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Digital Financial Literacy and AI-Driven Digital Finance Adoption: The Mediating Role of Customer Value Proposition in the Banking Industry in Cameroon

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Abstract

The rapid integration of artificial intelligence (AI) in digital finance has transformed the banking landscape, necessitating a deeper understanding of the factors influencing its adoption. This study investigates the effect of digital financial literacy on customers' intention to adopt AI-driven digital finance, with customer value proposition (CVP) serving as a mediating variable. Surveys were employed to collect data from 466 banking customers in Cameroon, which were analyzed using partial least squares-based structural equation modeling (PLS-SEM). It was revealed that DFL influences CVP, including Functional, Benefit, Symbolic and Emotional Value, which are involved in the intention to use digital finance. The mediation of the nexus between DFL and the intention to use digital finance was carried out using the four dimensions of CVP. Theoretical and practical insights into the development of digital finance services in a developing country are provided by this study's findings. Theoretically, the research on drivers of the customer value proposition in financial services is extended. As practical implications, financial institutions are advised to focus on emotional and symbolic values such as brand image, customer experience, and trust. It is also recommended that the government and institutions continue activities that promote digital financial literacy.

Keywords: digital financial literacy, banking industry, artificial intelligence, customer value proposition, adoption intention

1. Introduction

The banking industry has witnessed a significant transformation with the advent of digital finance, driven by technological advancements and changing customer expectations (Gomber et al., 2018). Artificial intelligence (AI) has emerged as a key driver of digital finance, enabling banks to offer personalized services, improve operational efficiency, and enhance customer experience (Kumar et al., 2022). However, the adoption of AI-driven digital finance remains a challenge, with digital financial literacy and customer value proposition (CVP) playing a crucial role in shaping customers' intentions (Ajzen, 1991).

Financial inclusion is sought through digital finance, which is expected to encourage access to appropriate and affordable financial services by all members of the population in order to ensure a sustainable economy, income equality, and poverty alleviation, aligning with one of the main goals of the SDGs. One of the promising technologies in digital finance technology 4.0 is Artificial Intelligence (AI) (Sfounis et al., 2024). The influence of AI on digital financial inclusion has been noted (Mhlanga, 2020). AI has been utilized in various sectors as a form of technological progress, including in the insurance industry.

The use of digital systems in the financial industry has necessitated the redesign of operational models by banks, leading to the embrace of digital transformation to achieve bank 4.0. The banking industry's transformation is driven by the adoption of advanced technologies such as AI, blockchain, and mobile banking (King & Nesbitt, 201709). Also, the adoption of innovative business models, particularly within the Fourth Industrial Revolution such as open banking, fintech partnerships, and new payment systems (Zachariadis & Ozcan, 2017). The banking industry has utilized the development of AI to enhance services and product development, fostering more significant innovation. Although the application of AI banking in developing countries remains in its early stages, significant potential benefits are presented, including (1) improve efficiency such as AI automates routine tasks, freeing up human agents to focus on complex issues; (2) the provision of more personally responsive services, building trust and Loyalty; and (3) the development of more innovative banking products to meet customer needs.

AI-driven banking solutions have been implemented using artificial intelligence technologies to enhance, automate, and optimize various processes within the banking industry. AI algorithms, including machine learning, natural language processing, and data analytics, are leveraged to improve efficiency, personalize customer experiences, reduce risks, and make data-driven decisions. The critical applications of AI in banking include (1) Biometric authentication and virtual assistants and Risk Assessment, (2) Fraud Detection and prevention, (3) Customer service and AI-powered chatbots, (4) Personalized Product Recommendations, (5) Predictive Analytics, credit scoring and Insights used by bankers, and (6) personalized financial advice and regulatory compliance. AI-driven banking solutions are intended to streamline operations, enhance decision-making, and deliver better customer services, transforming the traditional banking landscape into a more agile and responsive industry (Nestor et al., 2024).

The potential for AI-driven banking in developing countries significantly enhances accessibility and efficiency, but solutions must be adapted to local contexts. The adoption of AI in the banking industry is expected to provide significant benefits by increasing market penetration in developing countries. However, several barriers have been identified, including high costs, lack of skills, regulatory compliance, customer trust and technological skepticism (Lopez-Garcia & Rojas, 2024).

Despite a growing body of literature investigating the determinants of intention to adopt digital finance (Anane & Nie, 2022; Bhuvana & Vasantha, 2019; Dewi et al., 2023; Frimpong et al., 2022; Jain & Raman, 2022; Jain & Raman, 2023; Kajol et al., 2022; Rahman et al., 2023), but still, limited studies have dealt with banking products, including digital banking products. Bongini et al. (2023) stated that although the banking industry has a significant economic role, few studies investigate the determinants of individuals' banking purchase decisions. Moreover, Kajol et al. (2022) suggest that the adoption behavior in banks needs to be studied. Factors found to be banking influencing purchase decisions have been explored in recent studies. Bongini et al. (2023) revealed that financial literacy affects individuals' bank customers purchase decisions. Higher literacy levels lead to greater participation in the banking business. Moreover, Tomasi and Ilankadhir (2024) stated that financial literacy and perceived trust positively impact digital finance adoption. Kajol et al. (2022) identify the factors influencing the adoption of digital financial transactions in banking and financial industries, including financial literacy, perceived usefulness, ease of use, trust, security, and cost of use. Therefore, this study addresses two research questions. First, does digital financial literacy affect customers' intention to adopt AI-driven digital financial services? Second, does customer value proposition mediate the nexus between digital financial literacy and financial services? This study develops a structural model based on the literature on customer value propositions, digital financial literacy, and customer acceptance. The main finding of this study is that the customer value proposition mediates the relationship between digital financial literacy and the intention to use digital finance. Practically, these findings contribute to financial institutions' ability to identify the value proposition of financial sector customers before offering their financial products. These findings also contribute to the literature, and this study's results serve as a reference for developing a financial literacy research model.

2. Literature Review

Digital financial literacy refers to the ability of individuals to understand and use digital financial services effectively (Lusardi & Mitchell, 2014). Previous studies have shown that digital financial literacy is a critical factor in determining customers' adoption of digital financial services (Kim et al., 2019). Customer value proposition (CVP) refers to the unique benefits and value that customers perceive from using a product or service (Osterwalder & Pigneur, 2010). In the context of AI-driven digital finance, CVP can play a mediating role in the relationship between digital financial literacy and adoption intention (Venkatesh et al., 2003).

Most research on adopting digital financial services relies on information technology (IT) adoption frameworks. The Technology Acceptance Model (TAM) is the most commonly used underpinning theory in studies on the intention to use digital finance. Huang et al. (2019) use TAM as theoretical basis to conduct the study on online insurance products. Song et al. (2024) used TAM to examine the consumer adoption of mobile augmented reality. This model explains that the intention to adopt a new technology or innovation is based on attitudes toward adoption, perceived ease of use, perceived usefulness, and external factors (Davis, 1989). According to Venkatesh and Davis (2000), TAM is based on the theory of reasoned action (TRA) and the theory of planned behavior (TPB). The TRA suggests that adopting new technology or innovation is an individual's behavioral process, primarily influenced by behavioural intentions shaped by attitudes and subjective norms (Fishbein & Ajzen, 1975). The TPB expands on the TRA by considering a further component called perceived behavioral control, which describes a person's perspective of the external and internal influences on behavior (Ajzen, 1991).

Numerous studies have attempted to explain consumer behavior in the intention to adopt digital financial services. Kajol et al. (2022) revealed that awareness of financial literacy is one factor in digital financial adoption. Individuals who perceive themselves as financially literate are likelier to engage with fintech services (Nguyen, 2022; Prabhakaran & Mynavathi, 2023). Krajčík et al. (2023) studied the digital literacy of the workforce. Higher levels of financial literacy can foster self-confidence and trust in fintech services, which is essential for overcoming an individual's hesitation to adopt new technologies. Ključnikov et al. (2020) explored barriers to adopting and using digital local currency and confirmed the impact of financial literacy on its credibility and trustworthiness.

This finding reinforces the idea that knowledgeable Individuals are more likely to appreciate and utilize the value propositions offered by fintech companies. Although financial technology (FinTech) is supposed to promote financial inclusion and improve financial literacy, FinTech and financial literacy go hand-in-hand and require a delicate balance (Moenjak et al., 2020). Financial literacy further develops into more sophisticated skills and knowledge in using digital financial services, which is known as digital financial literacy. Choung et al. (2023) define digital financial literacy (DFL) as the knowledge and skills required to conduct financial transactions on digital platforms. Morgan et al. (2019) proposed four DFL characteristics: knowledge of digital financial products and services, digital financial risk, digital financial risk control, and consumer rights and redress procedures. Individuals with higher digital financial literacy are more likely to understand the benefits and risks associated with digital finance.

Besides awareness of financial literacy, Kajol et al. (2022) revealed that perceived usefulness, perceived ease of use, compatibility, trust, and security are some factors that motivate the adoption of digital financial transactions, and cost of use, perceived risk, and complexity are some inhibitors of adoption. Another study found that the willingness to adopt digital financial services is affected by perceived value, defined as an individual's overall assessment of usefulness (Alaeddin et al., 2018). Interestingly, Buziene (2024) study revealed that digital financial literacy is declining. The customer-perceived value represents the benefits obtained from service and is shaped by the gap between benefits and costs, distinguishing companies from competitors (Rojas-Martínez et al., 2023). Perceived value influences behavior through emotional, social, and functional aspects (Sweeney & Soutar, 2001). Customer value dimensions are economical, functional, emotional, and symbolic, affecting consumer behavior (Rintamaki & Kuusela, 2007; Cajé & Saviranta, 2020).

Customer value proposition (CVP) refers to the unique benefits and value that customers perceive from using a product or service (Osterwalder & Pigneur, 2010). The customer value proposition (CVP) is a strategic tool that plays a vital role in communicating how a company intends to provide benefits or value to customers (Payne et al., 2017; Gubinelli, 2022) and affects customers' purchase decisions (Bischoff et al., 2023). The literature is yet to demonstrate how various dimensions of the CVP influence customer adoption behavior in AI-driven banking services. This highlights a fundamental gap in growing digital finance adoption behavior studies. This study addresses that gap by examining, developing, and empirically evaluating a conceptual model that explains how CVP dimensions drive adoption intention in the context of AI-driven banking services. Furthermore, this study explores how CVP mediates the relationship between digital financial literacy (DFL) and customer adoption intention in AI-driven services.

Considering all aspects mentioned, the following hypotheses are proposed:

H1: Digital Financial Literacy positively affects functional value.

H2: Digital Financial Literacy positively affects the economic value.

H3: Digital Financial Literacy positively affects emotional value.

H4: Digital Financial Literacy positively affects symbolic value.

H5: Functional value positively affects intention to use.

H6: Economic value positively affects intention to use.

H7: Emotional value positively affects intention to use.

H8: Symbolic value positively affects intention to use.

The conceptual model used in this study is illustrated in Figure.

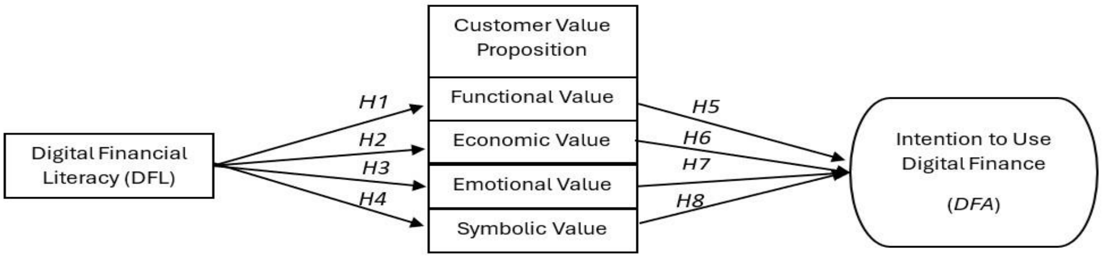

Figure 1. Conceptual Model

Source: Author (2025).

3. Research Methodology

This study used a survey-based approach to collect data from banking customers. A total of 466 responses were collected, and structural equation modeling (SEM) was used to analyze the data (Hair et al., 2019). The measurement model was assessed for reliability and validity, and the structural model was used to test the hypotheses.

Based on existing literature, a research instrument was developed to examine the customer value proposition of digital finance products and services and customer intention to use banking Technology. Dimensions and indicators to measure customer value propositions were identified in previous studies. Functional, economic, emotional, and symbolic value dimensions were utilized to measure the customer value proposition as a mediation variable (Rintamaki & Kuusela, 2007).

Seven indicators of digital financial literacy were adapted from (Morgan et al., 2019) and applied. A 7-point Likert scale was used to assess all operationalized constructs. A pilot test was conducted with 30 respondents to ensure the reliability and validity of the research instrument. Data analysis was performed using PLS-SEM, with Cronbach's alpha values used to assess internal consistency and reliability. The study was conducted between January and April 2024. The research population was defined as bank mobile application users in Cameroon, and a non-probability, purposive sampling method was applied. Screening questions were administered to determine respondents' familiarity with banking products or services. Data collection was carried out through self-administered online surveys. 427 respondents filled out the questionnaire and after cleaning the data, 418 valid responses were included for hypothesis testing. The sample size required to meet the research criteria was five to eight times the number of indicators (Hair et al., 2017). Therefore, the 44 indicators required a minimum sample size of 220–352 respondents. As this study employed 418 samples, it met the minimum sample requirement.

4. Results

The sample in this study comprised 52.72% males and 47.28% females. Most respondents were between 25 and 34 (38.11%) and between 35 and 44 (39.90%). The sample comprised 62.94% staff or employees, 41.55% businessmen, 11.20% self-employees, 9.8% students, and 7.06% housewives. Most respondents held a Bachelor's degree (42.53 %) and spent about \$123 to \$245 monthly.

Robust statistics is a branch of mathematical statistics that acknowledges that statistical models are, at best, only approximate representations of reality (AvellaMedina, 2020). Robustness testing typically involves nonlinearity, unobserved heterogeneity, and endogeneity. The results of the nonlinearity test indicate the model's nonlinearity (Vaithilingam et al., 2024). Nonlinearity testing, commonly used in the PLS-SEM method, particularly with the Smarts tool, involves bootstrapping on quadratic (nonlinear) models.

Table 1. Linearity Test

Variable	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	*t*-statistics (|O/STDEV|)	*p*-values
Digital Financial Literacy -> Customer Value Proposition					
QE (FL) ->EcV	-0.116	-0.115	0.027	4.344	0.000
QE (FL) ->	0.018	0.018	0.028	0,456944	0,354167

EmV					
QE (FL) -> FV	-0.039	-0.039	0.027	1.442	0,103472
QE (FL) -> SV	0.046	0.046	0.021	2.191	0.029
Customer Value Proposition -> Intention to use AI-driven Insurance					
QE (FV) -> IU	0.058	0.067	0.053	1.094	0,30625
QE (EcV) -> IU	-0.053	-0.050	0.038	1.417	0,167361
QE (EmV) -> IU	0.005	-0.013	0.061	0.082	0,298611
QE (SV) -> IU	-0.009	-0.008	0.049	0,129167	0,252083
FL= Financial Literacy; EcV= Economic Value; EmV= Emotional Value; FV= Functional Value; IU= Intention to Use; SV= Symbolic Value					

Source: Field (2025).

Table 1 shows that all variables in this study that directly impact the dependent variable (intention to use AI-driven banking) have p-values greater than 0.05, indicating that all independent variables directly influencing intention to use AI-driven banking have a linear relationship. Unobserved heterogeneity testing was conducted using the finite mixture partial least squares (FIMIX-PLS) method, with the best criteria for determining the optimal segments within the model being the minimum values of Akaike's information criterion modified with Factor 4 (AIC4) and the Bayesian information criterion (BIC) (Sarstedt et al., 2011). The requirements for an optimal segment were that the normed entropy statistic (EN) value must be higher than 0.5 and that the optimal segment must be higher than the segment indicated by the minimum description length with Factor 5 (MDL5) and lower than the segment indicated by Akaike's information criterion (AIC) (Hair et al., 2017). If these criteria are unmet, the model is free from unobserved heterogeneity (see Table 2).

Table 2. FIMIX-PLS Heterogeneity Test

Criteria	**Segment 1**	**Segment 2**	**Segment 3**	**Segment 4**	**Segment 5**	**Segment 6**
AIC	3.173,237	2.603,724	2.219,813	2.141,572	2.095,359	2.049,52
AIC3	3.186,237	2.630,724	2.260,813	2.196,572	2.164,359	2.132,52
AIC4	3.199,237	2.657,724	2.301,813	2.251,572	2.233,359	2.215,52
BIC	3.222,937	2.706,946	2.376,558	2.351,839	2.359,149	2.366,83
CAIC	3.235,937	2.733,946	2.417,558	2.406,839	2.428,149	2.449,83
HQ	3.193,045	2.644,862	2.282,282	2.225,372	2.200,491	2.175,98
MDL5	3.525,735	3.335,835	3.331,537	3.632,909	3.966,310	4.300,08
LnL	-1.573,619	-1.274,862	-1.068,906	-1.015,786	-978,680	-941,762
EN	0.000	0,533	0,576	0,510	0,494	0,506
NFI	0.000	0,563	0,581	0,496	0,469	0,469
NEC	0.000	78,477	57,376	89,886	97,686	91,961
AIC = Akaike's information criterion; BIC= Bayesian information criterion; CAIC= Consistent AIC; HQ = Hannan Quinn Criterion; MDL = minimum description length; LNL = Log-likelihood; EN = Normed entropy statistic; NFI = Non-Fuzzy Index; NEC= Normalized entropy criterion						

Table 2 shows that the results of the unobserved heterogeneity test indicated that the optimal segment, as demonstrated by the minimum BIC values (segment 4), was within the acceptable range, located between the segment with the lowest AIC (segment 6) and MDL5 (segment 1). However, as the EN value was higher than 0.5, it can be concluded that unobserved heterogeneity was present.

Table 3. Endogeneity–Gaussian Copula Test

Variable	**Original sample (O)**	**Sample mean (M)**	**Standard deviation (STDEV)**	***t*-statistics (|O/STDEV|)**	***p*-values**
GC (FL) -> FV	-0,030	-0,029	0,067	0,307	0,458
GC (FL) -> EcV	-0,174	-0,173	0,053	3285,000	0,001
GC (FL) -> EmV	0,081	0,079	0,056	1457,000	0,101
GC (FL) -> SV	0,081	0,079	0,051	2290,000	0,022
GC (FV) -> IU	0,010	0,008	0,039	0,183	0,549
GC (EcV) -> IU	-0,010	-0,011	0,036	0,188	0,547
GC (EmV) -> IU	-0,022	-0,028	0,040	0,392	0,398
GC (SV) -> IU	-0,026	-0,028	0,049	0,365	0,416
FL= Financial Literacy; EcV= Economic Value; EmV= Emotional Value; FV= Functional Value; IU= Intention to Use; SV= Symbolic Value					

Finally, endogeneity was checked using the Gaussian copula test (Becker et al., 2022). Table 3 shows the results of the endogeneity test. All independent variables directly related to the intention to use digital finance have values above 0.05, indicating that none have endogeneity issues.

Table 4. Harman's Single-Factor Test

Factor	**Initial Eigenvalues**			**Extraction Sums of Squared Loadings**		
	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	29.450	58.901	58.901	29.043	58.085	58.085

Table 4 shows the result of Harman's single-factor test applied through exploratory factor analysis (EFA) (unrotated, single-factor) to verify that common method bias (CMB) did not significantly affect this study's results. The analysis produced two factors with eigenvalues greater than 1. The first factor explained 58.085% of the variance, exceeding the 50% threshold, suggesting that CMB was a concern in this study.

4.1 Outer and Inner Models

Theses tables show the measurement model (outer model) used to evaluate the validity and reliability. On the other hand, its show the results of the structural model (inner model), which explains the relationships between Digital Financial Literacy, Customer Value Proposition, and Intention to Use. The evaluation of the outer model comprised the assessment of indicator reliability (loading factor value), composite reliability (CR), collinearity statistics (VIF), Cronbach's alpha, and average variance extracted (AVE) (see the following table), as well as discriminant validity (heterotrait–monotrait [HTMT] ratio and Fornell–Larcker criterion correlation.

Table 5. Validity and Reliability Test Results

Variable	**Item indicator**	**Loading factor**	**Composite reliability (CR)**	**Cronbach's alpha**	**Average variance extracted (AVE)**	***t-value***

Criteria		> 0.7	> 0.7	> 0.7	> 0.5	> 1.960
Digital Financial Literacy	DFL		0.949	0.946	0.758	
	DFL1	0.893				65.138
	DFL2	0.915				81.004
	DFL3	0.914				75.13
	DFL4	0.867				37.833
	DFL5	0.8				21.636
	DFL6	0.822				29.557
	DFL7	0.877				52.103
Functional Value	FV		0.973	0.971	0.651	
	CVC1	0.831				31.907
	CVC2	0.809				26.461
	CVC3	0.822				29.388
	CVC4	0.834				33.467
	EOU1	0.847				38.126
	EOU2	0.833				24.700
	EOU3	0.887				62.957
	EOU4	0.817				27.942
	FCT1	0.785				25.475
	FCT2	0.813				26.047
	FCT3	0.858				44.504
	PAS1	0.859				42.381
	PAS2	0.848				35.679
	PQU1	0.847				33.799
	PQU2	0.817				23.752
	PQU3	0.813				33.261
	SCR1	0.712				23.352
Variable	**Item indicator**	**Loading factor**	**Composite reliability (CR)**	**Cronbach's alpha**	**Average variance extracted (AVE)**	***t-value***
	SCR2	0.707				22.416
	SCR3	0.700				24.067
	SCR4	0.652				19.331
Symbolic Value	SV		0.906	0.904	0.912	
	PTI1	0.953				100.393
	PTI2	0.958				143.404
Economic Value	EV		0.922	0.920	0.716	

	AFD1	0.794				26,115
	CSB1	0.784				23,272
	CSB2	0.848				27,318
	CSB3	0.869				41,936
	TMB1	0.884				41,413
	TMB2	0.892				50,355
Emotional Value	EV		0.948	0.946	0.787	
	PEX1	0.906				54,019
	PEX2	0.907				65,227
	PEX3	0.856				33,808
	REX1	0.881				54,174
	TST1	0.877				38,966
	TST2	0.895				59,254
Intention to Use	IU		0.935	0.931	0.879	
	AKD1	0.953				136.353
	AKD2	0.952				108.029
	AKD3	0.906				54.979

Table 5 shows that all indicators had a loading factor greater than 0.6. All latent variables had an AVE of more than 0.6 and a CR value of more than 0.7. This means that all constructs used in the model were reliable, and the indicators used to measure the constructs were valid (Setiawan et al., 2022).

Table 6. Discriminant Validity: Fornell–Larcker Criterion

Variable	Digital Financial Literacy	Economic Value	Emotional Value	Functional Value	Intention to Use	Symbolic Value
Digital Financial Literacy	0.871					
Economic Value	0.779	0.846				
Emotional Value	0.773	0.795	0.887			
Functional Value	0.734	0.783	0.812	0.807		
Intention to Use	0.762	0.722	0.786	0.736	0.938	
Symbolic Value	0.770	0.708	0.827	0.732	0.739	0.955

Table 6 shows that each variable has a higher value than its correlation with other variables, meeting the Fornell-Larcker criterion. This means the variables in the model are distinct and do not overlap, fulfilling discriminant validity requirements. This study uses the Heterotrait–Monotrait Ratio (HTMT) for a more robust discriminant validity assessment.

Table 7. Discriminant Validity: Heterotrait–Monotrait Ratio (HTMT) Matrix

Variable	Digital Financial Literacy	Economic Value	Emotional Value	Functional Value	Intention to Use	Symbolic Value

Digital Financial Literacy						
Economic Value	0.833					
Emotional Value	0.812	0.845				
Functional Value	0.764	0.822	0.846			
Intention to Use	0.809	0.774	0.833	0.773		
Symbolic Value	0.829	0.771	0.893	0.782	0.804	

Table 7 shows that all HTMT ratio matrix values were less than 0.9 (Hair et al., 2022). Thus, all constructs in the model had good convergent consistency.

Table 8. Significance of Path Coefficients (t-statistics)

Hypothesis	**Path**	**Coefficient**	**Standard Deviation**	***t-statistic***	***p-values***	**Decision**
1	DFL -> EcV	0,779	0,031	24,773	0,000	Significant
Hypothesis	**Path**	**Coefficient**	**Standard Deviation**	***t-statistic***	***p-values***	**Decision**
2	DFL -> EmV	0,773	0,031	24,994	0,000	Significant
3	DFL -> FV	0,734	0,046	15,806	0,000	Significant
4	DFL -> SV	0,770	0,026	29,571	0,000	Significant
5	EcV -> IU	0,166	0,070	2,382	0,017	Significant
6	EmV -> IU	0,324	0,096	3,372	0,001	Significant
7	FV ->IU	0,182	0,079	2,314	0,021	Significant
8	SV-> IU	0,220	0,077	2,840	0,005	Significant
DFL= Digital Financial Literacy; EcV= Economic Value; EmV= Emotional Value; FV= Functional Value; SV= Symbolic Value; IU= Intention to Use						

Table 8 presents the path coefficients of each independent variable that affected the dependent variable. This revealed that Digital Financial literacy positively affected the Customer Value Proposition, which, in turn, affected the Intention to use AI driven banking services at the 5% confidence interval (CI) level.

Table 9. Coefficients of Determination (R^2)

	R2	*R2-adjusted*	Strength of the model
Economic Value	0.606	0.606	Medium
Emotional Value	0.598	0.597	Medium
Functional Value	0.539	0.538	Medium
Symbolic Value	0.593	0.593	Medium
Intention to Use	0.671	0.669	Medium

Table 9 presents the coefficient of Intention to Use of 0.669, which indicates that the direct contribution of the Customer Value proposition to Intention to Use amounted to approximately 66.9%. Therefore, this study revealed that the customer value proposition significantly predicted the intention to Use AI-driven insurance.

Table 10. Model Fit

	Saturated model	Estimated model
SRMR	0.061	0.114
d_ULS	3.691	12.853
d_G	2.231	2.546
Chi-square	3956.465	4275.243
NFI	0.78	0.762

Table 10 shows the model fit; the closer the Normed Fit Index (NFI) value is to 1, the better the fit (Schuberth & Rademaker, 2023). An NFI value of 0.780 in this model represents an acceptable fit (Henseler et al., 2014). The standardized root mean square residual (SRMR) was introduced as a goodness-of-fit measure for PLS-SEM to avoid model misspecification.

Table 11. Prediction Model Evaluation

	Q^2*predict*	RMSE	MAE
Economic Value	0.602	0.640	0.455
Emotional Value	0.592	0.643	0.469
Functional Value	0.532	0.691	0.465
Symbolic Value	0.590	0.644	0.494
Intention to Use	0.572	0.659	0.470
Note: Predictive relevance criteria: Q squared (Q^2) is more than zero (> 0) (Hair et al., 2017; Ringle et al., 2018); root mean square error (RMSE) is less than 1 (< 1); MAE = mean absolute error.			

Table 11 shows the prediction evaluation with Q^2. The values for the four customer value proposition dimensions and intention to use AI-driven insurance are 0.602, 0.592, 0.532, 0.590, and 0.572. Thus, they are higher than zero, which is the cutoff value. This indicates that the model has predictive relevance.

4.2 Discussion

The findings of this study have important implications for banks and financial institutions seeking to promote the adoption of AI-driven digital finance. By prioritizing customer education and emphasizing the unique value propositions of AI-driven digital finance, banks can increase customers' adoption intentions (Kim et al., 2019).

This study revealed that all hypotheses highlight a positive and significant relationship between digital financial literacy and all CVP dimensions: functional, economic, emotional, and symbolic. The results imply that customers with higher digital financial literacy are more capable of perceived values, are more motivated to adopt digital financial services, and are motivated to use and adapt new technology for their own, which aligns with previous studies (Nguyen, 2022; Prabhakaran & Mynavathi, 2023). With digital financial literacy, customers have the self-efficacy to experience the functional values of AI-driven services, such as ease of use and convenience. Literate customers can also explore the functionalities of AI-driven services and assess the assortment of products offered and the quality and security of AI-driven services. Customers with digital financial literacy can evaluate the economic benefits or values of AI-driven services in terms of cost, time, and other efforts. Moreover, they also appreciate the purchasing experience and have more trust in AI-driven services, which represents emotional value. Finally, digital financial literacy increases customers' symbolic value, which makes them more appreciated and creates more positive impressions among friends and relatives. Hence, banks and regulators should engage in more literacy-building activities, mainly digital financial literacy. Thus, customers will be able to perceive higher value in digital banking services.

This study found that all dimensions of customer value propositions positively and significantly affected the intention to adopt AI-driven banking services in Cameroon. Emotional and symbolic values had a more substantial impact on intention. This implies that building trust, purchasing experience, and other intangible values is essential when launching AI-driven services. Trust can be amplified by guaranteeing transaction security, such as end-to-end encryption and two-factor authentication, and preventing fraud. AI-driven services should be seamless, easy to use, prompt, and natural and should provide a personalized interface to boost a satisfying and rewarding experience. Banks should also improve their image and should be effectively fiduciary to provide trust and exclusivity, which increases their emotional and symbolic value. Therefore, it helps banks communicate the benefits of AI-driven services.

5. Conclusion

This study examined whether digital financial literacy affects the intention to use digital financial services, particularly AI-driven banking services, with customer perceived value as a mediating factor. Data were collected from 466 respondents in Cameroon and analyzed using partial least squares-based structural equation modeling (PLS-SEM).

The findings indicate that digital financial literacy positively influences all dimensions of customer value propositions in AI-driven banking services, affecting the intention to use these services. Enhancing digital financial literacy equips customers with the capability to perceive customer values in financial, economic, emotional, and symbolic aspects. Consequently, an improved perception of customer value enhances the intention and motivation to adopt AI-driven banking services. The study's theoretical and practical implications are substantial. Theoretically, it contributes to the literature on bank customer value propositions by identifying key drivers in financial services. From a practical perspective, financial institutions are encouraged to emphasize the intangible dimensions of customer values, particularly emotional and symbolic factors, by strengthening bank image, customer experience, and trust. This study contributes to the growing literature on digital finance adoption and provides practical insights for banking institutions seeking to leverage AI-driven technologies. The findings highlight the importance of digital financial literacy and CVP in shaping customers' intentions to adopt AI-driven digital finance.

6. Recommendations

Based on the findings, banks should:

(1) Prioritize customer education to enhance digital financial literacy. The Cameroonian government continue its efforts to promote digital financial literacy among financial institutions and consumers.

(2) Emphasize the unique value propositions of AI-driven digital finance.

(3) Develop targeted marketing strategies to promote adoption.

7. Limitations and Future Research Directions

This study has some limitations, including the use of a survey-based approach and the focus on only the Cameroon banking industry. Future studies can explore other factors influencing AI-driven digital finance adoption and examine the generalizability of the findings. Also, the limitation acknowledged in this study is an imbalance in the number of responses based on gender and occupation. This lack of balance may affect the result of the findings, as the data may not fully represent the perspectives of different demographic groups. To address this limitation in future research, the study could consider using quota sampling and intake-targeted sample strategies. Future studies can investigate the role of other factors, such as trust and security concerns, in shaping customers' intentions to adopt AI-driven digital finance.

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Author Contributions

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Data Availability

The data set generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declaration of Competing Interest

The authors declare no competing interest.

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