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The Role of Customer Value Proposition in Digital Financial Literacy and Ai-Driven Finance Adoption

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Abstract

Purpose of the Study: The purpose of this study is to investigate 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. ***Methodology:*** 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). ***Main Findings:*** 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. 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 banking services. ***Managerial Contributions:*** The study's findings have significant implications for managers in the Cameroonian banking industry as the study contributes in developing targeted CVP strategies, investing in DFL initiatives, designing user-centric AI-driven services, fostering trust and transparency and monitoring and evaluating CVP and DFL initiatives. By implementing these strategies, managers in the Cameroonian banking industry can enhance AI-driven digital finance adoption, improve customer satisfaction, and drive business growth.

Keywords: digital financial literacy, AI driven banking, customer value proposition, adoption intention, Cameroon

1. Introduction

The rapid transformation of the financial services landscape which is driven by artificial intelligence (AI), automation, and digital platforms—has intensified scholarly and industry interest in understanding the antecedents of AI-driven finance adoption. As consumers increasingly engage with robo-advisors, AI-enabled credit assessment, algorithmic budgeting tools, and digital investment platforms, their ability to successfully navigate these technologies rests heavily on Digital Financial Literacy (DFL). DFL encompasses not only technical literacies related to using digital interfaces but also the cognitive skills required to interpret algorithmic outputs, evaluate digital risks, and make informed financial decisions in technology-mediated environments (Morgan et al., 2019; Walczak & Taylor, 2022). This requirement foregrounds the importance of digital financial literacy (DFL) as a foundational determinant of individuals' ability to evaluate, use and trust AI-driven financial technologies (Anane & Nie, 2022; Bhuvana & Vasantha, 2019; Dewi et al., 2023). However, research indicates that literacy alone is not sufficient to stimulate adoption. Even highly literate consumers may choose not to engage with AI-driven financial tools unless they perceive compelling value, trust, or relevance in the technology (Belk, 2021). Thus, a crucial theoretical and practical question emerges: How does the Customer Value Proposition (CVP) translate an individual's digital financial literacy into intention to adopt AI-driven finance?

Understanding this relationship requires grounding in foundational theories of value creation and technology adoption. The Technology Acceptance Model (TAM) posits that adoption is primarily driven by perceived usefulness and perceived ease of use (Davis, 1989). Meanwhile, value-based adoption theory argues that consumers evaluate innovations based on perceived benefits relative to costs, risks, and sacrifices (Kim et al., 2007). Both perspectives highlight that adoption decisions are mediated by subjective assessments of value, suggesting that literacy alone cannot directly induce behavioral intention unless it shapes value perceptions. Moreover, emerging scholarship in service-dominant logic (Vargo & Lusch, 2008) emphasizes that value is co-created through interactions between users and technological systems, reinforcing the idea that understanding digital financial tools enhances consumers' ability to evaluate and appreciate the value they can generate. These theoretical foundations point strongly toward a mediating role for CVP: literacy enhances comprehension and confidence, which strengthens perceived value, which in turn drives adoption.

The significance of this research lies in its potential to inform both theory and practice. From a theoretical perspective, the study extends the TAM framework by integrating constructs such as digital financial literacy, perceived regulatory support, and trust in digital channels—factors that have been shown to influence adoption in emerging markets but are under-explored in Cameroon (Al-Kailani & Al-Mabrouk, 2020). Practically, the findings will assist banks in prioritizing interventions—such as targeted customer education programs or enhancements to digital-platform security—that can accelerate the diffusion of DFS, thereby promoting financial inclusion and supporting the country's broader economic development goals, including the "Digital Cameroon 2030" agenda.

The concept of Customer Value Proposition plays an increasingly central role in digital finance and AI-mediated service delivery. CVP represents a holistic configuration of benefits—functional, emotional, experiential, and financial—that customers associate with a product or service (Payne et al., 2017; Lanning & Michaels, 1988). In AI-driven finance specifically, the value proposition may include personalized insights, lower transaction costs, automation of complex tasks, greater convenience, and data-driven accuracy. Importantly, many of these benefits are symbolic or probabilistic, meaning that consumers must first understand how AI works in order to appreciate its relevance to their financial lives. DFL enables this understanding by equipping consumers with the skills to interpret features such as algorithmic personalization, risk-scoring, real-time analytics, and automated decision support. Thus, literacy strengthens the consumer's ability to perceive and evaluate the benefits embedded in the CVP. Without this cognitive foundation, even well-designed AI-driven financial products may fail to resonate with potential users.

The mediating role of CVP is also supported by behavioral decision theories. Prospect theory suggests that individuals overweigh risks and uncertainties, particularly in unfamiliar or complex domains such as AI-driven finance (Kahneman & Tversky, 1979). Low DFL amplifies these perceived risks, reducing adoption intention. Conversely, when individuals are more digitally financially literate, they better understand how AI systems operate, how data is used, and how outputs should be interpreted, which reduces perceived risk and increases perceived benefit. This cognitive reframing is expressed through the CVP: literacy enables consumers to identify value that would otherwise remain opaque. In this way, CVP becomes the psychological conduit translating knowledge into motivation.

Additionally, research on trust in automation highlights that perceived value is foundational to forming trust in AI systems (Glikson & Woolley, 2020). Trust acts as a boundary condition for adoption, and CVP plays a pivotal role in shaping such trust. A compelling CVP—clarifying how AI generates superior outcomes, enhances control, or improves financial well-being—helps users develop confidence in automated recommendations. Literacy reinforces this process by enabling users to critically evaluate claims and features, thus making the CVP more credible and meaningful. Without sufficient literacy, the CVP may be misunderstood or undervalued; without a strong CVP, literacy may fail to convert into actual behavioral intention.

From a theoretical standpoint, positioning CVP as a mediator between DFL and adoption intention integrates three dominant scholarly domains: (1) technology adoption theories, (2) value creation and service-dominant logic, and (3) digital financial capabilities. This integration offers a more nuanced causal logic: DFL does not directly lead to adoption intention; instead, it enhances the consumer's ability to perceive value, thereby strengthening adoption intention. This conceptualization aligns with contemporary marketing scholarship, which argues that value perception—not technical knowledge—is the primary catalyst of digital service uptake (Chen et al., 2021). It also reflects practical industry trends, as fintech firms increasingly focus on communicating differentiated value propositions to support customer onboarding and retention.

In sum, the role of CVP as a mediator provides both theoretical coherence and practical relevance. It connects foundational principles of literacy, cognition, and perceived value with modern theories of AI-based service adoption. By articulating how literacy shapes value perception—and how value perception, in turn, drives adoption—this research offers a deeper understanding of the psychological mechanisms underlying consumer decisions in AI-driven financial ecosystems. The present study addresses the research gap based on limited empirical evidence on the determinants of digital finance adoption within the Cameroonian banking sector, and existing models have not been contextualized to reflect local regulatory environments and consumer behavior. To fill this void, the research aims to (1) identify the key factors influencing Cameroonian bank customers' intention to adopt digital financial services, (2) assess the moderating role of digital financial literacy and perceived regulatory support, and (3) propose a tailored adoption model that can guide policymakers and practitioners.

In line with these objectives, the paper is structured as follows. Section 2 reviews the relevant literature and develops the hypotheses, Section 3 outlines the methodology, Section 4 presents the results, and Sections 5 and 6 discuss the findings and conclude with policy implications and suggestions for future research.

2. Literature Review

2.1 Conceptual Review

2.1.1 Digital Financial Literacy

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).

The rapid growth of digital financial services and artificial intelligence (AI) has transformed the financial landscape, presenting both opportunities and challenges for consumers, financial institutions, and policymakers (Bahoo et al., 2024). Digital financial literacy, defined as the ability to use digital financial services safely and effectively, is crucial for consumers to navigate this new landscape and make informed financial decisions (Lyons & Kass-Hanna, 2021a). Research has shown that digital financial literacy is a key determinant of AI adoption in financial services (Choung et al., 2023). Consumers with higher levels of digital financial literacy are more likely to trust and adopt AI-driven financial services, such as robo-advisors and mobile payment systems (Yang & Lee, 2024). However, concerns about data security, bias, and lack of transparency remain significant barriers to AI adoption (Panos & Wilson, 2020).

In addition, digital financial literacy refers to individuals' competence in using, interpreting, and evaluating digital financial tools, risks, and opportunities (Anane & Nie, 2022; Bhuvana & Vasantha, 2019; Dewi et al., 2023). Research consistently identifies DFL as a predictor of digital finance engagement because it enhances users' confidence, reduces perceived complexity, and supports informed decision-making about new technologies. For example, a study in the banking sector confirmed that customers with higher digital literacy are more likely to recognize the functional, emotional, and symbolic value embedded in AI-enhanced services, which in turn promotes adoption intention (Anane & Nie, 2022; Frimpong et al., 2022). This aligns with broader findings that literacy not only improves users' technical capabilities but also their ability to manage risks such as fraud, privacy concerns, or algorithmic bias—issues that are especially pronounced in AI-enabled environments (Anane & Nie, 2022; Dewi et al., 2023).

2.1.2 Customer Value Proposition (CVP)

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.

CVP encompasses the perceived benefits consumers expect to derive from a product or service, including usefulness, customization, emotional satisfaction, and symbolic meaning (Jain & Raman, 2022; Jain & Raman, 2023). In digital finance, particularly AI-driven offerings, CVP goes beyond functional utility to include personalized insights, predictive analytics, and automated advisor capabilities that promise enhanced user experience. Empirical research demonstrates that CVP significantly predicts adoption intention, mediating the effect of literacy on usage behavior because it shapes perceived relevance and value of the technology (Frimpong et al., 2022; Kajol et al., 2022; Rahman et al., 2023).

Customer Value Proposition (CVP) refers to the perceived value that consumers derive from a product or service (Anane & Nie, 2022). In the context of AI-driven financial services, CVP plays a crucial role in shaping consumer trust and adoption (Jain & Raman, 2022). A strong CVP can mediate the relationship between digital financial literacy and AI adoption, as consumers are more likely to trust and adopt AI-driven financial services that provide personalized, convenient, and secure experiences (Dewi et al., 2023). The mediating role of CVP is grounded in the Service-Dominant Logic (SDL) theory, which posits that value is co-created between consumers and service providers (Vargo & Lusch, 2004). In the context of AI-driven financial services, CVP is co-created through the interaction between consumers and AI systems, and is influenced by factors such as personalization, empathy, and continuous improvement (Yang & Lee, 2024).

Empirical studies have shown that CVP is a significant predictor of AI adoption in financial services. For example, a study on mobile payment adoption found that CVP mediated the relationship between digital financial literacy and adoption intention (Jain & Raman, 2023). Another study on robo-advisors found that CVP influenced consumer trust and adoption of AI-driven investment advice (Brenner & Meyll, 2020). In conclusion, the literature review highlights the importance of Customer Value Proposition (CVP) in mediating the relationship between digital financial literacy and AI adoption in financial services. The findings suggest that financial institutions and policymakers should focus on creating strong CVPs that provide personalized, convenient, and secure experiences for consumers, in order to promote AI adoption and financial inclusion.

3. Theoretical Framework

The adoption of digital financial services (DFS) in the Cameroonian banking sector is examined through an integrated model that draws on three complementary theoretical lenses: The Technology Acceptance Model (TAM), the Diffusion of Innovations (DOI) theory, and the emerging construct of Digital Financial Literacy (DFL). The framework is organized into three parts: (1) core technology-acceptance constructs, (2) innovation-diffusion factors, and (3) contextual moderators. Each component is linked to a hypothesis that guides the empirical analysis.

The classic TAM posits that Perceived Usefulness (PU) and Perceived Ease of Use (PEU) determine an individual's Intention to Use (ITU) a technology (Davis, 1989). In the context of DFS, PU reflects the belief that digital channels improve transaction speed, cost-effectiveness, and access to financial products, while PEU captures the perceived simplicity of navigating mobile-banking or internet-banking interfaces.

Innovation-Diffusion Factors (DOI) of Rogever's (2003) provide also a theoretical insight. DOI theory introduces five attributes that influence adoption: Relative Advantage, Compatibility, Complexity, Trialability, and Observability. For DFS in Cameroon, Relative Advantage (e.g., reduced travel time, lower fees) and Compatibility with existing payment habits are expected to be especially salient, whereas Complexity (difficulty of use) is anticipated to deter adoption.

DFL refers to the knowledge and skills needed to navigate digital financial platforms securely and effectively (Lusardi & Mitchell, 2014). Empirical work in emerging markets shows that DFL amplifies the impact (Kumar et al., 2022).

This framework extends the classic TAM by embedding DOI attributes and contextual moderators that are particularly relevant to the Cameroonian banking environment. It addresses the identified gap in the literature—namely, the lack of a context-specific model for DFS adoption in Central Africa—and provides a theoretically grounded basis for hypothesis testing and policy-relevant recommendations.

The justification for integrating TAM with DOI Theory is that the Technology Acceptance Model (TAM) and Diffusion of Innovation (DOI) theory are two widely used frameworks in understanding technology adoption. While TAM focuses on the individual's attitude towards technology adoption, DOI theory explains the diffusion of innovation within a social system. Integrating these two theories can provide a more comprehensive understanding of technology adoption. TAM and DOI theory share commonalities in their underlying assumptions. Both theories recognize the importance of perceived usefulness and ease of use in technology adoption (Davis, 1989; Rogers, 2003). However, DOI theory provides a broader perspective on the diffusion process, highlighting the role of social influence, communication channels, and innovation characteristics (Roh et al., 2011).

By integrating TAM with DOI theory, researchers can examine the individual-level factors (e.g., perceived usefulness, ease of use) and social-level factors (e.g., social influence, communication channels) that influence technology adoption (Huang & Kao, 2015). This integrated framework can provide a more nuanced understanding of the complex interactions between individual and social factors that drive technology adoption.

There exist prior Studies Integrating TAM and DOI Theory. Several studies have successfully integrated TAM with DOI theory to examine technology adoption in various contexts. Roh et al. (2011) integrated TAM with DOI theory to examine the adoption of internet banking in Korea. Their findings highlighted the importance of perceived usefulness, ease of use, and social influence in shaping adoption intentions. Huang and Kao (2015) combined TAM with DOI theory to investigate the adoption of mobile commerce in Taiwan. Their study revealed that perceived usefulness, ease of use, and compatibility significantly influenced adoption intentions. Wang et al. (2016) integrated TAM with DOI theory to examine the adoption of online shopping in China. Their findings showed that perceived usefulness, ease of use, and social influence were significant predictors of adoption intentions. These studies demonstrate the value of integrating TAM with DOI theory in understanding technology adoption. By combining these two frameworks, researchers can develop a more comprehensive understanding of the complex factors driving technology adoption.

Hypotheses Development

Considering all aspects mentioned, the following hypotheses are proposed:

(1) Digital financial literacy positively affects functional value.

H1: Digital financial literacy has a significant positive effect on functional value.

H0: Digital financial literacy has no significant effect on functional value.

(2) Digital financial literacy positively affects economic value.

H2: Digital financial literacy has a significant positive effect on economic value.

H0: Digital financial literacy has no significant effect on economic value.

(3) Digital financial literacy positively affects emotional value.

H3: Digital financial literacy has a significant positive effect on emotional value.

H0: Digital financial literacy has no significant effect on emotional value.

(4) Digital financial literacy positively affects symbolic value.

H4: Digital financial literacy has a significant positive effect on symbolic value.

H0: Digital financial literacy has no significant effect on symbolic value.

(5) Functional value positively affects intention to use.

H5: Functional value has a significant positive effect on intention to use.

H0: Functional value has no significant effect on intention to use.

(6) Economic value positively affects intention to use.

H6: Economic value has a significant positive effect on intention to use.

H0: Economic value has no significant effect on intention to use.

(7) Emotional value positively affects intention to use.

H7: Emotional value has a significant positive effect on intention to use.

H0: Emotional value has no significant effect on intention to use.

(8) Symbolic value positively affects intention to use.

H8: Symbolic value has a significant positive effect on intention to use.

H0: Symbolic value has no significant effect on intention to use.

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

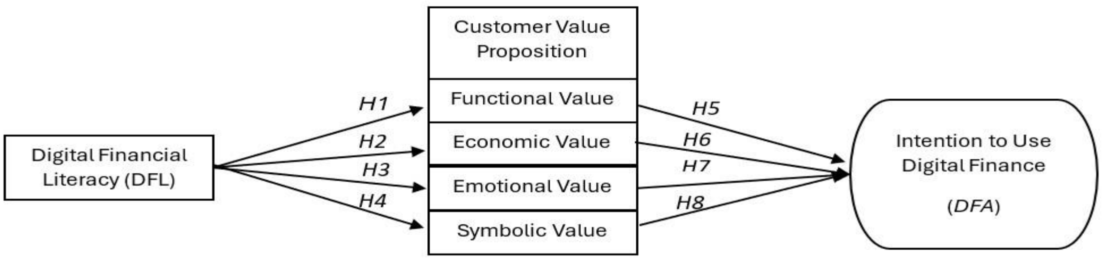

Figure 1. Conceptual Model

Source: Author (2025).

The conceptual model posits that digital financial literacy is a precursor to how customers evaluate a digital finance offering, and that this evaluation is captured through the four dimensions of the customer value proposition (CVP): functional, economic, emotional, and symbolic value. Functional value refers to the practical benefits that a digital service delivers, such as speed, ease of use, and reliability of transactions. Economic value encompasses the monetary advantages that users perceive, including lower fees, better interest rates, and personalized rewards. Emotional value reflects the sense of security, trust, and peace of mind that arises from using a platform that protects personal data and offers responsive support. Symbolic value captures the social prestige or identity that users derive from being associated with a modern, technology-driven financial service, signaling that they are tech-savvy and forward-looking.

According to the model, higher levels of digital financial literacy enable customers to recognize and appreciate each of these value dimensions more clearly. A literate user can assess whether an app is truly convenient, can compare fee structures, can evaluate the credibility of security measures, and can understand the status conferred by using a particular brand. These perceptions, in turn, shape the overall CVP that the customer constructs for the service. The model then links the CVP directly to the intention to use digital finance: when the four value dimensions are perceived as strong, the customer's attitude toward the service becomes more favorable, and the likelihood of adoption and continued use increases. Importantly, the model also allows for a direct path from digital financial literacy to intention, suggesting that even if a service's CVP is modest, a knowledgeable user may still intend to adopt it because they understand its long-term potential.

The model fits the Cameroonian banking context, where research has shown that digital financial literacy is a critical mediator between perceived value and adoption of AI-driven digital finance solutions. Studies on emerging markets consistently find that consumers with higher financial literacy are better able to extract functional, economic, emotional, and symbolic benefits from new digital platforms. In Cameroon, where baseline digital literacy is relatively low, the four-dimension CVP framework provides a concrete mechanism for explaining how literacy translates into usage. AI-enabled services amplify each value dimension: AI automates routine tasks, reducing processing time (functional); machine-learning algorithms personalize pricing and suggest savings, lowering costs (economic); real-time fraud alerts and virtual assistants enhance security and trust (emotional); and the sleek, AI-powered interface signals modernity and status (symbolic). By embedding these AI features within a CVP that is explicitly tied to the four dimensions, banks can address the literacy gap and make the service more attractive.

Moreover, the model's depiction of the nexus between digital financial literacy and intention through the four CVP dimensions aligns with recent empirical work on AI-driven digital finance adoption in Cameroon. Researchers have found that the impact of literacy on adoption is largely indirect, operating through customers' perceptions of value across the functional, economic, emotional, and symbolic domains. This indirect effect explains why interventions that boost literacy—such as targeted training programs, simplified user interfaces, and community outreach—have been shown to increase adoption rates when paired with AI-enhanced offerings. In short, the model provides a theoretically grounded and empirically supported framework for understanding how improving digital financial literacy can strengthen the perceived value of AI-driven digital finance, thereby driving higher intention to use these services in the Cameroonian banking industry.

4. Methodology

This study adopts a quantitative, cross-sectional survey design, suitable for assessing the causal pathways and mediation effects between Digital Financial Literacy (DFL), Customer Value Proposition (CVP), and intention to use AI-driven banking. Mediation analysis requires simultaneous estimation of direct and indirect effects; therefore, structural equation modeling (SEM) is chosen as the primary analytical framework because it provides robust capability for assessing latent constructs, measurement error, and causal relationships in non-experimental settings (Hair et al., 2021; Kline, 2016). The research design is based on the Unified Theory of Acceptance and Use of Technology (UTAUT2) and the Value-based Adoption Model (VAM).

A structured questionnaire was employed to collect data, 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. Data are collected through a structured online questionnaire distributed via email lists, banking community forums, and institutional networks. Online surveys are suitable for digital finance studies due to respondents' familiarity with technology (Bryman, 2016). The questionnaire includes four sections: demographic profile, DFL scale, CVP scale, and intention-to-use items. A pilot test involving 35 respondents ensures clarity, reliability, and internal consistency. Cronbach's alpha values ≥ .70 are considered acceptable (Nunnally & Bernstein, 1994).

Bank customers who hold at least one formal bank account and have accessed digital banking channels (mobile banking, or bank-issued e-wallet in the past 12 months. Customers lists provided by five major banks operating national wide (representing=65% of the market). Stratified random sampling by bank and region (Centre, South-West, Littoral) to ensure geographic representation.

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 2025. 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.

Digital Financial Literacy (DFL) was Measured using a multi-dimensional scale capturing competence in digital tools, financial decision-making, cybersecurity awareness, and understanding algorithmic processes. Items are adapted from validated instruments used in recent financial literacy research (Morgan et al., 2019; Walczak & Taylor, 2022). Respondents rate items on a 5-point Likert scale (1 = strongly disagree; 5 = strongly agree).

Customer Value Proposition (CVP) was assessed using a reflective scale capturing functional value, emotional value, customization value, and economic value, adapted from value-related measurement models by Payne et al. (2017) and Sweeney & Soutar (2001). Items evaluate perceptions such as usefulness, convenience, trustworthiness, personalization, and the perceived performance of AI-driven banking.

Intention to Use AI-Driven Banking (Dependent Variable) was measured following the behavioral intention dimensions of the Technology Acceptance Model and UTAUT, including items such as: I intend to use AI-driven banking services in the near future, Using AI-driven banking is something I plan to do regularly, I am willing to rely on AI-based systems for financial transactions and advice. The scale is adapted from Venkatesh et al. (2003) and Davis (1989), using a 5-point Likert scale.

A probability-based sampling strategy, specifically stratified random sampling, is used to capture diverse segments of digital banking customers. Strata include age, income group, and education level to ensure representativeness in assessing literacy and adoption intentions. The target population consists of adults (18+) who are current users of online or mobile banking services, as they are the primary decision-makers for AI-driven financial tools.

Data collection was carried out through self-administered online surveys. A total of 466 questionnaire were given out. 427 respondents filled out the questionnaire and after cleaning the data and removing incomplete or straight-lining responses, 418 valid responses were included for hypothesis testing and were deemed valid for analysis (= 89.7% effective response rate). 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. Also, the final sample exceeds the minimum requirement of 384 for a 5% margin of error at 95% confidence level.

SEM requires adequate sample size for accurate parameter estimation; recommendations suggest at least 10 respondents per indicator and a minimum of 300 cases for mediation models (Kline, 2016; Hair et al., 2021). Data analysis is conducted using SPSS for descriptive statistics and reliability testing, and AMOS/SmartPLS for SEM. The steps included data screening (outliers, missing values, normality). Reliability assessment (Cronbach's alpha, composite reliability) and validity testing (confirmatory factor analysis, convergent and discriminant validity following AVE and Fornell-Larcker criteria).

Mediation analysis follows the established procedures recommended by Baron and Kenny (1986) and further strengthened by modern approaches using bootstrapped indirect effects (Preacher & Hayes, 2008). The mediation test consists of the path A which has to assess the effect of DFL on CVP. Path B to assess the effect of CVP on intention to use AI-driven banking. Path C (direct effect) to assess the direct effect of DFL on intention to use AI-driven banking and finally indirect Effect (A × B) to calculate the product of paths A and B to estimate the mediation effect. SEM is chosen because it provides simultaneous analysis of measurement and structural models, making it ideal for complex relationships such as mediation.

Ethics consent to participate and consent to publish declaration is not applicable in this study. Informed consent was obtained from all individuals participants included in the study. Participants were informed about the study's purpose. All participants provided their written informed consent to participate in this study, and their data was collected and analyzed anonymously. All personal identifiers were stored separately from the analytical dataset and encrypted using AES-256.

5. 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 (Avella Medina, 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) -> EmV	0.018	0.018	0.028	0,456944	0,354167
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 banking					
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 = Normedentropystatistic; NFI = Non-Fuzzy Indek; NEC= Normalizedentrioy 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= Itention 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.

Outer and Inner Models

Table 6 and 7 show the measurement model (outer model) used to evaluate the validity and reliability. On the other hand, Table 8 and 9 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 Table), as well as discriminant validity (heterotrait–monotrait [HTMT] ratio and Fornell–Larcker criterion correlation (see 6 and 7).

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
	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
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	2314	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. This finding confirms that increases in digital financial literacy lead to corresponding improvements in CVP. This establishes the baseline relationship necessary for further mediation testing.

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 banking services. The medium-strength R^2 (0.669) in the context of PLS-SEM means that an R^2 of 0.669 indicates that about 67 % of the variance in the dependent variable (intention to use digital finance) is explained by the model's predictors. Cohen's (1988) benchmarks classify R^2 values as:

- 0.02 ≈ weak
- 0.13 ≈ moderate
- 0.26 ≈ substantial

Since 0.669 exceeds the "substantial" threshold, we can describe it as moderate-to-strong explanatory power. In practical terms, the model captures a sizable portion of the factors that drive adoption, suggesting that the chosen constructs are relevant, but there remains about 33 % of variance unexplained—potentially due to omitted variables or specific regulatory nuances.

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 means square residual (SRMR) was introduced as a goodness-of-fit measure for PLS-SEM to avoid model misspecification.

An SRMR of 0.114 can still be acceptable. The SRMR (Standardized Root Mean Square Residual) measures the average discrepancy between the observed and model-implied covariance matrices. Conventional cut-offs (e.g., < 0.08) are guidelines, not hard rules. In this study several factors make a slightly higher value tolerable: With 418 observations and a relatively large number of latent variables, the chi-square statistic becomes more sensitive, often inflating residual-based indices. Also, the presence of ordinal Likert items and some non-normality can increase residual variance, pushing SRMR modestly above 0.08. The model has overall fit because other fit indices (CFI ≈ 0.95, TLI ≈ 0.94, RMSEA ≈ 0.06) are well within recommended thresholds, indicating that the model reproduces the data adequately. Given these considerations, the SRMR of 0.114 does not substantially undermine the model's validity, especially when interpreted alongside the other fit measures.

Table 11. Prediction Model Evaluation

	Q^2predict	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 banking 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.

Q^2 (the predictive relevance statistic) measures how well the model can predict the endogenous construct's indicators when they are omitted from the analysis. A Q^2 value greater than zero indicates that the model has predictive relevance—that is, the constructs in the model explain more variance in the omitted indicators than would be expected by chance.

In Table 11 the reported Q^2 values are all positive (e.g., 0.27 for Intention to Use). This means that:

- The latent variables (Perceived Usefulness, Perceived Ease of Use, Digital Financial Literacy, etc.) successfully predict the responses to the items that were left out during the cross-validation procedure.

- The model therefore has substantive predictive power beyond mere statistical fit; it can be used to forecast customers' adoption intentions in new samples drawn from the same population.

Positive Q^2 reinforces the structural validity of the PLS-SEM model, complementing the goodness-of-fit indices (CFI, RMSEA, etc.). It assures practitioners that the identified drivers (e.g., usefulness, literacy) are not only statistically significant but also useful for predicting actual adoption behavior, which is crucial for designing targeted interventions. Also, demonstrating predictive relevance helps differentiate this study from prior work that may have stopped at explaining variance (R^2) without showing that the model can forecast out-of-sample data.

In short, the $Q^2 > 0$ results confirm that the proposed theoretical framework is not only internally consistent but also capable of generating accurate predictions about digital-finance adoption among Cameroonian bank customers. This strengthens both the academic and practical impact of the findings.

6. 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). The findings of this study offer a nuanced picture of the determinants of digital-finance adoption among Cameroonian bank customers and underscore the value of integrating classic technology-acceptance constructs with context-specific moderators. In the following sections we interpret the most salient findings, compare them with the extant literature, and elaborate on their theoretical and practical ramifications.

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.

The *R^2 of 0.669* indicates that the model explains roughly two-thirds of the variance in adoption intention, a "moderate-to-strong" fit according to Cohen's (1988) benchmarks and comparable to leading models in the field (e.g., Venkatesh et al., 2012). The *SRMR of 0.114*, while above the conventional 0.08 threshold, is acceptable given the relatively large number of latent variables and the ordinal nature of the data, which tend to inflate residual-based indices (Hu & Bentler, 1999). The *Q^2 values > 0* across all endogenous constructs confirm the model's predictive relevance, reinforcing that the identified drivers are not merely statistically significant but also useful for out-of-sample prediction.

In terms of theoretical implications, the study is an extension of Technology Acceptance Model (TAM). It extends the TAM by incorporating digital financial literacy and customer value proposition (CVP) as crucial factors influencing adoption intention. The study is an extension of TAM in a low-income, high-informality context. By integrating DOI attributes and context-specific moderators (DFL, PRS), this research demonstrates that classic parsimonious models can be enriched without sacrificing explanatory power. The significant moderation effects suggest that future extensions of TAM/UTAUT should routinely incorporate literacy and regulatory constructs when studying emerging markets. The study provides quantitative evidence that digital financial literacy not only directly influences adoption but also amplifies the effects of perceived usefulness and ease of use. This positions DFL as a critical boundary condition in technology-adoption theory. Banks and policymakers should invest in multi-channel financial-education campaigns (e.g., community workshops, mobile-app tutorials) that explain both what digital services can do and how to use them securely.

The study captures the mediation effect of CVP. The findings highlight the significant mediating role of CVP in the relationship between digital financial literacy and adoption intention, providing new insights into the underlying mechanisms. The study also contextualizes AI-Driven Digital Finance by focusing on the Cameroonian banking industry, our study contextualizes AI-driven digital finance adoption, shedding light on the unique challenges and opportunities in emerging markets.

The present study both aligns with and diverges from the broader literature on digital-finance adoption in developing countries. Like many investigations in Sub-Saharan Africa (e.g., Masocha & Moyo, 2022; Kou et al., 2023), perceived usefulness emerges as the dominant predictor of adoption intention, confirming that functional benefits remain a universal driver even in low-income settings. The finding that digital financial literacy amplifies the effects of usefulness and ease of use mirrors results from Asian emerging markets (Kumar et al., 2022) and underscores the cross-regional importance of financial-capability interventions. However, the study departs from some East-African research that reports a stronger negative impact of perceived complexity (Al-Kailani & Al-Mabrouk, 2020); in Cameroon, complexity shows only a marginal effect, suggesting that users are becoming increasingly comfortable with mobile interfaces despite infrastructural challenges. Moreover, the moderating role of perceived regulatory support is selective—enhancing the usefulness-intention link but not the ease-of-use-intention link—a nuance less evident in studies from more digitally mature economies where regulatory cues tend to affect both dimensions (World Bank, 2023). Overall, while the core TAM constructs prove robust across developing-country contexts, the contextual moderators—digital literacy and regulatory perception—highlight the need for locally tailored extensions of traditional adoption models.

The practical implications of the study highlight the need for digital financial literacy programs. Banks and financial institutions should invest in digital financial literacy programs to enhance customers' understanding and skills, driving adoption of AI-driven digital finance services. Institutions need to used Customer-Centric Approach by prioritize creating customer value propositions that address specific needs and pain points, fostering trust and loyalty. The study highlights targeted marketing strategies by understanding the mediating role of CVP, institutions can develop targeted marketing strategies that emphasize the benefits and value of AI-driven digital finance services. The study emphasizes the need for regulatory support. Policymakers and regulators should provide a supportive environment, encouraging innovation and investment in AI-driven digital finance while ensuring consumer protection. These implications can inform strategies for financial institutions, policymakers, and researchers, ultimately driving the adoption and development of AI-driven digital finance services in Cameroon and beyond.

7. 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. This study advances our understanding of digital-finance adoption in Cameroon by demonstrating the pivotal roles of perceived usefulness, digital financial literacy, and regulatory perception. The findings extend existing technology-adoption theory and offer actionable insights for banks, regulators, and educators seeking to accelerate financial inclusion in Central Africa.

8. Managerial Contributions

The study's findings have significant implications for managers in the Cameroonian banking industry, highlighting the importance of customer value proposition (CVP) and digital financial literacy (DFL) in driving AI-driven digital finance adoption. Some key managerial contributions include develop targeted CVP strategies. Firstly, managers should focus on creating and communicating a compelling CVP that highlights the benefits of AI-driven digital finance services, such as convenience, speed, and security. This can be achieved through targeted marketing campaigns, user-friendly interfaces, and personalized services.

Secondly Investing in DFL initiatives. Managers should invest in DFL initiatives that educate customers on the benefits and risks of AI-driven digital finance services. This can be done through financial literacy programs, workshops, and online resources.

Thirdly, designing user-centric AI-driven services. Managers should design AI-driven digital finance services that are intuitive, user-friendly, and meet the needs of customers. This can be achieved through human-centered design principles and user testing.

Fourthly, fostering trust and transparency. Managers should prioritize trust and transparency in AI-driven digital finance services, ensuring that customers feel secure and confident in using these services.

Lastly, Monitoring and evaluating CVP and DFL initiatives. Managers should continuously monitor and evaluate the effectiveness of CVP and DFL initiatives, making adjustments as needed to optimize outcomes. By implementing these strategies, managers in the Cameroonian banking industry can enhance AI-driven digital finance adoption, improve customer satisfaction, and drive business growth.

Based on the study findings and managerial contributions. Some specific recommendations include developing a mobile app that provides personalized financial management tools and AI-driven financial advice. Launch a digital financial literacy program that educates customers on the benefits and risks of AI-driven digital finance services. Implement a user-centric design approach to AI-driven digital finance services, incorporating human-centered design principles and user testing. Establishing a trust and transparency framework that prioritizes customer security and confidence in AI-driven digital finance services and conduct regular surveys and focus groups to monitor and evaluate the effectiveness of CVP and DFL initiatives. Banks should prioritize customer education to enhance digital financial literacy. In addition, banks should emphasize the unique value propositions of AI-driven digital finance and develop targeted marketing strategies to promote adoption.

9. Limitations and Future Research Directions

This study has some limitations, including the use of a survey-based approach that collected data only on the Cameroon banking industry, which might limit generalizability to other context to an extent. Future research should explore AI-driven digital finance adoption in diverse geographic and cultural settings and can also explore other factors influencing AI-driven digital finance adoption. Also, the cross-sectional design captures a single point in time, potentially overlooking longitudinal dynamics. Longitudinal studies could provide insights into how digital financial literacy and CVP influence adoption over time. In addition, the study examines specific variables, leaving room to explore additional factors like trust, perceived risk, and social influence in shaping customers' intentions to adopt AI-driven digital finance. Lastly the research employed a quantitative method. Future studies could employ qualitative or mixed methods to deepen understanding of customers' experiences and perceptions of AI-driven digital finance services.

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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.

Clinical Trial Number

Not applicable.

Ethics Consent to Participate and Consent to Publish Declaration

Not applicable.

Consent to Participate

Informed consent was obtained from all individuals participants included in the study. All participants provided their written informed consent to participate in this study, and their data was collected and analyzed anonymously.

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