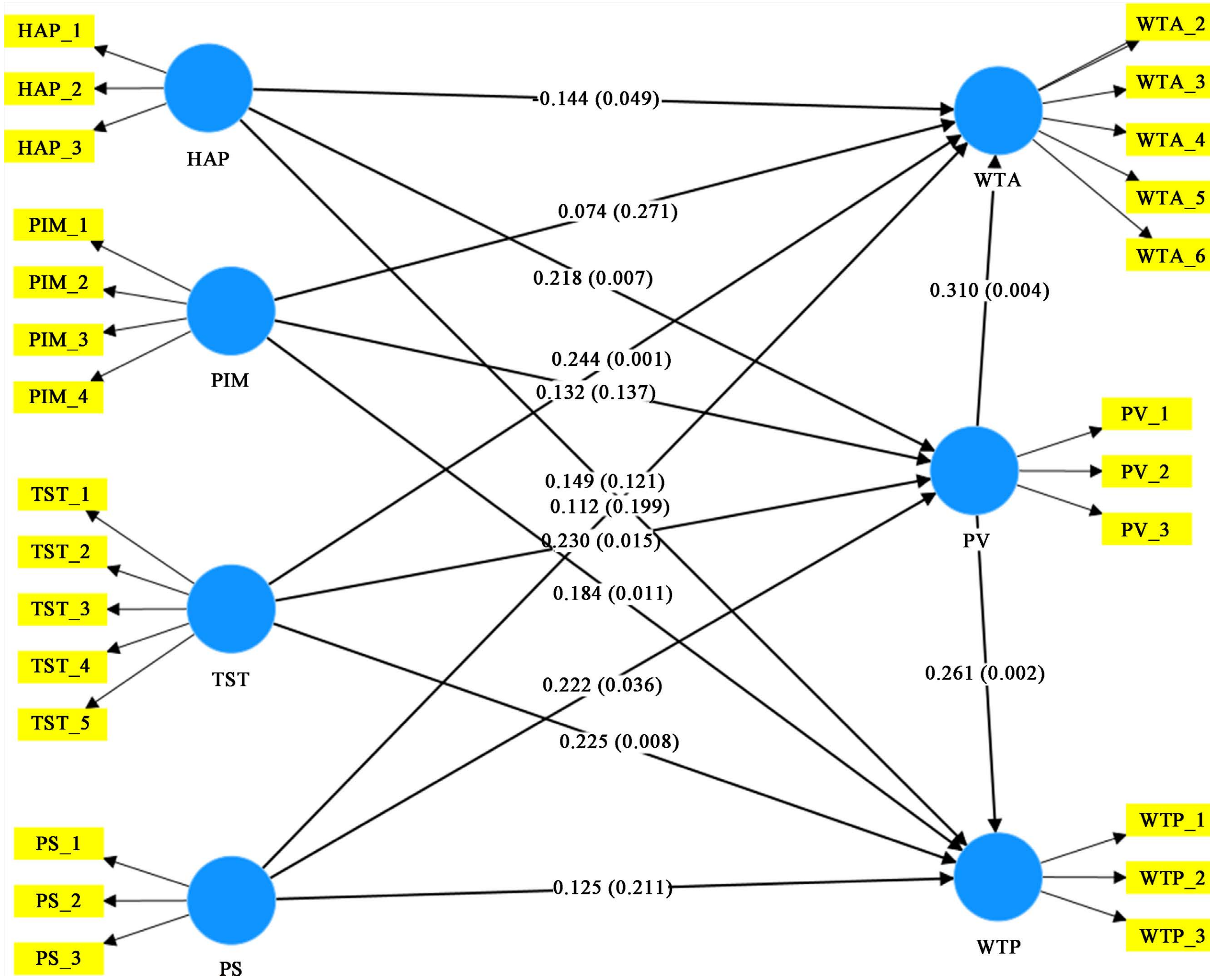
Table 4. Discriminant validity analysis (Fornel Larcker).

Constructs	1	2	3	4	5	6	7
HAP	0.8075						
PIM	0.426	0.7778					
PS	0.433	0.468	0.7912				
PV	0.408	0.402	0.418	0.8025			
TST	0.444	0.48	0.476	0.44	0.7463		
WTA	0.448	0.439	0.45	0.5	0.513	0.755	
WTP	0.442	0.47	0.45	0.47	0.499	0.422	0.8062

Note: Values on the diagonal (italicized) represent the square root of the average variance extracted, while the off diagonals are correlations.

Table 5. HTMT ratio.

Constructs	HAP	PIM	PS	PV	TST	WTA	WTP
HAP							
PIM	0.56						
PS	0.597	0.637					
PV	0.558	0.532	0.578				
TST	0.578	0.606	0.627	0.575			
WTA	0.565	0.537	0.572	0.633	0.62		
WTP	0.604	0.621	0.617	0.64	0.649	0.532	



Source: Figure created by the authors extracted by the PLS-SEM software presenting the results of the model.

Figure 2. Graphical representation of the structural model.

PIM (β = 0.111, 0.145, and 0.172) directly enhance customers' adoption of AI apps, WTA, and PV suggesting that customers are likely to be effectively committed when experiencing perceived immersion. The results support H3a, H3b, and H3c as TST is the variable that mostly impacts WTA, PV, and WTP supporting standardized β regression weights equal to β = 0.228, 0.208, 0.206, respectively. In addition, the support for H4a, H4b, and H4c indicates that PS has a positive and significant impact on WTA, PV, and WTP, since avoiding the risk of getting customers' personal financial abused may predict the acceptance of using and purchasing new AI apps. The results outlined that both hypotheses H5 and H6 named PV (β = 0.243 and β = 0.200) directly lead to WTA and WTP attitude, evaluating acceptance of AI banking app use.

Concerning the influence of the mediator variable of PV on WTA and WTP performance, consumer behavior based on PV has a positive and significant influence on adopting AI apps estimated as HAP -> PV -> WTA (β = 0.043), PIM

-> PV -> WTA (β = 0.035), TST -> PV -> WTA (β = 0.051), PS -> PV -> WTA (β = 0.042). The mediation effect results, supporting H5a-H5d, are shown in Table 7. Admittedly, when consumers obtain PV, they are feeling satisfaction and willingness to adopt and pay using those AI banking apps. Additionally, the results are similar for H6a, H6b, H6c, and H6d since PV mediates the relationship between the estimated HAP -> PV -> WTP (β = 0.036), PIM -> PV -> WTP (β = 0.029), TST -> PV -> WTP (β = 0.042), PS -> PV -> WTP (β = 0.035), showing that the PV a customer obtains may enhance the willingness to purchase banking

Table 6. Hypotheses testing direct effects.

Hypothesis	Direct Relationships	Std. Beta	Std. Error	*p* values	Result
H1a	HAP -> WTA	0.146	0.041	***	Supported
H1b	HAP -> PV	0.179	0.042	***	Supported
H1c	HAP -> WTP	0.141	0.05	**	Supported
H2a	PIM -> WTA	0.111	0.042	**	Supported
H2b	PIM -> PV	0.145	0.049	**	Supported
H2c	PIM -> WTP	0.172	0.039	***	Supported
H3a	TST -> WTA	0.228	0.04	***	Supported
H3b	TST -> PV	0.208	0.05	***	Supported
H3c	TST -> WTP	0.206	0.044	***	Supported
H4a	PS -> WTA	0.124	0.042	**	Supported
H4b	PS -> PV	0.173	0.046	***	Supported
H4c	PS -> WTP	0.126	0.045	**	Supported
H5	PV -> WTA	0.243	0.062	***	Supported
H6	PV -> WTP	0.200	0.041	***	Supported

*Indicates significant paths: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$, NS = not significant.

Table 7. Hypotheses testing mediation effect.

Hypothesis	Indirect Effects	Std. Beta	Std. Error	*p* values	Result
H5a	HAP -> PV -> WTA	0.043	0.014	**	Supported
H5b	PIM -> PV -> WTA	0.035	0.014	**	Supported
H5c	TST -> PV -> WTA	0.051	0.018	**	Supported
H5d	PS -> PV -> WTP	0.035	0.012	**	Supported
H6a	HAP -> PV -> WTP	0.036	0.012	**	Supported
H6b	PIM -> PV -> WTP	0.029	0.012	**	Supported
H6c	TST -> PV -> WTP	0.042	0.013	**	Supported
H6d	PS -> PV -> WTA	0.042	0.016	**	Supported

*Indicates significant paths: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$, NS = not significant.

conversational AI app.

As for the quality criteria, the results show that PV latent variable explains 45.3% (R^2 = 0.453) of the variability in the data, where the PV Adjusted R-squared (R^2 Adj. = 0.447) takes into account the number of predictors, suggesting that after adjusting for the predictors, approximately 44.7% of the variation is explained (**Table 8**). For WTA, the R^2 value is 0.534, indicating that around 53% of the variation in the data can be explained by the WTA latent variable. Moreover, the R^2Adj. value of WTA suggests that approximately 52.8% of the variation is explained after adjusting the predictors. Lastly, since the WTP variable has an R^2 value of 0.595, the WTP latent variable can explain approximately 59.5% of the variation in the data. The WTP R^2 Adj. value of 0.59, accounting for the number of predictors, indicates that around 59% of the variation is explained after adjusting the predictors.

Whereas R^2 measures predictive capacity, Q^2 measures predictive relevance. It is shown that all Q^2 values are positive (Ringle et al., 2015) ranging from 0.28 to 0.354, indicating that the model has predictive capacity suggesting a relatively higher level of predictive ability for the WTP variable compared to the other two variables. More specifically, the Q^2 value of 0.28 suggests a moderate level of predictive ability for the PV variable. The Q^2 value of 0.352 suggests a higher

Table 8. R^2, F^2 and Q^2.

Latent variables	R^2	R^2 Adj.	Q^2	F^2
WTA	0.534	0.528	0.352	
PV	0.453	0.447	0.28	
WTP	0.595	0.59	0.354	
HAP -> WTA				0.023
HAP -> PV				0.048
HAP -> WTP				0.029
PIM -> WTA				0.006
PIM -> PV				0.016
PIM -> WTP				0.042
PS -> WTA				0.012
PS -> PV				0.042
PS -> WTP				0.017
TST -> WTA				0.061
TST -> PV				0.048
TST -> WTP				0.059
PV -> WTA				0.113
PV -> WTP				0.092

level of predictive ability for the WTA variable. The Q^2 value of 0.354 suggests a relatively higher level of predictive ability for the WTP variable compared to the other two variables. The F^2 values range from 0.006 to 0.113 indicating the magnitude of the relationships between the variables, suggesting small to medium effect sizes showing that the relationships between the variables have a relatively modest impact or influence on each other.

6. Discussion

In this study, we investigate consumers' willingness to adopt AI banking apps by measuring the benefits and sacrifices, using a value maximization perspective, which mediates behavioral intentions affecting willingness to accept and pay for AI banking apps. We offer empirical evidence of the mediating role of perceived value in augmenting sales, contributing to business success, supporting the claim that financial institutions directly impact customers' value assessment (Dwivedi et al., 2021). By integrating the most relevant findings of AI adoption, our proposed and empirically tested framework for AI banking apps represents an innovative approach to understanding consumers' acceptance and willingness to purchase AI apps in the era of ChatGPT.

In the marketing concept, observing customer acceptance behavior towards the adoption of ChatGPT in financial services should be a priority for practitioners in the banking industry due to its mediating role in customer-perceived value (Lucey & Dowling, 2023). Since banks are well-known for embracing technology and adapting their processes accordingly (Abdulquadri et al., 2021), we assume that banking apps wishing to improve their customers' acceptance need to carefully adopt an orientation that creates feelings of happiness and trust in consumers. In banking surroundings, optimizing customer experience will continue to require technological inspiration melted into various aspects of services. Banks will always be essential in providing financial services and generating mutually beneficial data from customer engagement (Soetan et al., 2021).

Our results corroborate studies emphasizing the necessity of introducing customer orientation of the use of AI in services marketing acknowledging consumers' emotional interactions and perceptions. Fulfilling consumer needs will become a major issue when numerous banks decide to become digital, closing their physical branches, embracing financial technology to streaming operations (Nguyen & Mogaji, 2022). Banking services thrive on providing interpersonal interactions to create customer value. Thus, the important role of the banking sector is highlighted by the large number of processed customers' data, providing personalized services. Therefore, it is crucial for banks to effectively use ChatGPT's prospects and implications, since trust in service provision will be paramount (van Esterik-Plasmeijer & Van Raaij, 2017). Considering the high regulations in the sector of retail financial services for the claims being made by ChatGPT, banks should invest in human resources to aid in digital transformation (Diener & Špaček, 2021). Marketing communications should not rely solely on ChatGPT technology; banks directors and practitioners should consider of taking advantage the human involvement, as a necessary step to verify the trustworthiness of the available insights and the personalized offers.

7. Conclusion

Since in marketing, the creation of customer value must be the reason for the company's existence and certainly for its success (Sung et al., 2021), hence the study proposed and empirically tested a VAM of AI banking apps by integrating the most relevant findings of the ICT technology adoption and value literature. The combined framework represents a novel approach to understanding consumers' acceptance and willingness to buy conversational AI banking apps. The results showed that as customer perceived value is a driver for acceptance behavior it is suggested that its mediating role derived from the proposed model, should alert the banking industry to observe customer acceptance behavior when dealing with the adoption of ICT innovations, such as language models based on the GPT architecture.

The present study examined how AI application in the area of banking can effectively understand consumers' needs leading them to use AI apps for essential services. This research investigated the willingness of acceptance and the willingness to purchase AI banking apps as an impact of consumers' value perceived. It revealed that the mediating role of PV offers empirical evidence of this acceptance of AI app use and it may augment sales leading to business success, implying that banks directly impact customers' value assessment. The acceptance of AI technology is driven by the desire to multiply happiness. When customers have positive experiences, they are more likely to commit. Taking into account that experienced value in use is a dynamic concept that changes over time (Mustak et al., 2021), it is explained that consumer behavior based on this value greatly influences the adoption of AI banking apps. When customers experience PV, they feel satisfied and willing to adopt and pay for AI apps, especially those apps designed for banking services. However, further research is needed to fully understand this concept. Our results corroborate studies emphasizing the necessity of introducing the use of AI in services marketing (Khan & Dewan, 2014), acknowledging consumer's emotional interactions and perceptions, fulfilling consumer needs, strengthening customer engagement, moving one step forward the science of marketing.

Nevertheless, the current research has several limitations. First, a structured questionnaire was used to assess Greek AI banking apps between January to April. Given that it may limit customers' expression, future research may employ a mixed-methods approach. Second, this study investigated HAP, PIM, TST, PS, and PV, as outcomes of WTA and WTP. Further research could investigate the impact of other antecedents of WTA on the use of AI apps and the WTP to use AI apps that can be added to the current framework increasing the model's predictive power. Further studies focusing on specific sectors or industries would help generalize the strategic importance of AI-enabled technology which has metamorphosed customer-company interaction through reality-enhancing online interfaces (Haenlein & Kaplan, 2021).

In the coming future, banking apps are expected to have a very bright future. Industries using special apps will have the ability to stay ahead of the latest trends in the dynamic landscape of AI developments. Additionally, failure to adopt cutting-edge digital technology that meets customer demand would likely hinder sales and cause businesses to lag behind. As such, companies wishing to improve their customers' acceptance need to carefully adopt an orientation to ensure that they create feelings of trust and happiness in customers. Since in service surroundings, it is a fact that customer experience in service environments requires technology to be integrated into various aspects of communication, and innovators strive to create customer value through interpersonal interactions (Sirdeshmukh et al., 2002).

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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