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EXPLORING GENDER DIFFERENCES IN THE IMPACT OF DIGITAL FINANCIAL LITERACY ON PERSONAL FINANCIAL BEHAVIOR: A PLS-MGA APPROACH

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In the context of rapidly evolving digital finance, this study aims to assess the impact of digital financial literacy (DFL) on individual financial behavior (FB) within the framework of digital transformation in Vietnam, with a specific focus on examining gender as a theoretical moderator in this relationship, as posited by Gender Role Theory. Data were collected from 329 bank account-holding adults in urban areas through an online survey and analyzed using the SEM-PLS model, combined with 5,000-sample bootstrapping and the advanced PLS-MGA (Multi-Group Analysis) technique. The findings reveal that DFL positively influences FB, with a significantly stronger effect observed among males compared to females, thereby empirically validating the proposed moderating role of gender. Consequently, the study proposes policy recommendations for digital financial education and the design of gender-tailored financial services to promote positive financial behavior. Theoretically, this research provides a nuanced understanding by integrating digital financial literacy with gender role perspectives, contributing to the literature on financial behavior in digital environments. Methodologically, it demonstrates the utility of PLS-MGA in uncovering subgroup differences in emerging economy contexts.

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1. Introduction

In the context of rapid digital transformation, digital financial literacy (DFL) has emerged as a critical factor influencing personal financial behavior. DFL is defined as the integration of foundational financial knowledge and the ability to utilize digital tools and platforms for effective financial management (Prete, 2022; OECD, 2016). Recent studies suggest that gender differences may shape the impact of DFL on financial behaviors, such as saving, investing, or debt management (Bucher-Koenen et al., 2021; Lusardi & Mitchell, 2014; Rahayu et al., 2022). Women often exhibit lower levels of DFL compared to men, potentially due to social, cultural, or technological access constraints (Choung et al., 2023; Fonseca et al., 2012). These disparities are particularly pronounced in developing economies, where gender gaps in access to digital financial services remain significant (Demirguc-Kunt & Klapper, 2013).

This study aims to examine gender differences in the impact of DFL on personal financial behavior. Employing partial least squares structural equation modeling (PLS-SEM) combined with multi-group analysis (PLS-MGA), the research evaluates the relationship between DFL and financial behaviors, including saving, spending, and short- and long-term financial planning, while exploring gender-based variations in these relationships. The findings are expected to provide deeper insights into the role of gender in shaping financial behavior in the digital era, thereby informing policies and strategies to enhance DFL and promote gender equality in personal financial management, particularly in developing economies like Vietnam.

Therefore, this study has two primary objectives: (1) to assess the impact of DFL on individual financial behavior, and (2) to systematically examine the moderating role of gender in this relationship, drawing on gender role theory (Eagly & Wood, 1999). By employing a multi-group analysis (PLS-MGA), we aim to provide nuanced insights into how gender shapes the efficacy of DFL in promoting positive financial behaviors.

In this study, financial Behavior (FB) is conceptualized in this study as a holistic, second-order construct encompassing key behavioral domains: saving, spending, and planning (both short- and long-term). This comprehensive approach allows for assessing the general impact of DFL on overall financial conduct, rather than isolating a single behavior, which aligns with the multidimensional nature of personal financial management (Xiao, 2008).

The remainder of the paper is organized as follows: Section 2 reviews the theoretical framework and research hypotheses; Section 3 outlines the methodology; Section 4 presents the model analysis; and Section 5 offers conclusions and policy recommendations.

2. Literature review and hypothesis development

2.1. Theoretical foundations

This study employs Social Cognitive Learning Theory and Gender Role Theory to explain the impact of digital financial literacy (DFL) on personal financial behavior and the gender differences in this relationship.

According to Bandura's (1977) social cognitive learning theory, people pick up new behaviors by interacting with their social surroundings, imitating others, and observing them (Bandura, 1977; Nabavi & Sadegh Bijandi, 2012). According to Rahayu et al. (2022), DFL, which includes knowledge and abilities in using digital financial technologies, is created by learning from peers, family, or educational programs. By boosting confidence and the capacity to use financial knowledge, this literacy promotes sound financial practices like investing, saving, and debt management (Prete, 2022).

Gender role theory (Eagly & Wood, 1999) suggests that gender differences in social expectations, cognitive styles, and behaviors arise from cultural and social norms. Prior studies indicate that women tend to be more cautious in financial decision-making and exhibit lower confidence in adopting new technologies. Consequently, gender may moderate the relationship between DFL and financial behavior, reflecting differences in how men and women apply digital financial knowledge to personal financial practices.

2.2. Concepts and research hypotheses

Digital Financial Literacy (DFL)

DFL is defined as the ability to integrate foundational financial knowledge with skills in using digital tools and platforms for effective personal financial management (Prete, 2022; OECD, 2016). This concept encompasses understanding financial concepts (e.g., interest rates, investments) and applying them through digital tools, such as mobile banking apps, e-wallets, or online investment platforms. In this study, DFL is measured through a combination of financial knowledge, digital knowledge, practical knowledge, awareness, decision-making skills, and self-protection capabilities (Abdallah et al., 2025). Building on the multidimensional framework proposed by the OECD (2022) and operationalized by Abdallah et al. (2024), this study conceptualizes DFL as a second-order reflective-formative construct comprising six interrelated first-order dimensions: Financial Knowledge (FK), Digital Knowledge (DK), Practical Know-how (PK), Awareness (AW), Decision-Making (DM), and Self-Protection (SP). This structure reflects the integration of core financial competencies (FK, DM) with digital-specific capabilities (DK, PK, SP, AW), essential for navigating the digital finance ecosystem.

a. Financial Knowledge (FK): Refers to the basic understanding of key financial concepts such as interest rates, inflation, risk, and portfolio diversification. This knowledge enables individuals to make informed financial decisions, thereby contributing to the improvement of both personal and community financial well-being (Amalia et al., 2023).

b. Digital Knowledge (DK): Refers to the understanding and ability to use fundamental digital devices, software, and concepts related to digital finance. This includes knowledge of data security principles, digital account management, and the functionality of digital financial platforms (Lee, 2014; Lyons & Kass-Hanna, 2021; OECD, 2022). The four items for this construct (DK1-DK4 in the Appendix) were adapted from the digital competency components in the OECD (2022) survey instrument and validated scales by Lee (2014), ensuring content validity for the Vietnamese context.

c. Practical Know-how (PK): Denotes the ability to effectively utilize digital financial services in daily life, such as electronic payments, account management, and routine financial transactions. Individuals with high levels of practical know-how tend to use digital financial services more efficiently and flexibly (Malady & Law, 2016).

d. Awareness (AW): Reflects an individual's level of understanding regarding the purpose, benefits, and potential risks associated with digital financial services such as e-wallets, digital banking, and cryptocurrencies. A higher level of awareness helps users distinguish trustworthy services and enhances their intention to adopt digital finance (Rai et al., 2019).

e. Decision-Making (DM): Encompasses a positive financial attitude and the capability to select financial services that align with personal needs. Individuals with strong decision-making abilities are typically better at managing expenditures, saving effectively, and choosing secure digital financial service providers (Kumar et al., 2023).

f. Self-Protection (SP): Refers to the ability to identify and prevent risks related to fraud, data breaches, and cyberattacks in the digital financial environment. This includes both reactive skills and proactive behaviors aimed at safeguarding oneself when using digital financial services (Dewi et al., 2020).

Financial Behavior (FB)

Personal financial behavior refers to individuals' decisions and actions related to managing financial resources, including saving, investing, and debt management (Lusardi & Mitchell, 2014). In the context of digital transformation, financial behavior is manifested through the use of digital financial tools to perform activities such as regular saving via apps, investing in online funds or stocks, and tracking or repaying debt through digital platforms (Prete, 2022). This study focuses on four key aspects: saving, spending, and short- and long-term financial planning (Abdallah et al., 2025).

Saving Behavior (SB): Refers to the difference between an individual's income and expenditure over a specific period (J. M. Lee & Hanna, 2015). Saving plays a vital role in ensuring long-term financial stability, as individuals who intentionally set aside a portion of their income contribute to the accumulation and growth of personal wealth (Perez-Falcon, 2017).

Shopping Behavior (ShB): Represents a dynamic process in which individuals engage in searching for, evaluating, and selecting products or services to fulfill their needs and desires. According to Stofkova et al. (2022), key elements shaping shopping behavior include waiting for promotions, comparing alternatives, and carefully assessing the quality and value of products or services.

Long-term Planning Behavior (LtP): Involves setting future financial goals and developing strategies to achieve them through budgeting, investing, and saving for retirement over a period of one to two years (Zulaihati et al., 2020). Long-term planning is considered more challenging than short-term planning, as it requires comprehensive forecasting without immediate feedback, making it more difficult to adjust financial behaviors accordingly (Wagner, 2019).

Short-term Planning Behavior (StP): Refers to the management of cash flow and the tracking of income, credit, and expenses within a period of less than one year. According to Wagner (2019), this behavior is commonly assessed through indicators such as maintaining an emergency fund, spending within income limits, and avoiding account overdrafts. It serves as a fundamental component of effective short-term personal financial control.

Digital Financial Literacy and Financial Behavior

DFL equips individuals with the knowledge and skills to make effective financial decisions in digital environments, contributing to personal well-being and economic development (Dogra et al., 2023). DFL promotes positive financial behaviors, such as saving, investing, and debt management (Kumar et al., 2023; Rahayu et al., 2022). Conversely, a lack of DFL may lead to impulsive spending and increased debt (Panos & Wilson, 2020). DFL helps mitigate excessive debt, supports long-term financial planning, and protects consumers from digital financial risks (Koskelainen et al., 2023; A. Lusardi & Mitchell, 2011). Based on this, the following hypothesis is proposed:

Hypothesis H1: Digital financial literacy positively influences personal financial behavior.

The moderating role of gender in the relationship between DFL and FB

Gender is a key demographic factor that may influence how individuals adopt and apply technology in financial behaviors. According to gender role theory (Eagly & Wood, 1999), men and women exhibit differences in social expectations, cognitive styles, and decision-making, particularly in technology and finance-related domains. Additionally, men are more influenced by perceived usefulness when adopting technology, whereas women prioritize ease of use and social influences (Smith & Morris, 2000). In the financial context, women generally exhibit lower financial confidence and literacy than men, impacting their ability to apply financial technologies to practical behaviors (Lusardi & Mitchell, 2014). These differences highlight the potential moderating role of gender in the relationship between DFL and FB. Accordingly, this study proposes the following hypotheses:

Hypothesis H2a: Digital financial literacy positively influences personal financial behavior among males.

Hypothesis H2b: Digital financial literacy positively influences personal financial behavior among females.

Hypothesis H2c: There is a significant difference between males and female in the relationship between digital financial literacy and personal financial behavior.

3. Research methodology

3.1. Data collection and scale design

An online survey was conducted via Google Forms from February to March 2025, targeting individuals aged 20 and above, with bank accounts, residing in major Vietnamese cities, and having access to digital financial services. A snowball sampling technique was employed to reach the target population. During the data collection process, the questionnaire was administered in an anonymous online format and included a clear introductory section outlining the purpose of the study, the intended use of the data, and a commitment to protecting participants' personal information. Participants' decision to proceed and complete the survey after reading this introduction was considered as providing informed and voluntary consent to participate. This approach is consistent with standard research practices for online surveys and adheres to ethical principles governing research involving human subjects.

The questionnaire comprised three sections: (1) digital financial literacy (DFL), (2) personal financial behavior (FB), and (3) demographics for respondent screening. All measurement items were derived from established scales in the literature to ensure content validity. The items for DFL and FB were primarily adapted from Abdallah et al. (2024), which provides a comprehensive and recently validated multidimensional framework. To ensure contextual suitability, the items underwent a rigorous translation process: forward-translation from English to Vietnamese by a finance researcher, back-translation by an independent bilingual expert, and reconciliation of discrepancies by the research team. A pilot test was conducted with 30 respondents matching the target demographic to assess item clarity, comprehensibility, and face validity. Minor wording adjustments were made based on pilot feedback. For the main survey, a total of 451 responses were collected, with 122 excluded due to unmet criteria, resulting in 329 valid responses for analysis.

DFL was measured using a 5-point Likert scale with six components: financial knowledge (FK – 2 items), digital knowledge (DK – 4 items), practical know-how (PK – 4 items), awareness (AW – 4 items), decision-making skills (DM – 4 items), and self-protection capability (SP – 2 items). FB was assessed through four dimensions: saving behavior (SB – 4 items), shopping behavior (ShP – 3 items), long-term planning (LtP – 5 items), and short-term planning (StP – 6 items). The scales were adapted from Abdallah et al. (2024), translated, and adjusted to suit the Vietnamese context.

The financial knowledge (FK) dimension was measured using two items (FK1, FK2) adapted from Abdallah et al. (2024). These items capture fundamental concepts of risk-return trade-off and inflation, which are core to basic financial literacy (Lusardi & Mitchell, 2014). While longer scales exist, this concise measure was chosen to maintain a reasonable survey length and participant engagement, a common consideration in comprehensive surveys covering multiple constructs (Hair et al., 2017). The focus of this study's DFL construct is on the integration and application of financial knowledge within digital contexts (through other dimensions like PK, DM, SP), rather than on deep, granular assessment of financial knowledge per se.

The scales for DFL and FB were adapted from Abdallah et al. (2024), which itself draws upon established frameworks like the OECD (2022) and prior validated studies. All items were translated into Vietnamese using a back-translation procedure to ensure conceptual equivalence and were pre-tested with a small group for clarity and contextual relevance. The FB scales, including the shopping behavior (ShB) construct, were adopted unchanged from Abdallah et al. (2024). This approach ensures comparability with emerging international research on DFL. The ShB scale is designed to capture a unidimensional construct of "spending deliberateness" by including both positive (e.g., comparing prices) and reverse-coded (e.g., impulse buying) items. This is a common practice in behavioral scales to mitigate acquiescence bias and capture a broader spectrum of the construct (Spector, 1992).

3.2. Analytical methods

SmartPLS 3.0 was employed for: (1) evaluating the measurement model to assess the reliability, convergent validity, and discriminant validity of the scales. Observed variables failing to meet the requirements were removed to ensure model fit; (2) conducting bootstrapping and multigroup analysis (PLS-MGA) to examine gender differences in the relationship between (DFL and FB.

Prior to performing the multi-group analysis, measurement invariance across gender groups was assessed to ensure the comparability of the constructs. Following Henseler et al. (2016), we employed the Measurement Invariance of Composite Models (MICOM) procedure, which involves three steps: configural invariance, compositional invariance, and the equality of composite mean values and variances. The results confirmed the establishment of partial measurement invariance (specifically, configural and compositional invariance), which is a sufficient condition for conducting meaningful comparisons of path coefficients across groups using PLS-MGA (Henseler et al., 2016).

PLS-MGA, a non-parametric approach, does not require normally distributed data, making it suitable for social science research using survey data and Likert scales. This method enables the comparison of statistically significant differences in path coefficients across groups in the structural equation model (SEM), facilitating the detection of whether causal relationships are influenced by gender.

4. Results and discussion

Appendix 2 (see Appendix 2) describes the demographic characteristics of the sample. The valid sample consisted of 329 respondents, with females accounting for 68%. The majority were young, with 76.9% aged 20–30 years and the remainder over 30 years. Regarding monthly income, 60.8% earned less than VND 8 million, 30% earned between VND 8–21 million, and 9.2% earned above VND 21 million. Full-time employees comprised 60,8% of the sample.

4.1. Measurement model assessment

As digital financial literacy (DFL) and financial behavior (FB) are conceptualized as second-order constructs (SOCs) comprising multiple interrelated first-order dimensions, the study employed a combination of the repeated indicator approach (Hair et al., 2017) for the first step and the two-stage approach for the second step. This technique involves assigning all indicators from the first-order constructs directly to the second-order construct to ensure consistency and completeness in structural estimation. Step 1, apply the repeated indicator technique, specifically: (i) Evaluate the measurement model for the first-order constructs. Depending on whether the model is reflective or formative, appropriate measurement criteria are used; (ii) Extract the factor scores (latent variable scores) of the first-order constructs and add them to the dataset for use in the next step. The results presented in Figure 1.

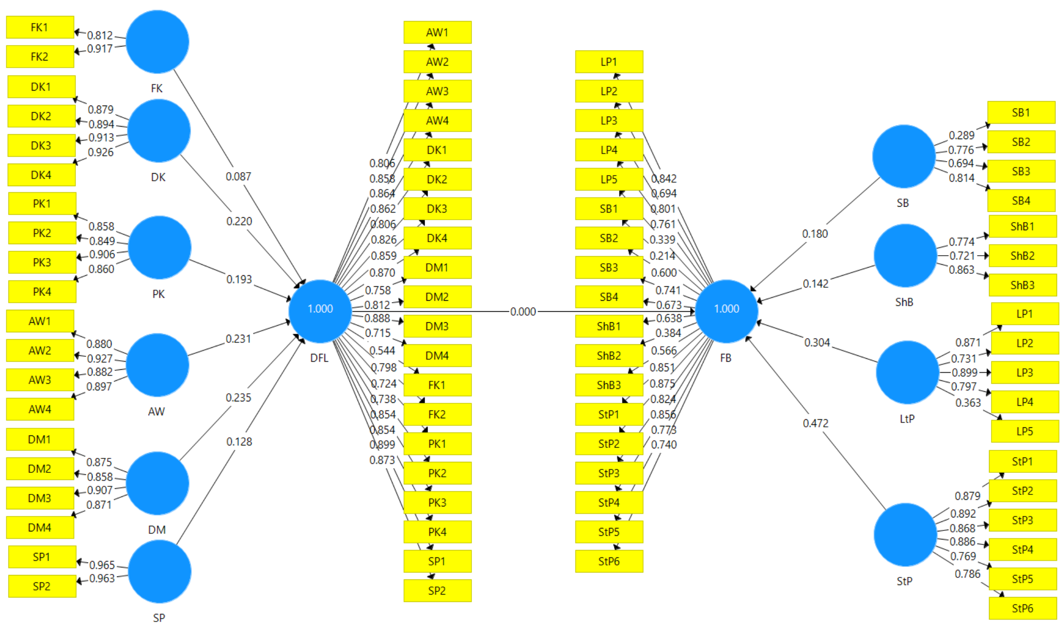

Figure 1. First step - Repeated indicator approach

The structural model was developed and estimated using SmartPLS 3, a software widely used for Partial Least Squares Structural Equation Modeling (PLS-SEM). In the initial stage, the measurement model was assessed by examining the reliability and validity of the first-order constructs. During this process, individual item loadings were analyzed to determine whether they met the commonly accepted threshold of 0.7, which indicates adequate indicator reliability (Hair et al., 2017).

The evaluation revealed that two indicators - SB1 and LtP5 - had factor loadings below the threshold of 0.7, suggesting weak contributions to their respective latent constructs. As a result, these items were removed from further analysis to improve the overall quality of the measurement model. Meanwhile, the indicator SB3, despite having a loading slightly below the cutoff point (0.697), was retained due to its proximity to the acceptable value and its theoretical relevance.

A summary of the refined measurement model, including the final set of indicators and their loadings, is presented in Appendix 3.

Subsequently, the author conducted a thorough assessment of the reliability and convergent validity of the measurement scales employed in the study. This step involved evaluating key indicators such as Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE), all of which are essential for establishing the internal consistency and convergent validity of the constructs (Hair et al., 2017). The results of this evaluation are systematically summarized and presented in Table 3.

Table 1. Reliability and convergent validity of first-order construct (FOC) scales

FOC	Cronbach's Alpha (CA)	Composite Reliability (CR)	Average Variance Extracted (AVE)	FOC	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
FK	0,677	0,857	0,750	SP	0,924	0,963	0,929
DK	0,924	0,946	0,815	SB	0,654	0,812	0,591
PK	0,891	0,925	0,754	ShP	0,703	0,829	0,619
AW	0,919	0,943	0,804	LtP	0,850	0,900	0,695
DM	0,901	0,931	0,771	StP	0,921	0,939	0,719

Table 1 indicates that the Cronbach's Alpha (CA) coefficients for FK (0.677) and SB (0.654) are slightly below the conventional threshold of 0.7. This is not uncommon for constructs with a very small number of items (FK has only 2 items), as CA is sensitive to scale length (Cortina, 1993). More importantly, the Composite Reliability (CR) values for both constructs (FK = 0.857, SB = 0.812) exceed 0.7, which is a more appropriate indicator of internal consistency for models with few indicators and is prioritized in PLS-SEM (Hair et al., 2017; Henseler & Sarstedt, 2013). Furthermore, the Average Variance Extracted (AVE) for FK is high (0.750), indicating that the two items converge well in representing the latent construct. Therefore, the reliability of the FK scale is deemed acceptable for the purposes of this study. Additionally, the discriminant validity of the scales is presented in Table 4.

Table 2. Discriminant validity assessment based on the fornell-larcker criterion

	AW	DK	DM	FK	LtP	PK	SB	SP	ShP	StP
AW	0,897									
DK	0,836	0,903								
DM	0,852	0,764	0,878							
FK	0,702	0,806	0,641	0,866						
LtP	0,724	0,588	0,807	0,506	0,834					
PK	0,834	0,866	0,742	0,701	0,599	0,868				
SB	0,716	0,514	0,705	0,451	0,815	0,479	0,769			

	AW	DK	DM	FK	LtP	PK	SB	SP	ShP	StP
SP	0,855	0,797	0,863	0,649	0,745	0,829	0,627	0,964		
ShP	0,301	0,259	0,445	0,314	0,513	0,131	0,586	0,252	0,787	
StP	0,691	0,649	0,779	0,585	0,874	0,563	0,804	0,683	0,603	0,848

As presented in Table 2, the square roots of the Average Variance Extracted (AVE) for each construct (displayed as the diagonal values in each column) are consistently higher than the corresponding inter-construct correlation coefficients (shown below the diagonal). This pattern indicates that each construct shares more variance with its own indicators than with any other construct in the model, thereby providing strong evidence of discriminant validity according to the Fornell & Larcker (1981) criterion.

Step 2 of the Second-order construct modeling procedure, apply the second stage of the two-stage approach, specifically: (i) Construct a new diagram representing the first-order constructs using the factor scores obtained in Step 1. Then evaluate the measurement model for this second-stage diagram; (ii) Evaluate the structural model. The results presented in Figure 2.

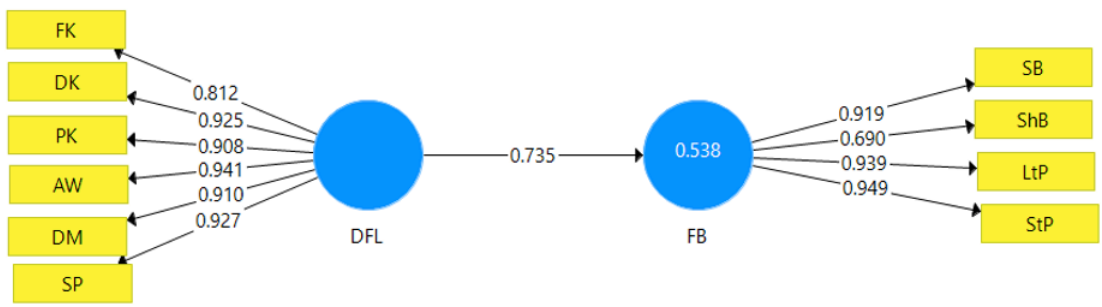

Figure 2. Second step – Two stages approach for estimating a second-order model

Following the initial evaluation, the PLS Algorithm was executed once again to obtain the factor weights associated with the latent variables. These factor weights, which correspond to the first-order constructs, were then incorporated into the dataset to refine the second-order construct estimation. Subsequently, the measurement model was re-evaluated, including a reassessment of construct reliability and convergent validity, in accordance with established methodological standards. The updated results from this reassessment are comprehensively presented in Table 3.

Table 3. Factor loadings of first-order constructs

SOC	FOC	Factor Loading	CA	CR	AVE	SOC	FOC	Factor Loading	AC	CR	AVE
DFL	FK	0,812	0,956	0,964	0,819	**FB**	SB	0,919	0,903	0,932	0,776
	DK	0,925					ShP	0,690			
	PK	0,908					LtP	0,939			
	AW	0,941					StP	0,949			
	DM	0,910									
	SP	0,927									

Table 3 indicates that the factor loading for the first-order variable ShP is 0.690, close to the 0.7 threshold and thus deemed acceptable, confirming the significance of all first-order variables. Additionally, all variables exhibit Cronbach's Alpha (CA) and Composite Reliability (CR) values greater than 0.7, and Average Variance Extracted (AVE) values above 0.5, demonstrating that the scales meet the requirements for reliability and convergent validity.

4.2. Results of bootstrapping and PLS-MGA analysis

The study conducted bootstrapping analysis with 5,000 iterations and partial least squares multi-group analysis (PLS-MGA) to compare differences in the structural equation model (SEM) between male and female groups. The results are presented in Figure 3 and Table 6.

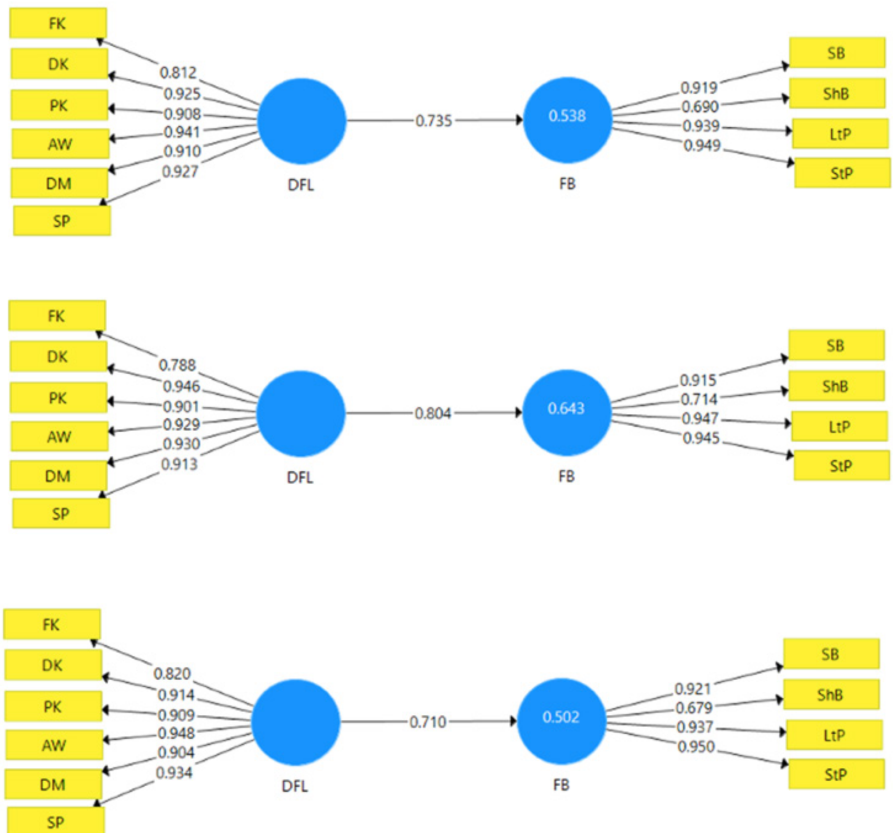

Figure 3. The impact of DFL on FB for the overall sample, male group, and female group

Prior to examining the path coefficients, we assessed the structural model for potential multicollinearity. The inner Variance Inflation Factor (VIF) value for the path from DFL to FB is 1.000, which is well below the recommended threshold of 3 (Hair et al., 2017). This indicates the absence of significant multicollinearity concerns, ensuring the stability and reliability of the subsequent estimates. The bootstrapping results presented in Table 6 indicate that the impact of DFL on FB is statistically significant for the overall sample, the male subgroup, and the female subgroup, with all p-values equal to 0.000 (< 0.05). Accordingly, DFL exerts a positive influence on FB, with path coefficients of 0.735 for the overall sample, 0.804 for males, and 0.710 for females. Thus, hypotheses H1, H2a, and H2b are supported.

Table 4. Hypothesis testing results

Hypothesis	Relationship	PLS-MGA results			Bootstrapping Results			Results
		Path Coefficients-diff (Male - Female)	p-Value original 1-tailed (Male vs. Female)	p-Value new (Male vs. Female)	Original Sample	Standard Deviation (STDEV)	p Values	
H1	DFL -> FB				0,735***	0,022	0,000	Accepted
H2a	DFL -> FB (Male)				0,804***	0,034	0,000	Accepted
H2b	DFL -> FB (Female)				0,710***	0,027	0,000	Accepted
H2c	DFL -> FB (Male vs Female)	0,094***	0,021	0,041				Accepted

Note: **p<0,1; **p<0,05; ***p<0,01.*

Notably, the multi-group analysis (PLS-MGA) results in Table 4 reveal a statistically significant difference between males and females in the relationship between DFL and FB (p-value = 0.041), confirming hypothesis H2c. This suggests that gender moderates the relationship. Specifically, the path coefficient difference (Male – Female) is 0.094, indicating that the influence of DFL on FB is stronger among males than females.

This finding aligns with previous research (Venkatesh Robert Smith & Morris, 2000), which found that males tend to be more proactive in adopting technology and more confident in making decisions in digital environments, thereby enhancing the effectiveness of financial behaviors. Similarly, Eagly and Wood (1999), within the framework of gender role theory, argued that women tend to exhibit more cautious behavior, prioritize safety, and seek external advice, while men are more likely to be independent, self-directed, and risk-tolerant. These gender-based differences may explain why DFL has a greater impact on the financial behavior of males, who are more active in acquiring, processing, and applying digital financial information in practice.

The analysis further reveals that the impact of DFL on FB is substantively strong. This is evidenced by the adjusted R^2 values of 0.538, 0.643, and 0.502 for the overall sample, male, and female groups, respectively, indicating that the model explains a substantial portion of the variance in financial behavior. The effect sizes (f^2) all exceed 0.35, confirming DFL as a decisive factor within the proposed model (Hair et al., 2017). These findings on the positive main effect (H1) align with and extend prior work on financial literacy (Lusardi & Mitchell, 2014) into the digital realm, supporting the argument that competence in using digital financial tools is crucial for shaping financial habits (OECD, 2022).

More importantly, the significant gender difference (H2c supported) provides a key theoretical contribution. It offers empirical validation for the propositions of Gender Role Theory (Eagly & Wood, 1999) within digital finance, demonstrating how socially constructed roles influence technology adoption and financial decision-making. This result corroborates international findings that men often exhibit greater confidence in technology use (Venkatesh & Morris, 2000), which appears to enhance the translation of their digital financial knowledge into action. However, the positive and significant path coefficient for women (H2b supported) is a crucial nuance, suggesting that DFL remains a powerful tool for enhancing financial behavior across all genders, even if its efficacy is moderated.

This moves beyond a simple deficit narrative about women and finance, highlighting instead the universal value of DFL while underscoring the need for gender-tailored approaches to maximize its impact.

The substantial explanatory power of DFL in the current model also implies that other variables may play a secondary role or act as potential mediators/moderators not yet incorporated. This opens avenues for future research to explore factors such as financial self-efficacy, perceived risk, or social influence, which might further elucidate the mechanisms linking DFL to financial behavior.

5. Conclusion and recommendations

The findings of this study reveal that digital financial literacy (DFL) exerts a positive and significant impact on individual financial behavior (FB), with a notably stronger effect observed among males compared to females. This result aligns with prior studies such as Venkatesh and Morris (2000) and Eagly and Wood (1999), which emphasize the influence of gender roles on individuals' reception, processing, and application of financial technologies. Males often exhibit greater confidence in using digital tools, thereby enabling DFL to produce more substantial behavioral changes. In contrast, females may adopt more conservative financial behavior and may require additional supportive factors, such as communication campaigns, financial advisory services, or social networks, to fully leverage their digital financial capabilities.

These insights offer several policy implications for different stakeholder groups. Policymakers should implement comprehensive digital financial education programs tailored by gender, age, and residential location, with particular emphasis on females and young individuals with low DFL. Providers of digital financial services are encouraged to design user-friendly, intuitive, and highly personalized products, platforms, and financial communication content aimed at attracting female users and those with limited digital experience. Enhancing system security and transparency is also crucial for building user trust. Consumers, meanwhile, are urged to proactively develop digital financial competencies and master modern financial tools to form better habits of spending, saving, financial planning, and investment in the digital environment.

Despite these contributions, the study is subject to several limitations. First, the survey sample was primarily drawn from major urban areas, which may not fully capture the financial behaviors of rural populations or other minority groups. Second, the cross-sectional design of the research limits the ability to draw causal inferences over time regarding the relationship between DFL and FB. Future research should expand the sample scope, employ longitudinal data or intervention-based experimental designs to more robustly test the impact of DFL. Third, regarding measurement, the financial knowledge (FK) component of our DFL construct relied on only two items. Although these items cover key concepts and the overall DFL measurement model demonstrated adequate reliability and validity, future research would benefit from incorporating a more comprehensive, multi-item financial knowledge scale to enhance the robustness and content coverage of this critical dimension. Additionally, incorporating potential mediators such as perceived financial risk, financial self-efficacy, or technological factors (e.g., attitudes toward Fintech) could further elucidate the mechanisms linking DFL and individual financial behavior. Future research could disaggregate this composite FB construct to examine whether the impact of DFL and the moderating effect of gender vary across specific behavioral domains such as investment or debt management.

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