



What Shapes FinTech Impact in the Digital Banking Era? Evidence from Kosovo, Albania, and North Macedonia

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ABSTRACT

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This study examines how Digital Marketing (DM), Behavioral and Trust Factors (BTF), and Financial Literacy (FL) are related to Perceived FinTech Impact (PFI) among respondents in Kosovo, Albania, and North Macedonia. PFI is operationalized as a six-item observed component (Q15-Q20). Using 262 survey responses, the measurement phase assessed the internal consistency and structure of the exploratory items via Cronbach's alpha and Principal Axis Factoring (PAF) with Promax rotation. Formal hypotheses were tested with a four-block hierarchical Ordinary Least Squares (OLS) model using 255 full cases; demographic controls were entered first, followed by standardized key predictors, all two-way interactions, and the three-way interaction. The final model explained 38.5% of the variance ($R^2 = 0.385$; adjusted $R^2 = 0.343$; $F(16, 238) = 9.294$, $p < 0.001$). The BTF ($\beta = 0.438$, $p < 0.001$) and FL ($\beta = 0.287$, $p < 0.001$) showed significant positive adjusted relationships, while DM was positive but not significant ($\beta = 0.127$, $p = 0.076$). The DM $\times$ FL interaction was positive and significant ($\beta = 0.266$, $p = 0.004$), while the three-way interaction was not significant ($\beta = -0.176$, $p = 0.083$). Simple slope analysis showed a significant positive association of DM only with high FL (+1 SD; $B = 0.277$, $p = 0.002$). A sensitivity analysis of user status and robust inference to heteroskedasticity maintained the core hypothesis decisions. Country-specific models are treated only as supplementary within-country evidence because national subsamples are unbalanced and measurement invariance was not established. The findings highlight factors related to trust and FL as the strongest adjusted correlates of PFI and show that the association of DM varies with FL. For banks, the findings suggest that strengthening trust, perceptions of security, and supporting FL may be more effective in improving PFI than relying solely on DM. For FinTech users, higher FL can enhance their ability to evaluate and benefit from digital financial services, while trust and security remain central to positive FinTech experiences.

1. INTRODUCTION

Financial technology has become an important driver of transformation in the banking sector, reshaping the way individuals access financial services, make payments, manage savings, obtain credit, and interact with financial institutions. Rather than representing only a digital extension of traditional banking, FinTech has increasingly become part of a broader transformation that supports service efficiency, customer engagement, financial inclusion, and sustainable financial development. Through the introduction of new technologies, digital platforms, and innovative business models, FinTech continues to influence the structure of financial services and the operational logic of banking institutions [1, 2].

This transformation is particularly relevant for emerging and transition economies, where digital financial services have the potential to reduce access barriers, improve the availability of financial products, and support more inclusive financial systems. Kosovo, Albania, and North Macedonia represent an important Western Balkan context for examining this issue because all three countries are experiencing ongoing banking digitalization, increasing use of internet and mobile technologies, and gradual alignment with European financial standards. However, the adoption of FinTech in these countries does not depend only on technological availability. It is also shaped by cash-oriented payment habits, uneven levels of financial and digital literacy, consumer trust, cybersecurity concerns, and data protection issues. For this

reason, FinTech adoption in these economies should be understood not merely as a technological process, but as a behavioral, institutional, and socio-economic phenomenon [3].

Within this study, FinTech adoption and impact are treated through respondents' reported use and perceived practical outcomes rather than as a direct measure of sustainability. The empirical outcome captures time saving, transaction efficiency, increased use of digital financial services, expense monitoring, perceived improvement in personal financial management, and recommendation/advocacy. Broader sustainability dimensions—such as financial inclusion, consumer protection, operational resilience, responsible innovation, and long-term financial well-being—remain important in the wider literature but are not operationalized as components of the dependent variable in this study [4, 5]. Accordingly, the empirical claims are limited to FinTech adoption/impact and users' perceived practical and financial outcomes. This distinction ensures that the study does not infer sustainable or long-term adoption from a cross-sectional perception-based measure.

The theoretical foundation of this study is based mainly on technology acceptance and Financial Literacy (FL) perspectives. The Technology Acceptance Model (TAM) explains technology adoption through perceived usefulness and perceived ease of use, while broader technology acceptance frameworks emphasize performance expectancy, effort expectancy, social influence, and facilitating conditions [6-8]. In the FinTech context, however, these models need to be extended because digital financial services involve not only technology use, but also financial decisions, personal data, security concerns, and risk evaluation. Consequently, factors such as trust, perceived risk, security, behavioral attitudes, and FL become essential for explaining whether users accept, use, and benefit from FinTech services [9-12].

Despite the growing importance of FinTech, empirical evidence from smaller emerging European economies remains limited. Existing studies often focus on larger markets or examine FinTech adoption through general TAM, without sufficiently integrating Digital Marketing (DM), Behavioral and Trust Factors (BTF), and FL into a unified explanatory framework. Moreover, regional studies on the Western Balkans have often relied on macro-level indicators, while micro-level evidence based on individual perceptions remains comparatively scarce [3]. This creates an important research gap, especially because the Perceived FinTech Impact (PFI) depends on how users experience digital banking services in practice.

The main research problem addressed in this study is that the factors associated with PFI in the Western Balkans remain insufficiently examined at the individual level. Although digital banking and payment technologies are expanding, it is still unclear whether users perceive FinTech as a practical source of financial benefit and which factors are associated with this perceived impact. In particular, limited empirical evidence exists on whether DM, BTF, and FL are independently associated with PFI, and whether these dimensions interact in shaping users' perceived financial outcomes [13-15].

Based on this research gap, the main aim of this study is to examine the adjusted associations with PFI in the banking sector in Kosovo, Albania, and North Macedonia. The study focuses on three explanatory dimensions: DM, BTF, and FL. The dependent measure is operationalized as one six-item

observed composite (Q15-Q20), hereafter referred to as PFI. The items cover time saving, transaction efficiency, increased use of digital financial services, expense monitoring, perceived improvement in personal financial management, and recommendation/advocacy. A focused dimensional assessment did not support treating Usage and Financial Performance as two distinct first-order factors; these labels are therefore not used as separate validated constructs [2, 4].

To achieve this aim, the study first examines the adjusted association of DM with PFI, particularly through online visibility, digital communication, platform presentation, promotional exposure, and information credibility. It then assesses BTF, including perceived security, attitudes toward innovation, preference for digital services, and social influence, together with FL, which reflects users' ability to understand, assess, and use financial information. Beyond these main associations, the study evaluates specified two-way and three-way interaction terms. Pearson correlations among the main observed composites are reported only as preliminary bivariate associations and are not used for formal hypothesis decisions. Country-specific regressions are used only to describe supplementary within-country sensitivity patterns.

Accordingly, the study is guided by the following research questions: i) What are the adjusted associations of DM, BTF, and FL with PFI? ii) Does FL strengthen the association between DM and PFI? iii) Is the three-way interaction among DM, BTF, and FL statistically associated with PFI? iv) What within-country patterns are observed in the supplementary country-specific regressions for Kosovo, Albania, and North Macedonia?

In line with these research questions, the study proposes five formal hypotheses.

H1 predicts a positive association between DM and PFI.

H2 predicts a positive relationship between BTF and PFI.

H3 predicts a positive relationship between FL and PFI.

H4 FL strengthens the positive relationship between DM and PFI.

H5 predicts that the three-way interaction between DM, BTF, and FL is statistically significantly associated with PFI.

This study contributes to the literature in three main ways. First, it provides multi-country micro-level evidence from Kosovo, Albania, and North Macedonia, three under-researched Western Balkan economies undergoing digital financial transformation. The country-specific estimates are used as supplementary regional context rather than as formal tests of cross-country coefficient differences. Second, it extends technology adoption perspectives by integrating DM, BTF, and FL into a single explanatory framework of PFI. Third, it moves beyond simple adoption or usage intention by examining PFI as a broader outcome that includes perceived improvements in usage, transaction efficiency, financial management, expense monitoring, and willingness to recommend FinTech services [3, 6, 10].

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature and develops the conceptual logic of the study. Section 3 presents the methodology, including the research design, sample, measurement of variables, construction of indices, and empirical models. Section 4 reports the empirical results. Section 5 discusses the findings in relation to previous literature and the regional context. Section 6 concludes the paper by presenting theoretical contributions, practical implications, limitations, and directions for future research.

2. LITERATURE REVIEW

This section reviews the theoretical and empirical literature related to FinTech adoption and PFI in banking. Broader sustainability themes are discussed as contextual literature where relevant, but they are not treated as an empirically measured construct in this study. The literature review follows a theory-driven structure, moving from the broader role of FinTech in emerging banking systems to the specific mechanisms examined in this study: DM, BTF, FL, and interaction effects. For clarity, the abbreviations used throughout the study are listed in Appendix A.

2.1 Theoretical foundations of FinTech adoption and impact

The theoretical foundation of this study is mainly based on the TAM and the Unified Theory of Acceptance and Use of Technology (UTAUT). TAM explains technology adoption through two key factors: perceived usefulness and perceived ease of use, suggesting that users are more likely to accept a technology when they believe it improves their performance and is easy to use. Similarly, UTAUT explains technology acceptance and usage through factors such as performance expectancy, effort expectancy, social influence, and facilitating conditions [6]. This logic is relevant to FinTech because digital financial services require users to evaluate both the practical benefits and the ease of using digital platforms.

UTAUT extends this perspective by emphasizing performance expectancy, effort expectancy, social influence, and facilitating conditions as key determinants of technology use [7]. Later extensions of TAM also show that adoption decisions may be shaped by social influence, cognitive evaluations, and perceptions of system quality or usefulness [8]. These perspectives justify the inclusion of DM, BTF, and FL in this study.

In the context of FinTech, TAM needs to be extended with behavioral and knowledge-based factors. Users' adoption decisions are rarely based only on technical usability; instead, they are also influenced by trust, perceived security, perceived risk, digital confidence, social influence, and FL. These factors are particularly important in digital finance because users interact with financial services through digital platforms and often share sensitive personal and financial information [9-12].

2.2 FinTech adoption and Perceived FinTech Impact

FinTech adoption has become an important dimension of banking transformation, especially in emerging and transition economies. FinTech can reduce transaction costs, expand access to financial services, increase payment efficiency, and support financial inclusion. Research on digital finance shows that FinTech changes the organization of financial services by combining new business models, digital platforms, and technological infrastructures [1, 2].

FinTech can support financial inclusion and sustainable development when it is supported by adequate infrastructure, regulation, and institutional safeguards [4, 5]. However, the impact of FinTech should not be treated as automatically positive, because digital financial innovation may also generate risks related to financial stability, consumer protection, cybersecurity, and unequal access to digital capabilities [4].

This study therefore analyzes FinTech beyond simple adoption. Adoption indicates whether users start using digital financial services, while impact reflects whether these services generate meaningful practical and financial benefits. PFI is treated as a broader dependent construct that includes time saving, transaction efficiency, increased use of digital services, better monitoring of monthly expenses, improved personal financial management, and willingness to recommend FinTech services [1, 2].

2.3 Digital Marketing and Perceived FinTech Impact

DM plays an important role in shaping users' perceptions of FinTech services. In digital finance, marketing does not function only as a promotional tool, but also as an informational mechanism that reduces uncertainty, increases awareness, explains service benefits, and builds familiarity with digital platforms. Social media advertisements, credible online information, application design, online promotions, and continuous digital communication may influence how users perceive the usefulness, ease of use, and reliability of FinTech services. This argument is consistent with technology acceptance theory, which suggests that perceived usefulness and ease of use are central to technology adoption [6, 7].

DM can also strengthen users' awareness and engagement by communicating the practical benefits of digital financial services, such as time saving, transaction efficiency, easier access to financial tools, and improved financial management. Prior studies on digital finance show that new financial technologies reshape service delivery and customer interaction, making digital communication and platform-based engagement increasingly important for financial service providers [1, 2].

In the context of FinTech, DM may increase perceived value by making users more familiar with service features, promotional benefits, security messages, and platform usability. However, marketing alone may not be sufficient if users do not trust digital providers or lack the FL required to interpret financial information. Therefore, DM is hypothesized to have a positive association with PFI, while the magnitude of this association may vary with users' behavioral readiness and FL [10-12].

2.4 Behavioral and Trust Factors

The behavioral dimension is central to FinTech adoption because digital financial services involve payments, personal data, savings, banking information, and financial decision-making. Users' trust, perceived risk, security perceptions, attitudes toward innovation, and social influence play a key role in shaping adoption and impact. Mobile payment research shows that perceived security, performance expectations, innovativeness, and social influence are important determinants of adoption and recommendation intentions [11].

Trust and perceived security are particularly important in digital financial contexts because users must believe that platforms can protect their personal and financial data. Zhao and Bacao [12] showed that perceived security, trust, perceived benefits, and social influence jointly shape mobile payment adoption intentions. Similarly, Appiah and Agblewornu [13] showed that perceived benefits, perceived risks, and trust are important mechanisms explaining FinTech adoption.

In this study, BTF capture perceived security and trust in

FinTech platforms, attitudes toward FinTech innovation, preference for digital financial services, and the influence of family and friends. Stronger values on these dimensions are expected to be positively associated with PFI [11-13].

2.5 Financial Literacy and Perceived FinTech Impact

FL is an important cognitive capability that enables users to understand and benefit from FinTech services. Financially literate users are more capable of evaluating risks, comparing financial alternatives, understanding costs and benefits, and making informed decisions. FL has been conceptualized as a form of human capital that supports better financial decision-making and welfare outcomes [9].

In modern financial markets, FL has become increasingly important because individuals face more complex financial choices, many of which are mediated by digital platforms and financial technologies [10]. In the FinTech context, this means that users need not only access to digital tools but also the knowledge and confidence to use them responsibly.

Recent empirical evidence also supports the role of literacy-related capabilities in FinTech adoption. Islam and Khan [14] showed that FL, digital literacy, and financial self-efficacy positively influence FinTech adoption. Sumartini et al. [15] further connected digital FL and self-efficacy with intention to use digital banking through a TAM-based approach. Therefore, FL is hypothesized to have a positive association with PFI because financially literate users may be better positioned to interpret and use digital financial services.

2.6 Interaction effects between Digital Marketing and Financial Literacy

The interaction between DM and FL is important because DM may expose users to FinTech services, but users need FL to interpret and evaluate the information they receive. Without sufficient FL, online promotions and digital communication may increase awareness but may not necessarily lead to meaningful financial outcomes. Financially literate users are more capable of assessing the credibility of digital financial information, comparing alternatives, understanding potential costs and risks, and deciding whether a FinTech service fits their financial needs [9, 10].

This moderating logic is supported by recent studies showing that FL, digital literacy, and financial self-efficacy have positive effects on FinTech adoption and digital banking use [14, 15]. These findings suggest that FL can strengthen the relationship between DM and PFI because users with higher FL are better able to transform digital information into informed financial behavior.

The study also examines a three-way interaction among BTF, FL, and DM. This interaction is based on the argument that PFI is not shaped by isolated factors only, but by the combined influence of digital information, behavioral readiness, and financial capability. DM creates awareness and communicates value; BTF determine whether users feel secure and willing to adopt FinTech services; and FL enables users to evaluate and use these services responsibly [11-13].

The three-way interaction is expected to capture the conditional and potentially non-linear nature of PFI. For example, marketing may be more effective when users trust digital financial platforms and possess sufficient FL, while high FL may also make some users more selective and less influenced by promotional communication. Therefore, the

interaction model provides a more nuanced explanation of PFI than a direct-effects model alone [6, 7, 10].

2.7 Research gap and observed-composite analytical framework

Although the literature on FinTech adoption has expanded rapidly, several gaps remain. First, many studies focus on larger or more digitally advanced economies, while evidence from smaller emerging European economies remains limited. Second, studies on the Western Balkans frequently analyze FinTech through macro-level indicators such as digital payment penetration, mobile banking usage, internet access, regulatory quality, FL, and trust in digital finance. While such studies are useful, they do not fully explain how individual users perceive, evaluate, and experience FinTech services [3].

Third, existing research often examines adoption determinants separately, focusing on either technology acceptance, trust, perceived risk, or FL. However, FinTech adoption and impact may reflect the combined roles of digital communication, behavioral readiness, and financial capability. Fourth, limited attention has been given to PFI as a broader outcome that goes beyond intention or usage [1, 2, 4].

To address these gaps, this study specifies an observed-composite analytical framework for Kosovo, Albania, and North Macedonia. DM, BTF, and FL are represented by arithmetic composite scores and are examined in relation to the PFI composite through adjusted main terms and precomputed interaction terms. Country, age, and income are included as observed control variables. The framework is conceptual only in the sense of organizing the regression variables and hypotheses; it does not represent a latent-variable measurement or structural model [6, 7, 10].

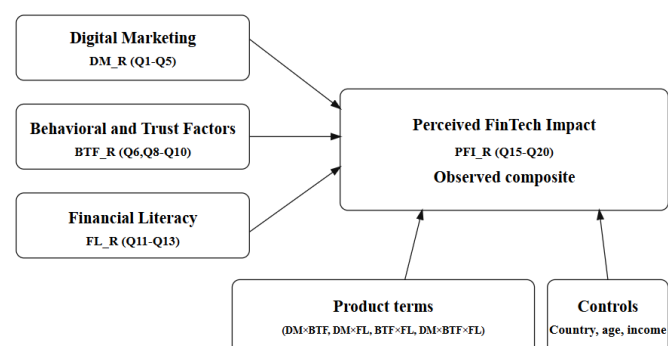


Figure 1. Observed-composite analytical framework for Perceived FinTech Impact (PFI)

Note. DM_R is the arithmetic mean of Q1-Q5; BTF_R is the arithmetic mean of Q6 and Q8-Q10; FL_R is the arithmetic mean of Q11-Q13; and PFI_R is the arithmetic mean of Q15-Q20. Interaction terms are products of the standardized predictor composites. Rectangles denote observed variables, and arrows denote modeled statistical associations rather than latent-variable paths or causal effects. Country, age, and income are observed controls.

Source: Authors' formulation.

Figure 1 summarizes the study variables as observed arithmetic composites rather than latent constructs. DM is represented by DM_R (Q1-Q5), and H1 concerns its adjusted association with PFI (PFI_R). The graphical arrow is therefore a schematic representation of the regression association tested in OLS, not a latent structural path and not a causal effect. The theoretical rationale remains grounded in technology-acceptance and digital-marketing literature [1, 2].

BTF form the second explanatory dimension of the model.

These factors include risk perception, trust in digital financial platforms, perceived security, attitudes toward FinTech, and social influence. Their inclusion is justified by behavioral finance and trust theory, which suggest that financial decisions are shaped by risk perceptions, uncertainty, psychological factors, and trust in digital environments [3, 4]. Accordingly, users who perceive FinTech platforms as secure, reliable, and socially accepted are expected to experience stronger PFI, representing H2. FL represents the third independent variable. It reflects users' FL, ability to evaluate risk, and capacity to make informed financial decisions. Since FinTech services require users not only to access digital tools but also to understand financial information and assess potential risks, FL is expected to support more effective and responsible FinTech use [5, 6]. This relationship represents H3.

At the center of the framework is PFI, the dependent observed composite of the study. It is calculated directly from Q15-Q20 and captures use-related benefits, perceived financial-management outcomes, and recommendation/advocacy. The six items are not interpreted as two validated latent dimensions of Usage and Financial Performance. In particular, Q20 (willingness to recommend FinTech) is treated as an advocacy/recommendation indicator rather than as Financial Performance. This observed-composite interpretation is consistent with the focused factor assessment reported in the Results section and avoids imposing a higher-order latent structure that was not estimated [7, 9]. FinTech may support sustainable financial inclusion when regulation, institutional readiness, and digital infrastructure are adequate [5], while FL remains important because knowledge gaps and overconfidence may weaken financial decision-making outcomes [16]. The framework also includes interaction effects. H4 proposes that FL strengthens the relationship between DM and PFI because financially literate users may be better able to interpret and evaluate

digital financial information. H5 evaluates the three-way interaction among BTF, FL, and DM. Pearson correlations among the observed composites are reported separately as preliminary bivariate associations and are not treated as an additional formal hypothesis.

Finally, country, age, and income are included as observed control variables because FinTech adoption and impact may vary across socio-demographic and national contexts. Kosovo, Albania, and North Macedonia share a Western Balkan setting but differ in banking digitalization, income levels, digital readiness, FL, and institutional trust. The three-country design broadens regional coverage beyond a single-country study; however, the country-specific regressions are treated as supplementary sensitivity analyses rather than as evidence of statistically established cross-country coefficient differences.

2.8 Theoretical integration and empirical justification of the research model

The synthesis of the reviewed studies provides a concise basis for linking the literature review with the development of the research model. The studies summarized in Table 1 indicate that the literature supporting this research model can be grouped into three main analytical streams. The first stream focuses on technology acceptance and digital finance, showing that FinTech adoption is influenced by perceived usefulness, ease of use, performance expectations, digital innovation, and the transformation of financial services. The second stream emphasizes behavioral and trust-related factors, particularly perceived risk, perceived benefit, security, and user confidence, which explain why individuals may accept or resist digital financial services. The third stream highlights the role of FL and institutional readiness, suggesting that users' FL, digital capability, and the broader regulatory environment are essential for achieving meaningful FinTech outcomes.

Table 1. Summary of the literature review

Author(s)	Year	Key Findings
Alt et al. [1]	2018	FinTech transforms financial services, business models, and digital financial markets.
Gomber et al. [2]	2017	Digital finance improves innovation, efficiency, and future development of financial services.
Radulović and Jovović [3]	2025	FinTech development in the Balkans depends on payments, regulation, literacy, and trust.
Sant'Anna and Figueiredo [4]	2024	FinTech supports financial inclusion but may create stability risks when appropriate safeguards are absent.
Arner et al. [5]	2019	FinTech can support financial inclusion and sustainable development when adequate regulatory and technological conditions are in place.
Davis [6]	1989	Technology adoption depends on perceived usefulness and perceived ease of use.
Venkatesh et al. [7]	2003	Technology acceptance is shaped by performance expectancy, effort expectancy, social influence, and facilitating conditions.
Venkatesh and Bala [8]	2008	TAM3 explains technology acceptance through extended determinants of perceived usefulness and perceived ease of use.
Lusardi and Mitchell [9]	2014	Financial Literacy (FL) supports informed decisions regarding saving, investment, and financial risk.
Lusardi and Mitchell [10]	2023	Financial Literacy (FL) is increasingly important in complex and digital financial markets.
Oliveira et al. [11]	2016	Mobile payment adoption is influenced by usefulness, trust, security, and compatibility.
Zhao and Bacao [12]	2021	Mobile payment adoption during the COVID-19 pandemic was supported by convenience and safety perceptions.
Appiah and Agblewornu [13]	2025	FinTech adoption is shaped by perceived benefits, perceived risks, and trust.
Islam and Khan [14]	2024	Financial Literacy (FL), digital literacy, and financial self-efficacy contribute positively to FinTech adoption.
Sumartini et al. [15]	2024	Digital Financial Literacy (FL) and self-efficacy strengthen the intention to use

Note: The table summarizes the main theoretical and empirical studies used to support the research model and hypotheses.
Source: Authors' formulation.

A particularly important contribution comes from the technology acceptance literature, which explains FinTech adoption through perceived usefulness, ease of use, performance expectations, and facilitating conditions [6-8], while the FL literature shows that users' knowledge and capability influence the quality of digital financial decision-making [9, 10].

The literature portrays PFI as a multidimensional phenomenon in which technological innovation interacts with behavioral readiness, financial capability, and institutional context. Foundational studies show that FinTech and digital finance alter financial-service delivery, business models, and market structures [1, 2]. Yet the technology-acceptance literature indicates that innovation alone is insufficient: perceived usefulness and ease of use [6], together with performance expectancy, effort expectancy, social influence, and facilitating conditions [7], shape users' willingness to engage with new technologies. TAM3 further demonstrates that these perceptions are themselves influenced by broader cognitive and contextual determinants [8]. This theoretical progression supports treating users' perceptions of PFI as the outcome of both technological exposure and individual evaluation rather than as a purely technical consequence.

Empirical evidence reinforces this interpretation. In mobile-payment settings, usefulness, trust, security, and compatibility are closely linked to adoption [11], while the pandemic context increased the salience of convenience and safety perceptions [12]. More recent FinTech evidence similarly identifies perceived benefits, perceived risks, and trust as central behavioral mechanisms [13]. These findings provide a strong rationale for incorporating BTF alongside DM: digital exposure may increase awareness and engagement, but its relationship with PFI is likely to depend on whether users consider digital financial services credible, beneficial, and sufficiently safe.

Financial capability adds a further explanatory layer. Lusardi and Mitchell [9, 10] established FL as a key resource for informed financial decision-making, particularly as financial markets become more complex and digitalized. FinTech-specific studies extend this logic by showing that FL, digital literacy, and financial self-efficacy are associated with stronger adoption [14], while digital FL and self-efficacy reinforce intentions to use digital banking [15]. Conversely, knowledge gaps and overconfidence may weaken decision quality [16]. FL can therefore be viewed not only as an independent correlate of PFI, but also as a plausible moderator that conditions how effectively individuals interpret and respond to digital financial information.

Finally, the institutional environment places these individual-level mechanisms within a broader system. Evidence from the Balkans emphasizes the importance of payments infrastructure, regulation, literacy, and trust [3], while research on financial inclusion and sustainability shows that FinTech benefits depend on appropriate safeguards, regulatory quality, and technological readiness [4, 5]. Taken together, the literature supports an integrated empirical model in which DM, BTF, and FL are examined jointly, with interaction terms capturing whether their associations with PFI are conditional rather than merely additive. This framework is

theoretically coherent because it links technology acceptance, behavioral trust, financial capability, and institutional context within a single explanatory structure while avoiding unsupported causal claims.

3. METHODOLOGY

This section explains the methodological approach used to examine the adjusted associations of DM, BTF, and FL with PFI in Kosovo, Albania, and North Macedonia. The study follows a quantitative, cross-sectional survey design based on primary data collected through a structured questionnaire (Appendix B). The design supports analysis of user perceptions, observed composite scores, adjusted associations, and moderation effects using regression-based methods [17, 18].

3.1 Research design, methodological process, and econometric procedures

This study applies a quantitative research design to examine individual-level associations with the PFI index in Kosovo, Albania, and North Macedonia. Primary data were collected through an online questionnaire open to actual and potential users of digital financial and banking services. Because the dependent items Q15-Q20 refer to use-related benefits, financial-management outcomes, and recommendation/advocacy, respondent use status was audited at the case level before the sensitivity analysis.

The questionnaire distinguished general FinTech use, independent FinTech applications, and bank-based FinTech applications. A respondent was classified as having no recorded FinTech use only when an explicit non-use response was accompanied by no recorded independent or bank-based FinTech application. These countries were selected because they represent Western Balkan economies where banking digitalization is expanding, while FL, trust, and digital readiness remain important challenges for FinTech adoption.

The independent-application item is not interpreted as a measure of overall FinTech non-use because respondents could use bank-based FinTech services without using independent applications. A case-level audit of the $N = 262$ analytical sample classified use status across both independent and bank-based services and identified 15 respondents (5.7%) with no recorded FinTech use. Because the questionnaire did not apply skip logic to Q15-Q20, responses from these 15 cases may reflect hypothetical or anticipated evaluations rather than experience-based assessments. The primary model uses the frozen analytical sample, and a separate user-status sensitivity analysis excludes these cases to evaluate whether the substantive conclusions depend on their inclusion.

The questionnaire included 20 closed-ended items measured on a five-point Likert scale, ranging from 1 = strongly disagree to 5 = strongly agree. The theory-based instrument distinguished DM, BTF, FL, FinTech Usage, and perceived Financial Performance. These item groupings were evaluated through exploratory factor and reliability analyses rather than treated as validated latent constructs. The final

analytical sample consisted of 262 respondents. Because the survey is cross-sectional, it captures perceptions at one point in time and does not measure continuance intention, repeated use, retention, responsible-use behavior, or persistence of FinTech adoption over time.

After data collection, the dataset was screened, coded, and cleaned. The empirical analysis began with an exploratory

measurement assessment based on internal-consistency reliability and Exploratory Factor Analysis (EFA), followed by correlation analysis, regression modeling, interaction testing, hierarchical regression, and model diagnostics. EFA was used to examine item structure rather than to claim confirmatory latent-construct validity.

Table 2. Summary of the methodological and econometric framework

Stage	Method	Purpose	Output
Research design & data	Online questionnaire	Collect primary data in three countries	Cross-sectional N = 262
Data preparation	Screening, coding, cleaning	Prepare analytical dataset	Cleaned dataset
Variable construction	Arithmetic composites	Construct study measures	DM_R, BTF_R, FL_R, PFI_R
Measurement assessment	Cronbach α ; PAF/Promax EFA	Assess consistency and exploratory item structure	Reliability and respecified composites
Preliminary analysis	Descriptives; Pearson r	Describe variables and bivariate associations	Descriptives and correlations
OLS estimation	Hierarchical OLS	Estimate controls and main predictors	Blocks 1–2
Conditional effects	Two- and three-way interactions	Test incremental interaction terms	Blocks 3–4
Diagnostics	Residual, influence, heteroskedasticity; robust covariance	Assess assumptions and inference	Diagnostics and robust check
Interpretation	Hypothesis evaluation	Interpret findings within study design	Hypothesis decisions

Note: MLR refers to Multiple Linear Regression, while OLS refers to the estimation method used to estimate the regression parameters.

Source: Authors' formulation.

This methodological and econometric structure follows a sequential empirical logic (Table 2). First, internal consistency and the exploratory item structure are assessed; second, preliminary relationships are examined; third, the direct and conditional associations are estimated through regression models; and finally, diagnostic tests are applied to evaluate model adequacy. The measurement stage is explicitly exploratory and does not treat the observed composite indices as CFA-validated latent constructs.

3.2 Variable construction and composite indices

The main explanatory variables are theory-guided observed composite scores informed by item-level exploratory factor evidence. DM is represented by Q1-Q5. The BTF composite uses Q6 and Q8-Q10; the reverse-coded perceived-risk item Q7R is retained as a separate observed indicator because it showed weak communality and reduced internal consistency when included in the composite. These scores are used as observed variables rather than as validated latent factors.

FL is represented by Q11-Q13. Q14, which measures participation in training or reading financial-management materials, was retained as a separate observed indicator because it did not cluster with Q11-Q13 in the exploratory solution and its removal improved internal consistency. The respecification therefore distinguishes core financial-literacy knowledge/assessment items from training exposure.

$$Index_i = (Q_{1i} + Q_{2i} + \dots + Q_{ki}) / (k) \quad (1)$$

where,

$Index_i$ is the composite index score for respondent i ,
 $Q_{1i}, Q_{2i}, \dots, Q_{ki}$ are questionnaire items included in the specific construct for respondent i ,
 Q is individual questionnaire item,
 k is total number of items included in the construct,
 i is individual respondent/observation.

$$Perceived_{FinTechImpact_i} = (Q15_i + Q16_i + Q17_i + Q18_i + Q19_i + Q20_i) / 6 \quad (2)$$

where,

$Perceived_{FinTechImpact_i}$ is six-item observed composite score for respondent i , $Q15_i$ - $Q20_i$ are questionnaire items representing use-related benefits, perceived financial-management outcomes, and recommendation/advocacy, 6 is number of items included in the composite, i is individual respondent/observation.

The dependent variable is calculated as the arithmetic mean of Q15-Q20 and is interpreted as a broad PFI observed composite. Although Q15-Q17 and Q18-Q20 were examined as separate three-item blocks in a sensitivity analysis, the focused factor assessment did not establish them as distinct first-order factors. Consequently, the regression analysis uses the single six-item composite rather than separate Usage and Performance indices.

This operationalization captures perceived use-related benefits and financial-management outcomes while explicitly treating Q20 as recommendation/advocacy rather than Financial Performance. The score is an observed arithmetic composite and is not presented as a higher-order latent construct.

Table 3 summarizes the operational specification. The indices are arithmetic observed composites used for reliability, descriptive, correlation, and OLS analyses; they are not presented as latent constructs whose convergent or discriminant validity has been established by EFA.

The construction of composite indices from structured questionnaire items is a widely used practice in quantitative studies on FinTech adoption, FL, and financial behavior. Hassan et al. [19] used a structured questionnaire to examine consumers' intention to adopt FinTech through an extended TAM-UTAUT model incorporating trust-related factors. Similarly, Aoun et al. [20] analyzed the role of FinTech adoption, FL, and financial attitudes in shaping millennials' financial behavior using questionnaire-based data. Módosné

Szalai et al. [21] provided a direct methodological example by constructing composite indicators related to FL, digital financial behavior, and financial self-assessment. Rumianti and Launtu [22] also applied a quantitative survey approach to examine the effect of digital FL on financial behavior.

Mohapatra et al. [23] investigated the role of FL in FinTech adoption among micro and small enterprises, while Suresh et al. [24] used a five-point Likert-scale questionnaire to measure the factors influencing attitudes and intentions toward adopting FinTech services.

Table 3. Construction of variable indices from the questionnaire

Variable	Type	Items	Description	Formula
Perceived FinTech Impact (PFI)	DV	Q15–Q20	Use benefits, financial management, advocacy	MEAN(Q15–Q20)
Usage-related block	Exploratory	Q15–Q17	Time saving, efficiency, increased use	No separate index
Outcome/advocacy block	Exploratory	Q18–Q20	Expense monitoring, management, advocacy	No separate index
Digital Marketing (DM)	IV	Q1–Q5	Advertising, credibility, design, promotions	MEAN(Q1–Q5)
Behavioral and Trust Factors (BTF)	IV	Q6, Q8–Q10	Trust/security, attitude, preference, social influence	MEAN(Q6, Q8, Q9, Q10)
Financial Literacy (FL)	IV / moderator	Q11–Q13	Knowledge, risk assessment, informed decisions	MEAN(Q11, Q12, Q13)
Perceived Risk (Q7R)	Standalone	Q7R	Reverse-coded; excluded from revised Behavioral and Trust Factors (BTF) composite	6–Q7
Training Exposure (Q14)	Standalone	Q14	Training/reading on financial management	Q14

Note: Behavioral and Trust Factors (BTF) and Financial Literacy (FL) are theory-guided observed composites informed by EFA and reliability assessment. Q7R and Q14 are retained as standalone indicators and are not included in those composite scores. Q15–Q20 form one Perceived FinTech Impact observed composite; the Q15–Q17 and Q18–Q20 blocks were examined only as exploratory sensitivity checks and are not used as separate regression indices. Q20 is classified as recommendation/advocacy, not Financial Performance. Source: Authors' calculations.

Accordingly, composite scores are used in the OLS framework with conservative interpretation. Reliability and EFA provide internal-consistency and exploratory structural evidence, but they do not establish confirmatory construct validity. The theory-guided indices are therefore treated as observed composites rather than empirically validated latent constructs.

3.2.1 Standardization and interaction terms

Before estimating the interaction models, the main continuous explanatory variables were standardized using Z-score transformation. Standardization facilitates interpretation and comparison when product terms are included in regression models [25, 26]:

$$Z_i = \frac{X_i - \bar{X}}{SD_x} \quad (3)$$

where,

Z_i is standardized value of variable X for observation i ; X_i is original value of variable X for observation i ; $\bar{X}$ is mean of X ; SD_x is standard deviation of X ; i is individual observation/respondent.

Construction of interaction terms: After the main predictors were standardized, all lower-order interaction terms required for the three-way model were computed from the z-scores: $DM \times BTF$, $DM \times FL$, and $BTF \times FL$. The three-way term $DM \times BTF \times FL$ was then computed from the same standardized predictors. This hierarchical specification includes all constituent main effects and lower-order interactions before the three-way interaction is evaluated.

$$FL_DM_i = ZFL_i \times ZDM_i \quad (4)$$

where,

FL_DM_i : interaction term between Financial Literacy (FL) and Digital Marketing (DM) for respondent i ;

ZFL_i : standardized Financial Literacy (FL) index for respondent i ;

ZDM_i : standardized Digital Marketing (DM) index for

respondent i ;

$\times$: multiplication operator used to construct the interaction term;

i : individual respondent or observation.

$$BTF_FL_DM_i = ZBTF_i \times ZFL_i \times ZDM_i \quad (5)$$

where,

$BTF_FL_DM_i$: three-way interaction term among Behavioral and Trust Factors (BTF), Financial Literacy (FL), and Digital Marketing (DM) for respondent i ;

$ZBTF_i$: standardized Behavioral and Trust Factors (BTF) index for respondent i ;

ZFL_i : standardized Financial Literacy (FL) index for respondent i ;

ZDM_i : standardized Digital Marketing (DM) index for respondent i ;

$\times$: multiplication operator used to construct the interaction term;

i : individual respondent or observation.

All three two-way interaction terms were entered together before the three-way interaction. This ordering ensures that any incremental contribution attributed to the three-way term is assessed after controlling for the relevant main effects and lower-order interactions.

Simple-slope probing was used for statistically significant interaction terms. For the significant $DM \times FL$ interaction, standardized FL was evaluated at -1 SD, the mean (0), and +1 SD while retaining the demographic controls, focal main effects, lower-order interactions, and the three-way term. Because the three-way interaction was not statistically significant, it was not decomposed into low/mean/high combinations of two moderators and no substantive mechanism was inferred from its sign. A Johnson-Neyman region-of-significance analysis was also derived from the final OLS coefficient estimates and coefficient covariance matrix. With BTF fixed at its standardized mean ($ZBTF_R = 0$), the conditional DM slope was expressed as a function of standardized FL. Johnson-Neyman boundaries were obtained

where the two-sided 95% confidence interval (CI) for this conditional slope included zero ($df = 238$; critical $t = 1.970$). The covariance between ZDM_R and DM_FL_R was computed from the Statistical Package for the Social Sciences (SPSS) coefficient correlation (0.115) and their standard errors (0.061 and 0.058), yielding covariance = 0.000407.

3.3 General theoretical Ordinary Least Squares model

Ordinary Least Squares (OLS) estimates linear regression coefficients by minimizing the sum of squared residuals between observed and fitted values of the dependent variable [27]. OLS is used here to estimate adjusted associations among observed composite scores and the specified interaction terms.

In its general theoretical form, the OLS model is expressed as follows:

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \varepsilon_i \quad (6)$$

where,

Y_i represents the dependent variable for observation i , while X_{1i} , X_{2i} , and X_{3i} represent the independent variables included in the model. The term β_0 represents the intercept, which indicates the expected value of the dependent variable when all independent variables are equal to zero. The coefficients β_1 , β_2 , and β_3 represent the expected conditional difference in the dependent variable associated with a one-unit increase in each independent variable, while holding the other variables constant. Finally, ε_i represents the error term, which captures unexplained variation associated with factors not explicitly included in the model.

3.4 Observed-composite regression framework

The empirical framework is an observed-composite hierarchical OLS regression. DM (DM_R), BTF (BTF_R), FL (FL_R), and PFI (PFI_R) enter the analysis as arithmetic scores computed from questionnaire items rather than as latent factors. DM_R captures online communication, promotional exposure, information clarity, and platform presentation; BTF_R captures perceived security/trust, innovation attitude, preference for FinTech relative to traditional banking, and social influence; and FL_R captures financial knowledge, risk assessment, and informed financial decision-making. Q7R (perceived risk) and Q14 (training exposure) are retained as separate observed indicators rather than included in the main composites.

Figure 2 depicts the empirical estimation sequence rather than a CFA/SEM structure. Demographic controls are entered first, followed by the three standardized observed-composite predictors, the three two-way product terms, and the three-way product term. PFI (PFI_R) is the observed dependent composite. FL is evaluated as an observed predictor and through the precomputed $DM \times FL$ interaction term; no latent moderator, measurement-error term, or structural-equation path is estimated.

Therefore, the model provides a more comprehensive framework for analysing PFI in Kosovo, Albania, and North Macedonia.

3.4.1 Ordinary Least Squares regression framework for empirical analysis

After defining the general OLS model and the conceptual structure of the study, the empirical model is specified using

the observed study variables. Multiple linear regression estimated by OLS is used to examine whether DM, BTF, and FL are associated with variation in PFI [27].

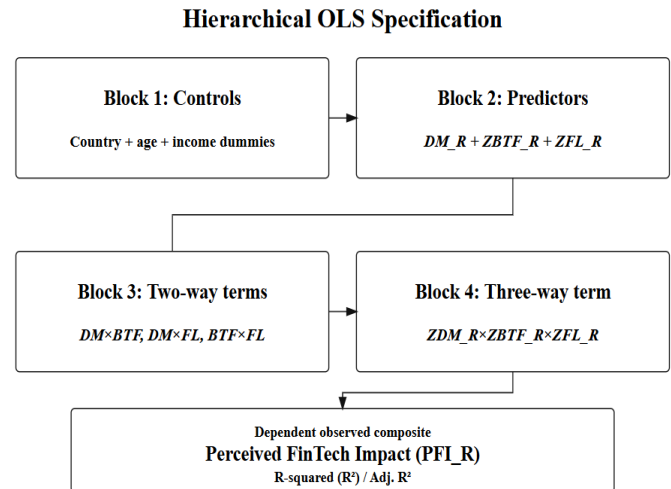


Figure 2. Hierarchical Ordinary Least Squares (OLS)

Specification using observed composite scores

Note: Block 1 contains demographic controls; Block 2 contains standardized observed-composite predictors (DM_R+ZBTF_R+ZFL_R); Block 3 contains the three precomputed two-way product terms; and Block 4 contains the precomputed three-way product term. PFI_R is the observed dependent composite. The arrows show the sequence of hierarchical OLS entry and do not represent latent-variable structural paths.

Source: Authors' formulation

The baseline empirical model is specified as follows:

$$I_i = \beta_0 + \beta_1 DM_i + \beta_2 BTF_i + \beta_3 FL_i + \varepsilon_i \quad (7)$$

where, I_i represents the PFI Index for respondent i , DM_i represents the DM index, BTF_i represents the Behavioral Factors index, FL_i represents the FL index, β_0 is the constant term, β_1 – β_3 are the regression coefficients, and ε_i is the error term.

DM is constructed from Q1-Q5. The BTF observed composite is constructed from Q6 and Q8-Q10, while Q7R is retained separately as a perceived-risk indicator. FL is constructed from Q11-Q13, while Q14 is retained separately as training exposure. The dependent score is the arithmetic mean of Q15-Q20 and is interpreted as one broader PFI observed composite. A focused factor assessment supported a dominant one-factor solution for these six items; Q20 is treated as recommendation/advocacy rather than Financial Performance. All scores are treated as observed variables in the OLS framework rather than as latent variables validated through CFA.

3.4.2 Hierarchical Ordinary Least Squares regression models

Hierarchical OLS regression is specified as a four-block model so that the sequence of entry is explicit and theoretically interpretable. Block 1 contains demographic controls. Country is dummy-coded with Kosovo as the reference category; age group and income category are also represented by dummy variables with their first categories as the respective references. Block 2 adds standardized DM, BTF, and FL. Block 3 adds the three lower-order two-way interactions ($DM \times BTF$, $DM \times FL$, and $BTF \times FL$). Block 4 adds the three-way interaction ($DM \times BTF \times FL$). All blocks were entered using the Enter method. Because age and income contained missing

values, the hierarchical regression uses 255 complete cases with listwise deletion.

The increase in explanatory power is assessed through the change in R^2 :

$$\Delta R^2 = R^2_{Model2} - R^2_{Model1} \quad (8)$$

Incremental explanatory power was evaluated using R^2 , adjusted R^2 , ΔR^2 , and the F-change test for each block. A significant F-change indicates that the newly entered block explains additional variance in PFI beyond variables already in the model.

The full interaction model is specified as follows:

$$\begin{aligned} PFI_i = & \beta_0 + Controls_i + \beta_1 ZDM_i + \beta_2 ZBTF_i \\ & + \beta_3 ZFL_i + \beta_4 (DM \times BTF)_i + \beta_5 (DM \times FL)_i \\ & + \beta_6 (BTF \times FL)_i + \beta_7 (DM \times BTF \times FL)_i + \varepsilon_i \end{aligned} \quad (9)$$

This specification tests the main effects only after the demographic controls and evaluates interaction effects in hierarchical order. The three two-way terms are entered before the three-way term, allowing the final ΔR^2 and F-change to quantify whether the three-way interaction contributes information beyond controls, main effects, and lower-order interactions.

The continuous focal predictors were standardized before interaction terms were formed. Model reporting includes block-specific R^2 , adjusted R^2 , ΔR^2 and F-change, together with final-model B, SE, standardized β , t, p, Variance Inflation Factor (VIF), and cross-sectional OLS diagnostics focused on residual linearity, heteroskedasticity, influential observations, centered leverage, Cook's Distance, and heteroskedasticity-robust covariance estimates. Durbin-Watson is retained only as a supplementary residual-dependence descriptor rather than as the primary diagnostic for these individual-level cross-sectional data.

The hierarchical model is used as the primary pooled regression specification for hypothesis testing. Country-specific regressions are reported separately only as supplementary sensitivity analyses. Because the study uses observed composite scores and does not estimate a multi-group CFA measurement model, measurement invariance across countries is not established; consequently, the country models are not interpreted as formal tests of equivalent or different regression coefficients across countries.

3.5 Reliability, factor structure, common-method assessment, and diagnostic tests

Before hypothesis testing, the measurement instrument was assessed using internal-consistency reliability and EFA. Because the empirical models use arithmetic composite scores and OLS rather than a latent-variable SEM, this stage evaluates coherence and exploratory item structure without claiming confirmatory latent-construct validity.

First, Cronbach's alpha was used to assess internal consistency of the items included in each observed measure. Values of approximately 0.70 or higher are commonly used as a practical reliability guide [18, 28, 29].

$$\alpha = [k/(k - 1)] \times [1 - (\sum s_i^2 / s_t^2)] \quad (10)$$

where, k represents the number of items, s_i^2 represents the variance of each item, and s_t^2 represents the total variance of

the scale.

Second, EFA was conducted on the 20 questionnaire items using Principal Axis Factoring (PAF) with Promax oblique rotation. This approach was selected to examine common-factor structure while allowing the extracted factors to correlate. Sampling adequacy was evaluated using the Kaiser-Meyer-Olkin (KMO) statistic and Bartlett's Test of Sphericity. Item communalities, pattern coefficients, cross-loadings, the scree plot, and factor correlations were used to interpret the exploratory solution.

$$KMO = \sum \sum r_{ij}^2 / [\sum \sum r_{ij}^2 + \sum \sum p_{ij}^2] \quad (11)$$

The KMO value was 0.892, indicating strong sampling adequacy, and Bartlett's Test was statistically significant, $\chi^2(190) = 2603.962$, $p < 0.001$. Four factors had initial eigenvalues greater than 1 (7.582, 2.265, 1.460, and 1.167), and the four-factor PAF solution accounted for 53.319% of the extracted variance. Promax rotation was retained because the factor correlations ranged from 0.460 to 0.623. A sensitivity analysis forcing five factors did not recover the theory-imposed five-construct structure: the fifth initial eigenvalue was 0.881, and the additional factor was defined mainly by Q4 and Q5. The four-factor solution was therefore treated as exploratory evidence of cross-domain clustering rather than as confirmation of the original theoretical measurement model.

Third, potential common-method variance was addressed both procedurally and statistically. The online questionnaire did not request respondents' names or email addresses, reducing identity-linked evaluation pressure, and it included a reverse-worded perceived-risk item (Q7) to limit uniform acquiescent responding. Because the focal predictors and the dependent measure were reported by the same respondents in the same questionnaire, an unrotated one-factor PAF diagnostic was estimated across Q1-Q20. A single factor was forced solely as a common-method diagnostic and was not used as a substitute for the exploratory measurement model. Given the same-source cross-sectional design, this procedure can indicate whether a dominant general factor is present but cannot eliminate the possibility of common-method bias.

Residual distribution was evaluated visually using standardized residual diagnostics, including the residual histogram reported in the Results section. Formal normality testing was not used as the primary basis for assessing the OLS residual distribution.

Before estimating the regression models, Pearson correlation analysis was used as a preliminary bivariate assessment of the direction and strength of linear associations among DM, BTF, FL, and PFI [17, 30]. Correlations were not used to determine support for the formal hypotheses.

$$r = \sum (x_i - \bar{x})(y_i - \bar{y}) / \sqrt{[\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2]} \quad (12)$$

A positive and statistically significant correlation indicates that two variables move in the same direction, while the strength of the coefficient shows how closely the variables are linearly related. Therefore, Pearson correlation served as an initial empirical check of the relationships among the main constructs prior to regression-based hypothesis testing.

Sixth, regression diagnostics were refocused on assumptions and influence checks that are directly relevant to individual-level cross-sectional OLS. Multicollinearity was assessed with VIF and Tolerance; residual linearity and variance were examined with a standardized residual-versus-

standardized-predicted plot; and potentially influential observations were screened using standardized and studentized residuals, Cook's Distance, centered leverage, and Mahalanobis Distance. VIF values below 5 and Tolerance values above 0.20 were treated as common screening guides rather than absolute decision rules [17, 18].

$$VIF = 1/(1 - R_i^2) \quad (13)$$

$$Tolerance = 1/VIF \quad (14)$$

The Durbin-Watson statistic was retained as a supplementary residual-dependence descriptor, but it is not treated as the principal diagnostic for this ordinary cross-sectional survey model. Greater emphasis is placed on residual form, heteroskedasticity, leverage, and case influence.

$$DW = \sum(e_t - e_{t-1})^2 / \sum e_t^2 \quad (15)$$

Heteroskedasticity was assessed with a Breusch-Pagan-type auxiliary regression in which squared standardized OLS residuals were regressed on the 16 predictors in the final specification. The LM statistic was calculated as $N \times R^2$ from this auxiliary model. Because this test indicated non-constant residual variance, the identical linear specification was also estimated in GENLIN using a normal distribution with identity link and the robust (sandwich) covariance estimator. The robust standard errors, Wald CI, and p values are reported as a sensitivity check on OLS inference.

Overall model fit was evaluated using the coefficient of determination (R^2), adjusted R^2 , and the F-test. R^2 describes the proportion of sample variance in PFI accounted for by the model, adjusted R^2 incorporates the number of explanatory terms, and the F-test evaluates whether the model is jointly statistically significant [27, 31, 32].

$$R^2 = 1 - (SS_{res}/SS_{tot}) \quad (16)$$

$$Adjusted R^2 = 1 - [(1 - R^2)(n - 1)/(n - k - 1)] \quad (17)$$

$$F = (SSR/k)/[SSE/(n - k - 1)] \quad (18)$$

Together, the reliability, exploratory measurement, descriptive, correlation, regression, interaction, and diagnostic procedures support use of observed composite scores in the analyses. These procedures do not establish CFA-level convergent or discriminant validity.

4. RESULTS

This section presents the empirical results. The analysis was conducted in SPSS 27 and begins with descriptive statistics and sample characteristics. Internal consistency was assessed with Cronbach's alpha, and exploratory item structure was examined using PAF with Promax rotation. Formal hypotheses were evaluated with the four-block hierarchical OLS model, followed by interaction probing, diagnostics, user-status sensitivity analysis, and supplementary country-specific models.

4.1 Descriptive statistics

This section presents the empirical results. The analysis was

conducted in SPSS 27 and begins with descriptive statistics and sample characteristics. Internal consistency was assessed with Cronbach's alpha, and exploratory item structure was examined using PAF with Promax rotation. Formal hypotheses were evaluated with the four-block hierarchical OLS model, followed by interaction probing, diagnostics, user-status sensitivity analysis, and supplementary country-specific models. The descriptive statistics of the study variables are presented in Table 4 and Appendix C.

The dependent variable, PFI, is an observed composite based on Q15-Q20. Its mean is $M = 3.85$ ($SD = 0.87$). A focused factor assessment of the six items is reported below; the measure is not treated as a CFA-validated latent or higher-order construct.

The DM observed composite (Q1-Q5) reported $M = 3.50$ ($SD = 0.89$). The BTF (Q6 and Q8-Q10) reported $M = 3.64$ ($SD = 0.92$). Q7R is retained separately as a perceived-risk indicator because its inclusion weakened internal consistency and it showed low communality in EFA.

Table 4. Descriptive statistics of study variables

Variable	N	Min	Max	Mean	SD
Perceived FinTech Impact (PFI)	262	1.00	5.00	3.8492	0.86551
Digital Marketing (DM)	262	1.00	5.00	3.5000	0.88888
Behavioral and Trust Factors (BTF) (revised)	262	1.00	5.00	3.6355	0.91850
Financial Literacy (FL) (revised)	262	1.00	5.00	3.8066	0.93004

Note: $N = 262$. All observed composites were measured on a five-point Likert scale. Higher values indicate stronger agreement or higher levels of the respective measure.

Source: Authors' calculations.

The FL composite (Q11-Q13) reported $M = 3.81$ ($SD = 0.93$). Q14 is retained separately as training exposure because it did not cluster with Q11-Q13 and its exclusion improved reliability. These descriptive results correspond to the observed-composite specification used in the regression analyses.

4.2 Demographic analysis

The demographic analysis describes the realized sample according to country, age, gender, education, and income. Because the sample was not selected to represent national populations, these characteristics are descriptive of the respondents included in the study.

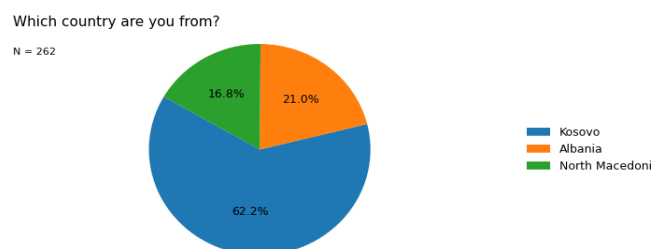


Figure 3. Sample distribution across Kosovo, Albania, and North Macedonia

The final analytical sample consisted of 262 respondents: Kosovo $n = 163$ (62.2%), Albania $n = 55$ (21.0%), and North

Macedonia n = 44 (16.8%). The distribution is substantially unbalanced, with Kosovo accounting for nearly two-thirds of the sample and North Macedonia representing the smallest subgroup (Figure 3). These proportions describe the realized analytical sample only; they are not population weights. The country subsamples were not designed to provide nationally representative estimates, so country-level descriptive and regression results are interpreted as evidence from the surveyed respondents rather than as estimates for the national populations.

Age was available for 260 respondents. The largest group was 21-30 years (n = 95, 36.5%), followed by 31-40 years (n = 55, 21.2%), 41-50 years (n = 43, 16.5%), over 50 years (n = 36, 13.8%), and under 20 years (n = 31, 11.9%); two cases had missing age data (Figure 4).

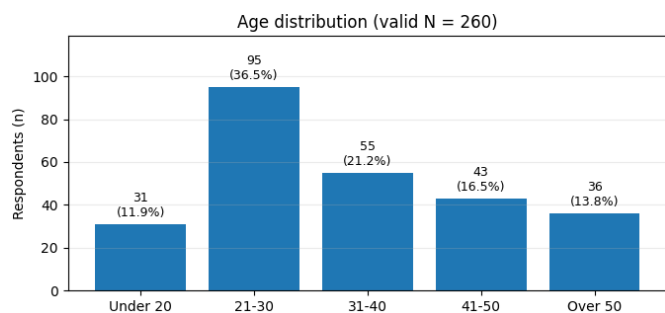


Figure 4. Age distribution

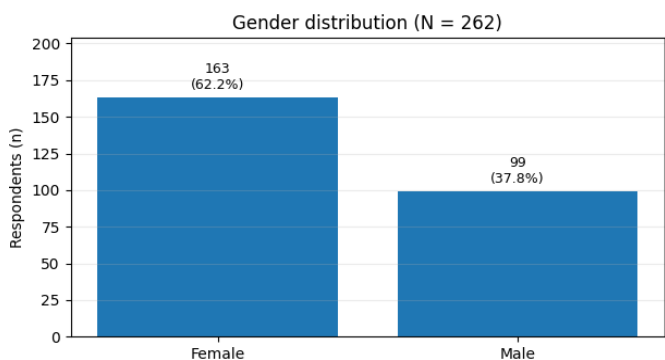


Figure 5. Gender distribution

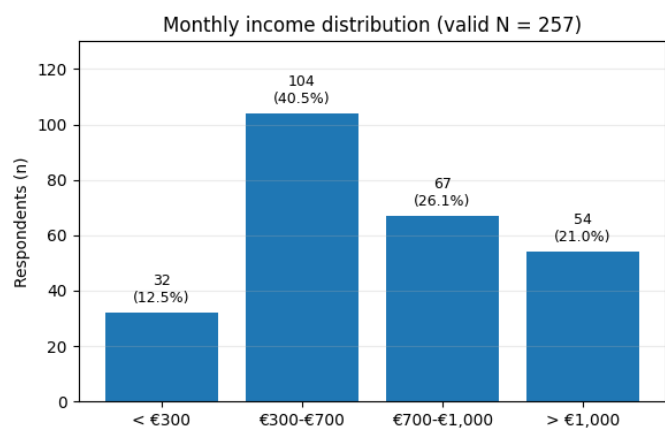


Figure 6. Monthly income distribution

Female respondents represented 62.2% of the analytical sample (n = 163), while male respondents represented 37.8% (n = 99) (Figure 5). Bachelor's and Master's degrees were the predominant education categories in the questionnaire

responses; education is reported descriptively and was not included as a control in the final hierarchical model.

Monthly income was available for 257 respondents. The largest group reported €300-€700 per month (n = 104, 40.5%), followed by €700-€1,000 (n = 67, 26.1%), above €1,000 (n = 54, 21.0%), and below €300 (n = 32, 12.5%); five cases had missing income data (Figure 6).

Among 231 respondents with valid app-specific selections, Paysera was selected by 62 respondents (26.8%), PayPal by 60 (26.0%), and Wise (TransferWise) by 51 (22.1%). Forty-eight respondents (20.8%) selected 'Bank-based FinTech only.' This category indicates use of bank-provided digital financial applications and is therefore not treated as FinTech non-use (Figure 7). Among the same 231 respondents with valid app-specific selections, Raiffeisen ON was selected by 92 respondents (39.8%), ProCredit Mobile by 65 (28.1%), TEB Mobile by 62 (26.8%), NLB Klik by 53 (22.9%), and BKT Mobile by 50 (21.6%). Five respondents (2.2%) selected 'Independent FinTech only,' indicating independent FinTech use without a bank-based application selection.

These are multiple-response application categories and are not used alone to define overall FinTech use status (Figure 8).

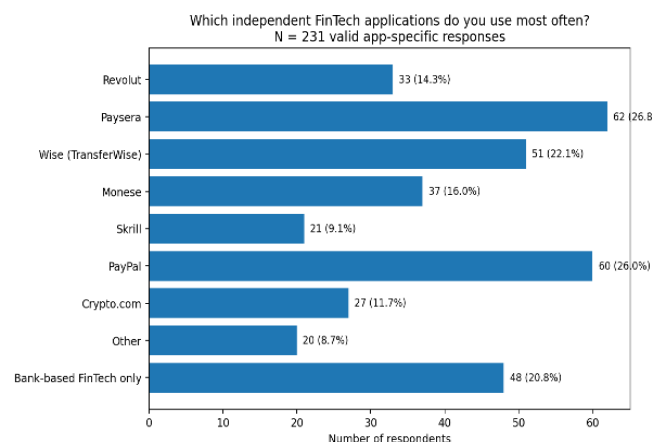


Figure 7. Independent FinTech application selections

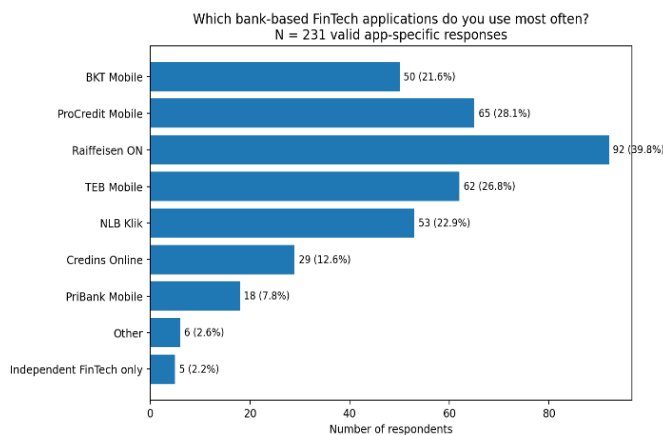


Figure 8. Bank-based FinTech application selections

4.3 Measurement and data-quality checks

This section reports internal-consistency reliability, the FinTech use-status audit, exploratory factor evidence, the focused assessment of PFI, and the common-method diagnostic used before formal hypothesis interpretation. The measurement analyses are exploratory and are not presented

as CFA-level construct validation.

4.3.1 Reliability analysis of study constructs

Internal consistency of the observed measures was assessed using Cronbach's alpha; results are presented in Table 5.

DM (Q1-Q5) showed good internal consistency (Cronbach's $\alpha = 0.829$). The original five-item BTF specification including Q7R produced $\alpha = 0.759$; excluding Q7R increased reliability to $\alpha = 0.796$ for Q6 and Q8-Q10. The original Q11-Q14 FL specification produced $\alpha = 0.780$; excluding Q14 increased reliability to $\alpha = 0.817$ for Q11-Q13. The six-item PFI block (Q15-Q20) showed high internal consistency ($\alpha = 0.890$). The exploratory three-item blocks were also internally consistent (Q15-Q17: $\alpha = 0.837$; Q18-Q20: $\alpha = 0.836$), but reliability alone does not establish that the two blocks are discriminable constructs.

Table 5. Reliability assessment of observed measures

Measure	Items	α	Decision
Digital Marketing (DM)	Q1–Q5	0.829	Retained
Behavioral and Trust Factors (BTF) (original)	Q6–Q10 (Q7R)	0.759	Respecified; $\alpha = 0.796$ without Q7R
Behavioral and Trust Factors (BTF) (revised)	Q6, Q8–Q10	0.796	Retained
Financial Literacy (FL) (original)	Q11–Q14	0.780	Respecified; $\alpha = 0.817$ without Q14
Financial Literacy (FL) (revised)	Q11–Q13	0.817	Retained
Perceived FinTech Impact (PFI)	Q15–Q20	0.890	Retained as one composite

Note: Cronbach's alpha values around or above 0.70 are used as a practical internal-consistency guide. Q7R was reverse-coded before reliability assessment.

Source: Authors' calculations.

Table 6. FinTech use-status audit in the analytical sample

Use Status	N	%	Definition
Recorded FinTech use	247	94.3	Independent and/or bank-based use recorded
No recorded FinTech use	15	5.7	No independent or bank-based use recorded
Total	262	100.0	Analytical sample

Note: Use status combines information from independent and bank-based FinTech application responses. The user-only sensitivity regression used N = 242 complete cases after age- and income-complete-case restrictions.

Source: Authors' calculations.

The reliability results support use of the main composite scores as internally consistent observed measures, while Q7R and Q14 remain separate indicators because they weakened or did not align with their original composite specifications.

Cronbach's alpha is interpreted here as evidence of internal consistency only. It is not treated as proof of convergent, discriminant, or latent-construct validity.

4.3.2 FinTech use-status audit

Because Q15-Q20 concern use-related benefits, financial-management outcomes, and recommendation/advocacy, FinTech use status was audited across both independent and bank-based application responses before sensitivity analysis.

The audit identified 247 respondents (94.3%) with recorded FinTech use and 15 respondents (5.7%) with no recorded FinTech use (Table 6). The 15 cases are not assumed to

provide experience-based evaluations of Q15-Q20; their responses may instead be hypothetical or anticipated.

To assess whether these cases affected inference, the hierarchical model was estimated again after excluding respondents without recorded FinTech use. The user-status sensitivity analysis is reported in Section 4.4.3 and preserves the substantive hypothesis pattern.

4.3.3 Exploratory factor analysis and measurement assessment

EFA was conducted on the 20 questionnaire items using PAF and Promax oblique rotation. The analysis evaluated sampling adequacy, factor retention, communalities, pattern coefficients, cross-loadings, and factor correlations. It is used as exploratory measurement evidence rather than as confirmatory latent-construct validation.

Table 7. Kaiser-Meyer-Olkin (KMO) and Bartlett's Test

Test / Indicator	Value
Kaiser-Meyer-Olkin Measure of Sampling Adequacy	0.892
Bartlett's Test of Sphericity - Approx. Chi-Square	2603.962
Degrees of freedom (df)	190
Significance (Sig.)	0.000

Note: KMO assesses sampling adequacy, while Bartlett's Test of Sphericity evaluates whether the correlation matrix is suitable for factor analysis.

Source: Authors' calculations.

Table 8. Initial eigenvalues and Principal Axis Factoring (PAF) extraction variance

Factor	Initial Eigenvalue (Initial %)	PAF Extraction Variance (%)	Cumulative Extraction (%)
1	7.582 (37.909%)	35.668	35.668
2	2.265 (11.323%)	9.190	44.858
3	1.460 (7.298%)	5.239	50.097
4	1.167 (5.833%)	3.222	53.319

Note: Extraction method: Principal Axis Factoring (PAF). Four factors were retained based on the eigenvalue pattern, scree plot, and interpretability.

Rotation method: Promax with Kaiser normalization.

Source: Authors' calculations.

The KMO value was 0.892 (Table 7), indicating very good sampling adequacy. Bartlett's Test of Sphericity was statistically significant, $\chi^2(190) = 2603.962$, $p < 0.001$ (Table 7), confirming that the item correlation matrix was suitable for factor analysis. These results support proceeding with EFA but do not, by themselves, establish construct validity.

Four factors had initial eigenvalues greater than 1 (7.582, 2.265, 1.460, and 1.167). Under PAF, the four retained factors accounted for 53.319% of the extracted variance (Table 8). The scree plot also showed a clear leveling after the fourth factor. Because the factors were correlated, Promax rotation was used rather than an orthogonal Varimax rotation.

As shown in Table 9, the Pattern Matrix shows that the first factor is dominated by Q15-Q20, with coefficients from 0.605 to 0.911. The second factor contains Q1-Q6, with coefficients from 0.420 to 0.866; Q4 (0.529 on Factor 2; 0.328 on Factor 4) and Q5 (0.420 on Factor 2; 0.380 on Factor 4) show cross-loadings. The third factor is defined clearly by Q11-Q13 (0.656-0.853). The fourth factor contains Q7R, Q8-Q10, and Q14 (0.335-0.668). This pattern demonstrates that the empirical item structure does not reproduce the original five theory-imposed dimensions cleanly.

The factor correlations ranged from 0.460 to 0.623,

supporting an oblique rotation. Q6 (perceived security/trust) clustered with DM items, while Q14 (training exposure) did not cluster with the core FL items; Q7R also showed weak communality (0.256). These results support a conservative

observed-composite specification and caution against treating the theory-imposed dimensions as EFA-validated latent constructs.

Table 9. Pattern matrix from Principal Axis Factoring (PAF) with Promax rotation

Item	Factor 1	Factor 2	Factor 3	Factor 4
Q1 social-media advertising		0.532		
Q2 information clarity/credibility		0.866		
Q3 UI/UX satisfaction		0.800		
Q4 online promotions		0.529		0.328
Q5 online communication		0.420		0.380
Q6 transaction security/trust		0.494		
Q7R perceived risk (reversed)				0.583
Q8 innovation attitude				0.335
Q9 trust vs. traditional banks				0.668
Q10 social influence				0.580
Q11 basic financial knowledge			0.853	
Q12 digital-investment risk assessment			0.830	
Q13 financial education supports decisions			0.656	
Q14 training/material exposure				0.434
Q15 time saving/financial management	0.605			
Q16 transaction efficiency	0.750			
Q17 increased digital-service use	0.802			
Q18 expense monitoring	0.911			
Q19 personal financial management	0.870			
Q20 recommendation/advocacy	0.670			

Note: Pattern coefficients below 0.30 are suppressed. Cross-loadings are reported where coefficients exceeded 0.30. Extraction method: Principal Axis Factoring; rotation: Promax with Kaiser normalization.

Source: Authors' calculations.

Table 10. Summary of exploratory measurement decision criteria

Criterion	Result	Decision
KMO	0.892	Proceed
Bartlett	$\chi^2(190) = 2603.962, p < 0.001$	Proceed
Natural retention	Four factors	Exploratory four-factor solution
PAF variance	53.319%	Adequate exploratory evidence
Pattern matrix	Theory/empirical mismatch	Respecify composites
Forced five-factor	5th eigenvalue = 0.881; mainly Q4/Q5	Reject five-factor solution
Latent validity	CFA/SEM not estimated	Not claimed

Note: The EFA decision combines KMO/Bartlett results, initial eigenvalues, PAF extraction, the Pattern Matrix, the scree plot, and a forced five-factor sensitivity check.

Source: Authors' formulation.

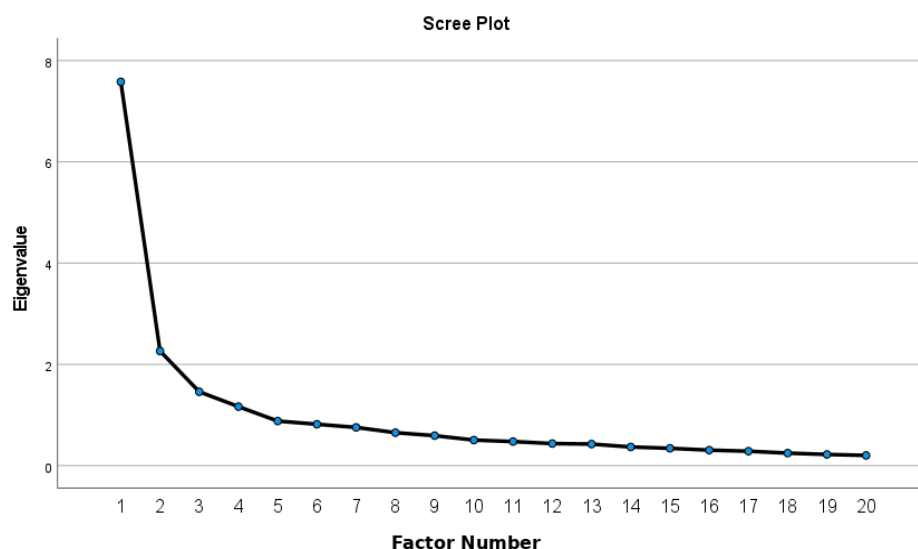


Figure 9. Scree plot for Exploratory Factor Analysis (EFA)

Note: The scree plot is used as an exploratory factor-retention aid. The leveling after the fourth factor is consistent with the four-factor EFA solution; factor retention was interpreted together with eigenvalues and substantive interpretability.

A forced five-factor sensitivity analysis was also estimated to reconcile the empirical solution with the original theoretical model. The fifth initial eigenvalue was 0.881, below 1, and the additional factor was defined mainly by Q4 and Q5 rather than by a theoretically distinct Usage or Performance dimension. The forced solution therefore did not provide convincing support for the original five-factor measurement structure.

Overall, the measurement evidence is interpreted conservatively (Table 10). The four-factor EFA describes how the items cluster in this sample, while the theory-guided composites used in OLS are treated as observed arithmetic scores. EFA is not treated as confirmatory construct validation, and CFA-level convergent or discriminant validity is not claimed.

The scree plot (Figure 9) and the eigenvalue pattern therefore support a four-factor exploratory solution for the present sample. This solution is not presented as a confirmatory latent measurement model; rather, it identifies the principal areas of agreement and mismatch between the empirical item structure and the original theoretical grouping.

Because no CFA/SEM measurement model is estimated, construct reliability, AVE, and discriminant-validity statistics are not presented as evidence of latent validity. Such confirmatory indices require a prespecified latent measurement model and are appropriate for future validation on an independent or enlarged sample. The present study limits its measurement claims to internal consistency and exploratory factor evidence for observed composites.

4.3.4 Focused dimensional assessment of Perceived FinTech Impact

To assess whether Q15-Q20 should be represented as separate FinTech Usage and Financial Performance

dimensions, the six items were examined using focused PAF. Sampling adequacy was good (KMO = 0.862), and Bartlett's Test of Sphericity was significant, $\chi^2(15) = 854.047$, $p < 0.001$. The first initial eigenvalue was 3.884 and the second was 0.716, indicating one dominant factor.

A one-factor PAF solution accounted for 57.847% of the variance, with loadings from 0.675 to 0.814, and the six-item scale showed high internal consistency (Cronbach's $\alpha = 0.890$). Although Q15-Q17 and Q18-Q20 were separately reliable ($\alpha = 0.837$ and 0.836), a forced two-factor extraction did not converge within 25 iterations, the rotated factors correlated strongly ($r = 0.727$), and Q17 cross-loaded (0.487 and 0.334). The evidence therefore does not support interpreting Usage and Financial Performance as two distinct first-order constructs. Q15-Q20 are retained as one PFI observed composite, and Q20 is classified as recommendation/advocacy rather than Financial Performance.

4.3.5 Common-method variance diagnostic

All 20 questionnaire items were entered into an unrotated one-factor PAF analysis. The first factor had an initial eigenvalue of 7.582 and represented 37.909% of the total initial variance. When a single factor was forced, the extraction sum of squared loadings was 6.952, accounting for 34.759% of the extracted variance; the one-factor loadings ranged from 0.303 to 0.712.

No single general factor therefore accounted for the majority of item variance. This result provides no evidence of a dominant single common-method factor, but it does not rule out common-method variance. Accordingly, the OLS coefficients and interaction estimates are interpreted as contemporaneous associations rather than causal effects.

Table 11. Four-block hierarchical Ordinary Least Squares (OLS) model summary

Block	Variables Entered	R	R ²	Adjusted R ²	ΔR^2	F-Change (p)
1	Country, age, income controls	0.111	0.012	-0.024	0.012	0.339 (0.961)
2	+ ZDM_R, ZBTF_R, ZFL_R	0.558	0.311	0.277	0.299	35.034 (< 0.001)
3	+ DM×BTF, DM×FL, BTF×FL	0.614	0.377	0.338	0.065	8.348 (< 0.001)
4	+ DM×BTF×FL	0.620	0.385	0.343	0.008	3.033 (0.083)

Note: N = 255 complete cases. Block 1 = country, age-group, and income dummy controls; Block 2 = ZDM_R, ZBTF_R, and ZFL_R; Block 3 = DM × BTF, DM × FL, and BTF × FL; Block 4 = DM × BTF × FL. ΔR^2 and F-change refer to improvement over the preceding block.

Source: Authors' calculations.

Table 12. Final four-block hierarchical regression coefficients

Predictor	B	SE	β	t	p	VIF
Constant	3.957	0.152	—	26.043	< 0.001	—
Albania_D	-0.098	0.116	-0.048	-0.846	0.398	1.236
NMacedonia_D	-0.072	0.125	-0.032	-0.574	0.566	1.211
Age2_D	0.072	0.154	0.041	0.468	0.640	2.949
Age3_D	-0.047	0.173	-0.023	-0.273	0.785	2.740
Age4_D	0.071	0.186	0.031	0.382	0.703	2.625
Age5_D	0.092	0.193	0.038	0.480	0.632	2.439
Inc2_D	-0.239	0.149	-0.139	-1.607	0.109	2.873
Inc3_D	-0.104	0.164	-0.054	-0.631	0.529	2.839
Inc4_D	-0.200	0.173	-0.097	-1.155	0.249	2.711
ZDM_R	0.109	0.061	0.127	1.781	0.076	1.980
ZBTF_R	0.371	0.065	0.438	5.716	< 0.001	2.270
ZFL_R	0.243	0.058	0.287	4.206	< 0.001	1.803
DM×BTF	-0.011	0.052	-0.017	-0.212	0.833	2.634
DM×FL	0.168	0.058	0.266	2.899	0.004	3.252
BTF×FL	-0.052	0.064	-0.083	-0.807	0.421	4.113
DM×BTF×FL	-0.048	0.028	-0.176	-1.742	0.083	3.931

Note: Dependent variable: Perceived FinTech Impact (PFI_R). B = unstandardized coefficient; SE = standard error; β = standardized coefficient. Country, age-group, and income terms are dummy variables; VIF = variance inflation factor.

Source: Authors' calculations.

4.4 Hypothesis testing using four-block hierarchical Ordinary Least Squares regression

The pooled hypotheses were tested using one four-block hierarchical OLS specification. PFI (PFI_R) was the dependent variable. Block 1 entered demographic controls; Block 2 added standardized DM (ZDM_R), BTF (ZBTF_R), and FL (ZFL_R); Block 3 added the three two-way interactions (DM × BTF, DM × FL, and BTF × FL); and Block 4 added the DM × BTF × FL three-way interaction. The regression used N = 255 complete cases (Table 11).

The demographic controls were dummy-coded rather than entered as linear 1-2-3 category scores. Kosovo served as the reference country, while the first age and income categories served as their reference groups. This specification makes the control block explicit and aligns the reported model sequence with the methodology.

Block 1, containing only demographic controls, explained 1.2% of the variance in PFI ($R^2 = 0.012$; adjusted $R^2 = -0.024$) and was not statistically significant, $F\text{-change}(9, 245) = 0.339$, $p = 0.961$. Adding the three main predictors in Block 2 produced a substantial improvement: R^2 increased to 0.311 (adjusted $R^2 = 0.277$), with $\Delta R^2 = 0.299$, $F\text{-change}(3, 242) = 35.034$, $p < 0.001$.

Block 3 added the three lower-order two-way interactions and increased R^2 from 0.311 to 0.377 (adjusted $R^2 = 0.338$). The additional 6.5% explained variance was statistically significant, $\Delta R^2 = 0.065$, $F\text{-change}(3, 239) = 8.348$, $p < 0.001$. Block 4 then added the three-way interaction; the final R^2 was 0.385 (adjusted $R^2 = 0.343$), but the additional 0.8% was not statistically significant, $\Delta R^2 = 0.008$, $F\text{-change}(1, 238) = 3.033$, $p = 0.083$. The complete final model was significant, $F(16, 238) = 9.294$, $p < 0.001$, with Durbin-Watson = 2.075.

Table 12 reports the coefficients of the final four-block model, including the demographic controls and all focal terms.

Final hierarchical regression equation:

$$\begin{aligned} PFI_R = & 3.957 + \text{controls} + 0.109ZDM_R \\ & + 0.371ZBTF_R + 0.243ZFL_R - 0.011(DM \times BTF) \\ & + 0.168(DM \times FL) - .052(BTF \times FL) \\ & - 0.048(DM \times BTF \times FL) + \varepsilon \end{aligned} \quad (19)$$

In the final model, BTF were the strongest positive predictor ($B = 0.371$, $\beta = 0.438$, $p < 0.001$), followed by FL ($B = 0.243$, $\beta = 0.287$, $p < 0.001$). DM remained positive but was not statistically significant at the 0.05 level ($B = 0.109$, $\beta = 0.127$, $p = 0.076$). None of the demographic controls reached statistical significance in the final model.

Interaction results:

Among the two-way interactions, only DM × FL was statistically significant ($B = 0.168$, $\beta = 0.266$, $p = 0.004$). DM × BTF was not significant ($\beta = -0.017$, $p = 0.833$), and BTF × FL was also not significant ($\beta = -0.083$, $p = 0.421$).

The three-way interaction was negative but did not reach the 0.05 significance threshold ($B = -0.048$, $\beta = -0.176$, $p = 0.083$; 95% CI for $B = [-0.102, 0.006]$). Its addition in Block 4 likewise did not significantly improve model fit ($\Delta R^2 = 0.008$, $p = 0.083$). Accordingly, the three-way term is not treated as evidence of a statistically established combined moderation effect.

The block sequence shows that demographic controls contribute little explanatory power, while the three main observed composites account for the largest incremental increase in R^2 . The two-way interaction block provides a

further statistically significant increment, driven principally by the positive DM × FL term.

The hierarchical sequence is therefore interpreted in the following order: demographic controls, main observed-composite associations, all two-way interactions, and the three-way interaction.

The final model therefore explains 38.5% of the variance in PFI, but the evidence does not support attributing additional explanatory power to the three-way interaction after the lower-order terms have been entered.

Interpretation is based on the fully specified hierarchical model, in which controls, main effects, lower-order interactions, and the three-way interaction are evaluated within one coherent specification.

For regression-based hypothesis testing (Table 13), H2 and H3 are supported because BTF and FL are positive and statistically significant in the final model. H4 is supported because DM × FL is positive and significant. H1 is not supported at the conventional 0.05 level in the final model because the direct DM coefficient is positive but non-significant ($p = 0.076$). H5 is not supported because the three-way interaction is non-significant ($p = 0.083$).

The final hypothesis decisions therefore distinguish significant direct and lower-order conditional associations from the unsupported three-way hypothesis. BTF and FL retain significant positive associations with PFI, and the significant DM × FL term supports the proposed moderating role of FL.

DM does not show an independently significant direct association after adjustment for controls, the other main effects, and interaction terms. The three-way term is also not statistically significant; H1 and H5 are therefore not supported in the pooled hierarchical model.

Substantively, the strongest evidence in the pooled model concerns BTF, FL, and the DM × FL interaction. These results are interpreted as associations within a cross-sectional observed-composite OLS model.

Because the three-way interaction is not statistically significant, no substantive mechanism such as information overload, selectivity, saturation, or diminishing returns is inferred from its negative sign.

Overall, the hierarchical model provides a coherent pooled specification. The final model explains 38.5% of the variance in PFI (adjusted $R^2 = 0.343$), with the largest explanatory gain occurring when the three main observed composites are added and a smaller but significant gain when the lower-order two-way interactions are added.

Table 13. Hypothesis decisions from the four-block hierarchical Ordinary Least Squares (OLS) model

Hypothesis	Tested Relationship	Final β	p	Final Decision
H1	DM → PFI (+)	0.127	0.076	Not supported
H2	BTF → PFI (+)	0.438	< 0.001	Supported
H3	FL → PFI (+)	0.287	< 0.001	Supported
H4	DM × FL → PFI (+)	0.266	0.004	Supported
H5	DM × BTF × FL → PFI	- 0.176	0.083	Not supported

Note: Decisions are based on the fully specified four-block hierarchical OLS model. β = standardized coefficient.

Source: Authors' calculations.

Figure 10 presents standardized coefficients for the focal terms in the hierarchical model. BTF shows the largest positive standardized coefficient ($\beta = 0.438$), followed by FL ($\beta = 0.287$) and the DM $\times$ FL interaction ($\beta = 0.266$). DM is positive but non-significant ($\beta = 0.127$, $p = 0.076$), while the three-way interaction is negative but non-significant ($\beta = -0.176$, $p = 0.083$).

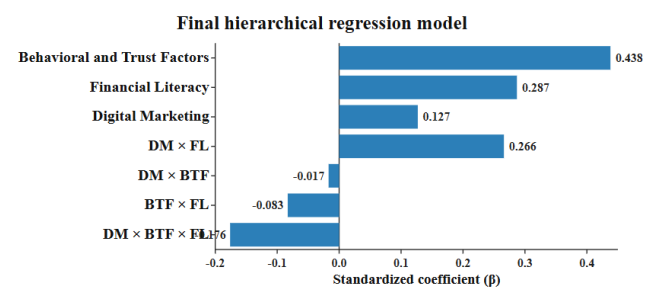


Figure 10. Standardized coefficients from the four-block hierarchical Ordinary Least Squares (OLS) model

4.4.1 Conditional simple-slope analysis of the interaction between Digital Marketing and Financial Literacy

The analysis first showed that the three-way interaction was not statistically significant ($B = -0.048$, $SE = 0.028$, $\beta = -0.176$, $t = -1.742$, $p = 0.083$, 95% CI [-0.102, 0.006]). In simple terms, this means that the combined effect of the three variables was not strong enough to be considered statistically reliable. The p-value of 0.083 is above the commonly used 0.05 threshold, while the CI includes zero. For this reason, the analysis then focused on the interaction between DM and FL, which was statistically significant ($B = 0.168$, $SE = 0.058$, $\beta = 0.266$, $t = 2.899$, $p = 0.004$, 95% CI [0.054, 0.282]).

This result shows that DM does not affect all FinTech users in the same way. Its effect changes depending on the level of FL. The positive coefficient $B = 0.168$ indicates that the higher the level of FL, the more positive the effect of DM on PFI becomes. The p-value of 0.004, which is much lower than 0.05, shows that this interaction is statistically reliable.

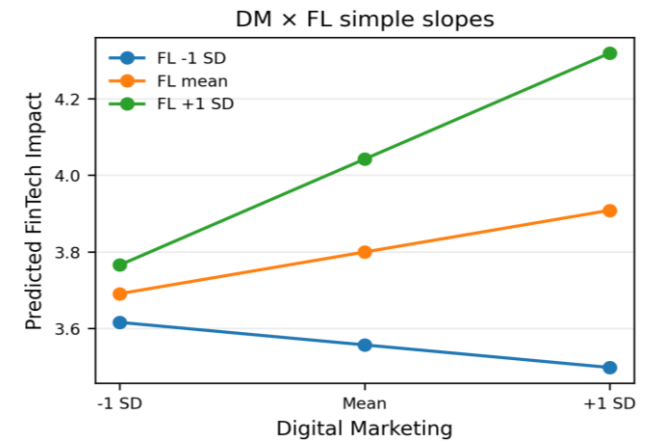


Figure 11. Simple slopes of Digital Marketing (DM) at low, mean, and high Financial Literacy (FL)

Note: Financial Literacy is shown at -1 SD, the mean, and +1 SD. Predictions are from the final adjusted hierarchical OLS specification, with Behavioral and Trust Factors (BTF) held at its standardized mean and demographic controls held at their sample proportions.
Source: Authors' calculations.

The simple-slope analysis makes this relationship even clearer (Figure 11). Among users with low FL (-1 SD), the

effect of DM was slightly negative but not statistically significant ($B = -0.059$, $SE = 0.079$, $t = -0.746$, $p = 0.456$, 95% CI [-0.215, 0.097]). In practical terms, this means that among users with lower FL, greater DM was not clearly associated with either a more positive or a more negative PFI. The p-value of 0.456 and the CI including zero show that this effect is highly uncertain.

Among users with an average level of FL, the relationship became positive ($B = 0.109$, $SE = 0.061$, $t = 1.781$, $p = 0.076$, 95% CI [-0.012, 0.229]). This suggests that DM begins to be associated with a more positive PFI when users have an average level of FL. However, $p = 0.076$ is still above 0.05, and the CI continues to include zero; therefore, this effect is still not considered statistically significant.

The clearest result appears among users with high FL (+1 SD). At this level, DM had a positive and statistically significant effect on PFI ($B = 0.277$, $SE = 0.089$, $t = 3.113$, $p = 0.002$, 95% CI [0.102, 0.451]). This means that among users with higher FL, an increase in DM is associated with a more positive PFI. The p-value of 0.002 is much lower than 0.05, and the CI is entirely positive, making this result statistically reliable.

Overall, the pattern is clear: when FL is low, the effect of DM is $B = -0.059$ and is not significant; at the average level, the effect becomes positive at $B = 0.109$ but is still not statistically significant; whereas at the high level, the effect increases to $B = 0.277$ and becomes statistically significant. Therefore, the results show that FL strengthens the positive relationship between DM and PFI. In practical terms, DM appears to work better among FinTech users who have stronger FL.

The Johnson-Neyman analysis provided additional information regarding the range of FL values over which the conditional DM effect was statistically significant. The estimated region-of-significance boundaries were approximately -2.28 SD and +0.07 SD relative to the sample mean. Between these two boundaries, the conditional DM slope was not statistically different from zero at the 0.05 level. Above approximately +0.07 SD, the conditional effect became positive and statistically significant, whereas below approximately -2.28 SD, the effect became negative and statistically significant. Because the lower Johnson-Neyman boundary lies within an extreme low-literacy region, the substantive interpretation emphasizes the transition occurring near +0.07 SD.

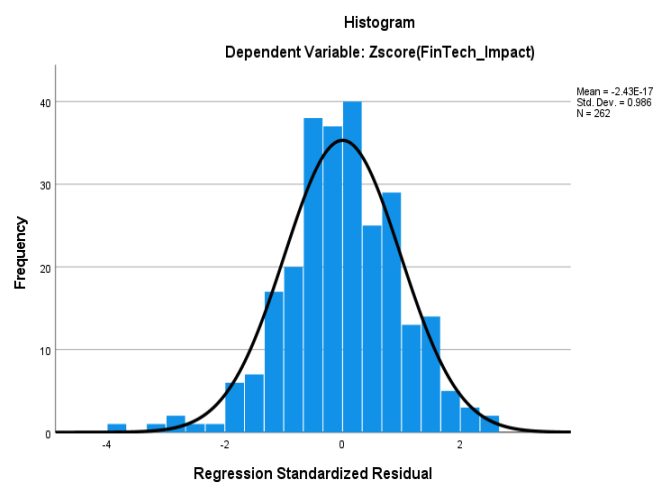


Figure 12. Histogram of standardized residuals for the Perceived FinTech Impact (PFI) model

•Normality of Residuals (Histogram)

The histogram of standardized residuals is approximately centered around zero and provides a visual assessment of the residual distribution (Figure 12). Because heteroskedasticity was detected, residual diagnostics and robust covariance estimates are emphasized rather than relying on normality alone.

4.4.2 Final hierarchical regression model for hypothesis testing

Before interpreting the final hypothesis-testing results, it is necessary to assess whether the hierarchical regression model

satisfies the main diagnostic conditions for reliable estimation.

The diagnostic values for the final $N = 255$ hierarchical model (Table 14) show that the maximum VIF was 4.113 and the maximum Condition Index was 9.143. Standardized residuals ranged from -3.402 to 2.698 and studentized residuals from -3.512 to 2.828. Cook's Distance reached a maximum of 0.168, below the conventional 1.0 screening rule, whereas centered leverage reached 0.443 and Mahalanobis Distance reached 112.599. These values identify several observations that warrant case-level influence review, but no observation was deleted automatically on the basis of a single diagnostic.

Table 14. Regression diagnostic tests for model stability and influence

Diagnostic Area	Indicator	Value / Range	Screening Guide	Interpretation
Collinearity	Maximum Condition Index	9.143	Context-dependent	No extreme condition index
Collinearity	VIF range	1.211-4.113	< 5	Within common screening threshold
Collinearity	Tolerance range	0.243-0.825	> 0.10	No severe tolerance problem
Residuals	Standardized residuals	-3.402 to 2.698	Approx. ± 3	A small number of tail cases require review
Residuals	Studentized residuals	-3.512 to 2.828	Approx. ± 3	A small number of tail cases require review
Influence	Cook's Distance	Max = 0.168	< 1	No case exceeds the conventional 1.0 rule
Influence	Mahalanobis Distance	Max = 112.599	Case-specific review	Potential multivariate outliers require inspection
Influence	Centered leverage	Max = 0.443	Case-specific review	High-leverage cases require inspection
Residual dep.	Durbin-Watson	2.075	Secondary	Not primary for cross-sectional OLS

Note: Dependent variable: Perceived FinTech Impact. VIF, Tolerance, and Condition Index assess multicollinearity, while residual and influence statistics assess model stability. Thresholds are reported to support interpretation of model acceptability; VIF = variance inflation factor.

Source: Authors' calculations.

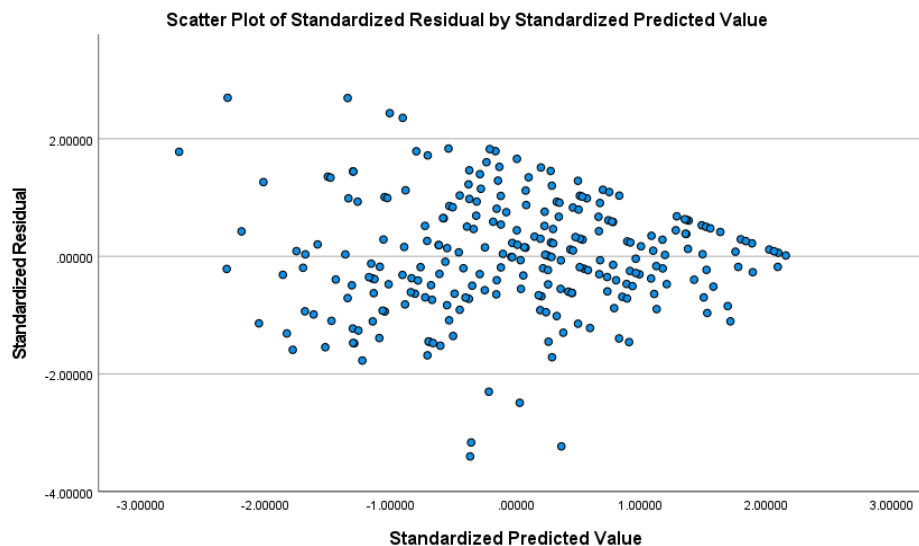


Figure 13. Standardized residuals versus standardized predicted values

The standardized residual-versus-standardized-predicted plot (Figure 13) shows residuals distributed around zero without a pronounced curved pattern, supporting approximate linearity. The spread is not perfectly uniform, which is consistent with the formal heteroskedasticity result and motivates robust covariance inference.

Because heteroskedasticity was detected, the same 16-predictor linear model was re-estimated in GENLIN using a normal identity link and robust sandwich covariance. In simple terms, this additional analysis was carried out to make sure that the statistical conclusions remained reliable even though the variability of the errors was not constant across observations. Importantly, the coefficient estimates did not change, which means that the estimated direction and size of the relationships remained the same. What changed was the way the uncertainty

around those estimates was calculated, making the statistical inference more robust.

For DM, the coefficient was positive ($B = 0.109$), with a robust standard error of 0.0569, a 95% CI from -0.003 to 0.220, and $p = 0.056$. This suggests that higher levels of DM were associated with a higher PFI. However, the p -value of 0.056 is slightly above the conventional 0.05 threshold, and the CI includes zero. Therefore, although the relationship is positive and close to statistical significance, the evidence is not strong enough to conclude with conventional statistical confidence that DM has a direct independent effect.

A much clearer result was observed for BTF. The coefficient was $B = 0.371$, with a robust standard error of 0.0709, a 95% CI from 0.233 to 0.510, and $p < 0.001$. This means that higher levels of behavioral and trust-related factors

were associated with higher PFI. The CI is entirely positive, and the very small p-value indicates strong statistical evidence for this relationship. For the audience, the practical message is straightforward: users who show stronger trust and more favorable behavioral attitudes toward FinTech are also more likely to perceive FinTech as having a positive impact.

FL also showed a positive and statistically significant relationship, with $B = 0.243$, robust $SE = 0.0621$, 95% CI $[0.121, 0.365]$, and $p < 0.001$. This indicates that users with higher FL tend to report a more positive PFI. The CI remains fully above zero and the p-value is well below 0.05, providing strong evidence that FL is an important factor in the model. In practical terms, people who better understand financial concepts may be more capable of recognizing and evaluating the benefits offered by FinTech services.

The interaction between DM and BTF ($DM \times BTF$) was very small and not statistically significant ($B = -0.011$, robust $SE = 0.0484$, $p = 0.819$). This means there is no reliable evidence that the effect of DM changes depending on the level of BTF. In other words, trust-related factors do not appear to strengthen or weaken the relationship between DM and PFI in a statistically meaningful way.

In contrast, the interaction between $DM \times FL$ was positive and statistically significant ($B = 0.168$, robust $SE = 0.0550$, 95% CI $[0.060, 0.276]$, $p = 0.002$). This is one of the most important findings in the model. The positive coefficient means that the relationship between DM and PFI becomes stronger as FL increases. The p-value of 0.002 is clearly below 0.05, while the CI $[0.060, 0.276]$ is entirely positive. In practical terms, DM appears to be more effective among FinTech users who have greater FL. Users who understand financial concepts more clearly may be better able to interpret DM messages, evaluate the information presented to them, and recognize the potential value of FinTech products and services.

The interaction between $BTF \times FL$ was negative but not statistically significant ($B = -0.052$, robust $SE = 0.0684$, $p = 0.450$). Therefore, there is no reliable evidence that FL meaningfully changes the relationship between BTF and PFI. Although the estimated coefficient is slightly negative, the relatively high p-value shows that this pattern could easily be due to random variation in the data.

Finally, the three-way interaction between $DM \times BTF \times FL$ was also not statistically significant ($B = -0.048$, robust $SE = 0.0313$, 95% CI $[-0.109, 0.013]$, $p = 0.125$). The negative coefficient suggests a small negative estimated three-way effect, but the p-value is above 0.05 and the CI includes zero. This means that there is insufficient evidence to conclude that the combined effect of DM and FL changes further depending on the level of BTF.

Overall, the robust analysis presents a clear pattern. BTF ($B = 0.371$, robust $SE = 0.0709$, 95% CI $[0.233, 0.510]$, $p < 0.001$) and FL ($B = 0.243$, robust $SE = 0.0621$, 95% CI $[0.121, 0.365]$, $p < 0.001$) show strong positive direct relationships with PFI. DM also shows a positive coefficient ($B = 0.109$, robust $SE = 0.0569$, 95% CI $[-0.003, 0.220]$, $p = 0.056$), although its direct effect falls just short of the conventional 0.05 significance level. Most importantly, the significant $DM \times FL$ interaction ($B = 0.168$, robust $SE = 0.0550$, 95% CI $[0.060, 0.276]$, $p = 0.002$) shows that the influence of DM becomes more positive when FL is higher. For a non-technical audience, the central message is that FinTech users appear to respond more positively when they both understand financial matters and are exposed to effective DM, while trust and Behavioral Factors

independently remain strong contributors to how positively FinTech is perceived.

All demographic controls remained non-significant under robust covariance estimation (smallest $p = 0.086$). The hypothesis pattern is unchanged: H1 and H5 are unsupported, whereas H2, H3, and H4 are supported.

4.4.3 User-status sensitivity analysis

FinTech use status combines independent and bank-based application responses. Respondents who reported bank-based FinTech use were classified as FinTech users even when they reported no independent FinTech application; 15 respondents (5.7%) had no recorded use in either category.

A case-level audit of the frozen $N = 262$ analytical sample identified 15 respondents (5.7%) who explicitly reported non-use and had no independent or bank-based FinTech application recorded. Because Q15-Q20 ask about experienced use-related benefits and outcomes, responses from these 15 cases may reflect hypothetical or anticipated evaluations. They were therefore excluded in a sensitivity analysis rather than being assumed to be equivalent to respondents with recorded FinTech use. The remaining user-status sample contained 247 respondents; after applying the same age- and income-complete-case requirements as in the primary model, the sensitivity regression used $N = 242$.

The identical four-block hierarchical specification was estimated for $N = 242$ complete user cases using the same pooled-sample standardized predictors, demographic controls, two-way interactions, and three-way interaction. The model remained statistically significant, $R^2 = 0.355$, adjusted $R^2 = 0.309$, $F(16, 225) = 7.741$, $p < 0.001$. The main-effect block remained significant ($\Delta R^2 = 0.276$, $p < 0.001$), as did the two-way interaction block ($\Delta R^2 = 0.064$, $p < 0.001$), whereas the three-way increment remained non-significant ($\Delta R^2 = 0.006$, $p = 0.146$).

The inferential pattern was unchanged. BTF remained positive and significant ($B = 0.335$, $\beta = 0.404$, $p < 0.001$), FL remained positive and significant ($B = 0.242$, $\beta = 0.296$, $p < 0.001$), and the $DM \times FL$ interaction remained positive and significant ($B = 0.163$, $\beta = 0.270$, $p = 0.006$). The direct DM coefficient remained positive but non-significant ($B = 0.109$, $\beta = 0.133$, $p = 0.078$), and the three-way interaction remained non-significant ($B = -0.041$, $\beta = -0.158$, $p = 0.146$).

Thus, the primary conclusions are not driven by the small number of respondents without recorded FinTech use. Accordingly, the sensitivity analysis supports the stability of the main inferential pattern among respondents with recorded FinTech use, while the 15 non-user responses are not interpreted as validated experience-based assessments of Q15-Q20.

4.5 Preliminary Pearson correlation analysis

Pearson correlation analysis was conducted as a preliminary bivariate assessment of the direction and strength of associations among four observed composites: DM (DM_R), BTF (BTF_R), FL (FL_R), and PFI (PFI_R). The analysis used the full sample of $N = 262$. These zero-order correlations are descriptive preliminary evidence and are not used to determine support for the formal hypotheses.

Table 15 shows that PFI is positively correlated with DM ($r = 0.402$, $p < 0.001$), BTF ($r = 0.533$, $p < 0.001$), and FL ($r = 0.418$, $p < 0.001$). These coefficients indicate positive bivariate associations but do not establish the adjusted

regression effects specified in H1-H3. The explanatory composites are also positively intercorrelated: DM with BTF ($r = 0.649$, $p < 0.001$), DM with FL ($r = 0.439$, $p < 0.001$), and BTF with FL ($r = 0.519$, $p < 0.001$). These correlations provide

descriptive context for the multivariable model and do not by themselves test moderation or higher-order interaction hypotheses.

Table 15. Preliminary Pearson correlations among observed composites

Variables Pair		DM_R	BTF_R	FL_R	PFI_R
DM_R	Pearson Correlation	1	0.649**	0.439**	0.402**
	Sig. (2-tailed)		0.000	0.000	0.000
	N	262	262	262	262
BTF_R	Pearson Correlation	0.649**	1	0.519**	0.533**
	Sig. (2-tailed)	0.000		0.000	0.000
	N	262	262	262	262
FL_R	Pearson Correlation	0.439**	0.519**	1	0.418**
	Sig. (2-tailed)	0.000	0.000		0.000
	N	262	262	262	262
PFI_R	Pearson Correlation	0.402**	0.533**	0.418**	1
	Sig. (2-tailed)	0.000	0.000	0.000	
	N	262	262	262	262

**. Correlation is significant at the 0.01 level (2-tailed).

Note: N = 262. All coefficients are Pearson zero-order correlations; two-tailed p values are shown. Correlations are preliminary bivariate associations and are not formal hypothesis tests.

Source: Authors' calculations.

Pearson correlations are reported only as preliminary descriptive evidence and are not treated as a separate formal hypothesis.

Formal hypothesis decisions are based exclusively on the correctly specified four-block hierarchical OLS model reported in Section 4.4 and Table 13, where each coefficient is evaluated while accounting for the other terms in the model.

Accordingly, H1 is not supported at the 0.05 level because the adjusted DM coefficient is positive but non-significant ($\beta = 0.127$, $p = 0.076$). H2 and H3 are supported because BTF ($\beta = 0.438$, $p < 0.001$) and FL ($\beta = 0.287$, $p < 0.001$) are positive and significant. H4 is supported by the significant DM $\times$ FL interaction ($\beta = 0.266$, $p = 0.004$), whereas H5 is not supported because the three-way interaction is non-significant ($\beta = -0.176$, $p = 0.083$).

This separation prevents bivariate correlations from being interpreted as evidence for adjusted direct associations or interaction hypotheses and aligns the hypothesis decisions with the regression model used for formal inference.

Figure 13 is the standard residual-versus-fitted diagnostic for the final pooled model: standardized residuals are plotted against standardized predicted values. Residuals are generally centered around zero and the plot does not show a pronounced systematic curve, which supports approximate linearity. The vertical spread is not fully constant and several tail observations are visible, so the graph is not used as evidence of model fit; instead, it motivates the formal heteroskedasticity and influence checks reported above.

Since the study includes respondents from three countries, country was included in the pooled regression model as a demographic control variable. Separate country-specific regressions are presented only as supplementary within-country sensitivity analyses and are not used to infer statistically established cross-country differences in regression coefficients or associations.

4.6 Country-specific regression comparison

Separate two-block OLS regressions were estimated for Kosovo, Albania, and North Macedonia using the observed composite measures. In each country, PFI_R was the dependent variable. Block 1 contained age-group dummies (Age2_D-Age5_D) and income-category dummies (Inc2_D-Inc4_D), with the first age and income categories serving as reference groups. Block 2 added DM_R, BTF_R, and FL_R. Country dummies were not included because country is constant within each national subsample. Complete-case analysis yielded N = 156 for Kosovo, N = 55 for Albania, and N = 44 for North Macedonia.

The country-specific models use the same two-block specification and are reported as supplementary within-country sensitivity analyses rather than as formal cross-country comparisons.

The country-specific model-fit results are reported in Table 16.

Table 16. Country-specific regression model fit and incremental explanatory power

Country	N	R ²	Adj. R ²	F(df), p	ΔR^2 Block 2 (p); DW
Kosovo	156	0.433	0.394	11.082 (10,145), $p < 0.001$	0.406 ($p < 0.001$); 1.875
Albania	55	0.379	0.237	2.680 (10,44), $p = 0.012$	0.293 ($p = 0.001$); 1.993
North Macedonia	44	0.210	-0.030	0.876 (10,33), $p = 0.564$	0.079 ($p = 0.360$); 2.207

Note: Dependent variable: Perceived FinTech Impact (PFI_R). Within each country, Block 1 contains Age2_D-Age5_D and Inc2_D-Inc4_D; Block 2 adds DM_R, BTF_R, and FL_R. Country dummies are omitted because country is constant within each subsample. ΔR^2 refers to the addition of the three focal predictors after demographic controls. DW = Durbin-Watson.

Source: Authors' calculations.

The country-specific regression analyses revealed notable differences in model performance across Kosovo, Albania,

and North Macedonia. For Kosovo (N = 156), the final regression model was statistically significant and explained a

substantial proportion of the variance in the outcome, $R^2 = 0.433$, adjusted $R^2 = 0.394$, $F(10, 145) = 11.082$, $p < 0.001$. After the demographic control variables were entered, the addition of DM (DM_R), BTF (BTF_R), and FL (FL_R) produced a considerable increase in explained variance, $\Delta R^2 = 0.406$, $F\text{-change}(3, 145) = 34.613$, $p < 0.001$. The Durbin-Watson statistic of 1.875 indicated no substantial concern regarding residual autocorrelation.

A similar, although weaker, pattern emerged for Albania (N = 55). The final model was statistically significant, $R^2 = 0.379$, adjusted $R^2 = 0.237$, $F(10, 44) = 2.680$, $p = 0.012$, indicating that the predictors collectively accounted for a meaningful proportion of the variation in the dependent variable. The introduction of the focal predictors after the demographic controls increased the explained variance by $\Delta R^2 = 0.293$, with this change being statistically significant, $F\text{-change}(3, 44) = 6.912$, $p = 0.001$. The Durbin-Watson value of 1.993 was close to the conventional reference value of 2, suggesting no

important residual autocorrelation.

In contrast, the results for North Macedonia (N = 44) were substantially weaker. The final model was not statistically significant, $R^2 = 0.210$, adjusted $R^2 = -0.030$, $F(10, 33) = 0.876$, $p = 0.564$. Moreover, adding DM_R, BTF_R, and FL_R after the demographic controls produced only a limited increase in explained variance, $\Delta R^2 = 0.079$, and this increment was not statistically significant, $F\text{-change}(3, 33) = 1.107$, $p = 0.360$. The Durbin-Watson statistic was 2.207, again indicating no major concern regarding residual autocorrelation. Overall, the country-specific findings suggest that the focal predictors demonstrated the strongest explanatory contribution in Kosovo, a moderate but statistically significant contribution in Albania, and no statistically significant contribution in North Macedonia.

The country-specific regression results in Table 17 reveal distinct patterns in the effects of DM, BTF, and FL across Kosovo, Albania, and North Macedonia.

Table 17. Country-specific coefficients for the focal predictors

Country / Predictor	B, SE, β , t, p, 95% CI, VIF
Kosovo - DM_R	B = 0.004; SE = 0.085; $\beta = 0.004$; t = 0.046; p = 0.963; CI [-0.163, 0.171]; VIF = 1.823
Kosovo - BTF_R	B = 0.489; SE = 0.081; $\beta = 0.523$; t = 6.019; p < 0.001; CI [0.328, 0.649]; VIF = 1.932
Kosovo - FL_R	B = 0.179; SE = 0.071; $\beta = 0.192$; t = 2.539; p = 0.012; CI [0.040, 0.319]; VIF = 1.466
Albania - DM_R	B = -0.062; SE = 0.164; $\beta = -0.060$; t = -0.381; p = 0.705; CI [-0.393, 0.268]; VIF = 1.763
Albania - BTF_R	B = 0.557; SE = 0.176; $\beta = 0.508$; t = 3.159; p = 0.003; CI [0.202, 0.912]; VIF = 1.832
Albania - FL_R	B = 0.189; SE = 0.128; $\beta = 0.222$; t = 1.476; p = 0.147; CI [-0.069, 0.446]; VIF = 1.601
North Macedonia - DM_R	B = 0.360; SE = 0.199; $\beta = 0.437$; t = 1.812; p = 0.079; CI [-0.044, 0.764]; VIF = 2.426
North Macedonia - BTF_R	B = -0.202; SE = 0.192; $\beta = -0.257$; t = -1.053; p = 0.300; CI [-0.593, 0.189]; VIF = 2.493
North Macedonia - FL_R	B = -0.009; SE = 0.192; $\beta = -0.010$; t = -0.048; p = 0.962; CI [-0.399, 0.380]; VIF = 1.911

Note: B = unstandardized coefficient; SE = standard error; β = standardized coefficient; CI = 95% confidence interval; VIF = variance inflation factor. The same age and income controls listed in Table 16 were retained in every country model. Focal-predictor VIF values are reported directly in the table. Maximum VIF among demographic controls was 2.342 in Kosovo, 12.540 in Albania, and 13.486 in North Macedonia, indicating instability among some dummy controls in the smaller country subsamples.

Source: Authors' calculations.

•Analysis for Kosovo

In Kosovo, DM (Table 17) was not statistically significant (B = 0.004, SE = 0.085, $\beta = 0.004$, t = 0.046, p = 0.963, 95% CI [-0.163, 0.171], VIF = 1.823). In contrast, BTF showed a positive and statistically significant association with the outcome (B = 0.489, SE = 0.081, $\beta = 0.523$, t = 6.019, p < 0.001, 95% CI [0.328, 0.649], VIF = 1.932). FL was also positively and significantly associated with the outcome (B = 0.179, SE = 0.071, $\beta = 0.192$, t = 2.539, p = 0.012, 95% CI [0.040, 0.319], VIF = 1.466). Thus, within the Kosovo subsample, BTF and FL emerged as significant focal predictors, whereas DM did not.

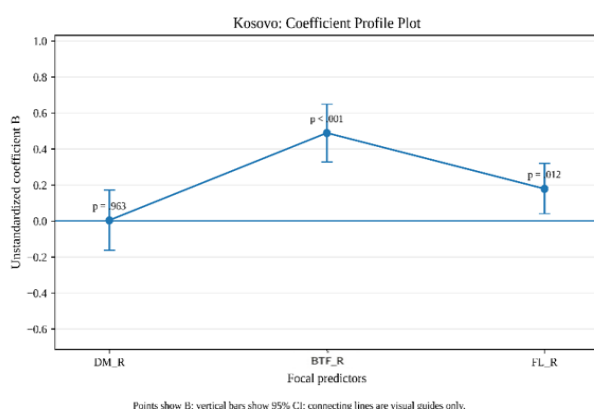


Figure 14. Country-specific coefficient profile of the focal predictors in Kosovo

Figure 14 presents the three focal predictors. BTF has the strongest positive association with PFI, with an unstandardized coefficient of B = 0.489 and a 95% CI of [0.328, 0.649]; the effect is statistically significant (p < 0.001). FL also shows a positive and statistically significant association, although smaller in magnitude (B = 0.179, 95% CI [0.040, 0.319], p = 0.012). By contrast, DM is positioned almost exactly at zero (B = 0.004, 95% CI [-0.163, 0.171], p = 0.963), and its CI crosses zero, indicating no statistically significant independent association.

The substantive content of the indices helps explain this visual pattern. BTF combine transaction security and trust (Q6), attitudes toward innovation (Q8), trust relative to traditional banks (Q9), and social influence (Q10), whereas FL comprises basic FL (Q11), digital-investment risk assessment (Q12), and the role of financial education in supporting decisions (Q13). DM includes social-media advertising (Q1), information clarity and credibility (Q2), UI/UX satisfaction (Q3), online promotions (Q4), and online communication (Q5). Overall, the graph and the regression estimates converge on the same conclusion: within the Kosovo subsample, trust-related factors and FL are more strongly associated with PFI than the combined DM index.

•Analysis for Albania

A similar but not identical pattern was observed in Albania (Table 17). DM was not statistically significant (B = -0.062, SE = 0.164, $\beta = -0.060$, t = -0.381, p = 0.705, 95% CI [-0.393, 0.268], VIF = 1.763). BTF, however, were positive and statistically significant (B = 0.557, SE = 0.176, $\beta = 0.508$, t =

3.159, $p = 0.003$, 95% CI [0.202, 0.912], VIF = 1.832). FL also showed a positive coefficient, but its effect did not reach statistical significance ($B = 0.189$, $SE = 0.128$, $\beta = 0.222$, $t = 1.476$, $p = 0.147$, 95% CI [-0.069, 0.446], VIF = 1.601). Accordingly, BTF were the only focal predictor that reached the conventional 0.05 significance level in the Albanian subsample.

The coefficient profile (Figure 15) shows that BTF have the strongest positive association with PFI ($B = 0.557$, 95% CI [0.202, 0.912], $p = 0.003$). The graph confirms this pattern because the CI remains entirely above zero. This index reflects transaction security and trust (Q6), attitudes toward innovation (Q8), trust relative to traditional banks (Q9), and social influence (Q10), suggesting that these trust-related dimensions are particularly important in the Albanian subsample.

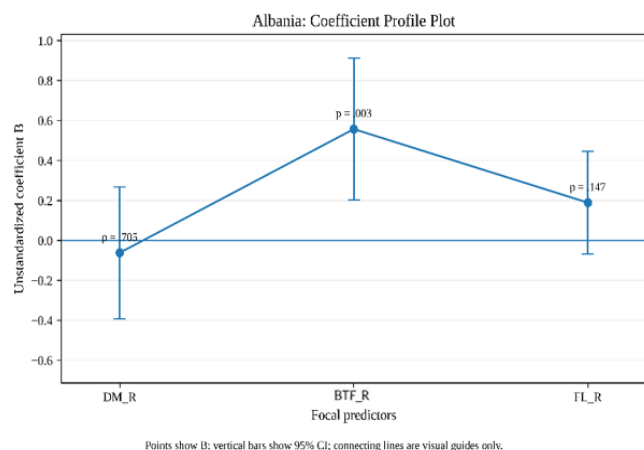


Figure 15. Country-specific coefficient profile of the focal predictors in Albania

FL also has a positive coefficient ($B = 0.189$), but its 95% CI [-0.069, 0.446] crosses zero and the effect is not statistically significant ($p = 0.147$). This index includes basic FL (Q11), digital-investment risk assessment (Q12), and financial education for informed decisions (Q13).

DM shows a small negative and non-significant coefficient ($B = -0.062$, 95% CI [-0.393, 0.268], $p = 0.705$). The index covers social-media advertising, information clarity and credibility, UI/UX satisfaction, online promotions, and online communication (Q1–Q5). Overall, the graph indicates that trust-related factors are the clearest correlate of PFI in Albania, while FL is positive but uncertain and DM remains statistically neutral.

•Analysis for North Macedonia

The results (Table 17) for North Macedonia were weaker, as none of the three focal predictors reached the 0.05 significance threshold. DM displayed a positive but non-significant association ($B = 0.360$, $SE = 0.199$, $\beta = 0.437$, $t = 1.812$, $p = 0.079$, 95% CI [-0.044, 0.764], VIF = 2.426). BTF were also non-significant and carried a negative coefficient ($B = -0.202$, $SE = 0.192$, $\beta = -0.257$, $t = -1.053$, $p = 0.300$, 95% CI [-0.593, 0.189], VIF = 2.493). FL was essentially null in this subsample ($B = -0.009$, $SE = 0.192$, $\beta = -0.010$, $t = -0.048$, $p = 0.962$, 95% CI [-0.399, 0.380], VIF = 1.911). These findings indicate that none of the three focal predictors provided statistically significant explanatory power at the 0.05 level within the North Macedonian subsample.

•Analysis for North Macedonia

The coefficient profile (Figure 16) indicates that none of the

three focal predictors reaches statistical significance at the 0.05 level. DM shows the largest positive coefficient ($B = 0.360$, 95% CI [-0.044, 0.764], $p = 0.079$), but its CI crosses zero, so the observed positive pattern remains statistically uncertain. This index includes social-media advertising, information clarity and credibility, UI/UX satisfaction, online promotions, and online communication (Q1–Q5). BTF show a negative but non-significant association ($B = -0.202$, 95% CI [-0.593, 0.189], $p = 0.300$). This composite reflects transaction security and trust (Q6), attitudes toward innovation (Q8), trust relative to traditional banks (Q9), and social influence (Q10). FL is essentially neutral ($B = -0.009$, 95% CI [-0.399, 0.380], $p = 0.962$) and comprises basic FL, digital-investment risk assessment, and financial education supporting informed decisions (Q11–Q13).

Overall, the graph shows wide CI and no statistically reliable focal predictor in North Macedonia, indicating greater uncertainty in this smaller subsample.

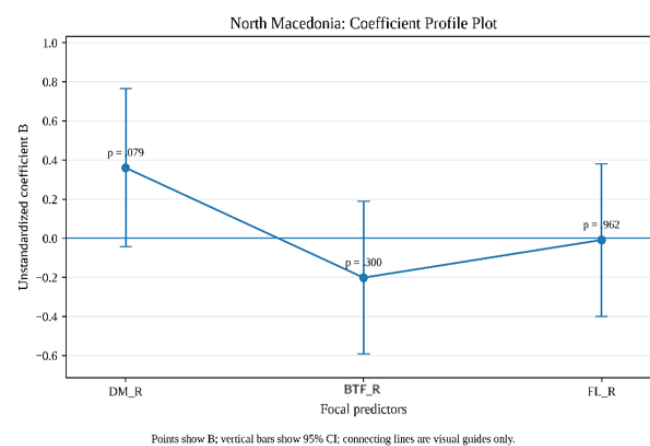


Figure 16. Country-specific coefficient profile of the focal predictors in North Macedonia

Taken together, Kosovo, Albania and North Macedonia, the country-specific pattern shows that BTF are statistically significant in both Kosovo and Albania, whereas FL is statistically significant only in Kosovo. In contrast, the North Macedonia model does not yield any statistically significant focal predictor at the 0.05 level. These country-specific results should therefore be interpreted as descriptive within-country sensitivity evidence rather than as formal tests of whether regression coefficients differ statistically across countries.

4.6.1 Scope and limits of country-specific estimates

The country-specific analyses are supplementary sensitivity analyses rather than evidence of stable cross-country structural differences. The full sample is substantially unbalanced: Kosovo $n = 163$ (62.2%), Albania $n = 55$ (21.0%), and North Macedonia $n = 44$ (16.8%); the corresponding complete-case regression samples are $N = 156$, $N = 55$, and $N = 44$. The small North Macedonia subsample limits precision and makes strong multi-group conclusions inappropriate. None of the country-specific coefficients, hypothesis decisions, or model-fit statistics is presented as nationally representative evidence. In the pooled regression, Kosovo is the reference category for the Albania and North Macedonia country dummies; this is a coding convention for estimating adjusted contrasts and does not make Kosovo a population benchmark.

Measurement equivalence across countries was not established. The exploratory measurement assessment was

conducted on the pooled sample using PAF and internal-consistency reliability; no multi-group CFA was estimated, so configural, metric, and scalar invariance are not claimed. Differences in coefficient magnitude or statistical significance across country regressions therefore cannot be interpreted as statistically demonstrated differences in the underlying relationships. The focal predictors show acceptable VIF values in all three models (1.466-2.493), whereas some demographic dummy controls have elevated VIFs in the smaller Albania and North Macedonia subsamples, further limiting subgroup precision.

Accordingly, the country-specific regressions provide reproducible within-country estimates under one common specification but do not constitute formal tests of equality of regression coefficients across countries. The pooled hierarchical OLS model remains the primary basis for inference, and subgroup estimates are used only to assess descriptive heterogeneity and sensitivity of the pooled pattern.

The supplementary country-specific regressions provide descriptive within-country evidence under a common specification. Kosovo shows significant positive BTF and FL associations; Albania shows a significant positive BTF association; and North Macedonia has no statistically significant focal predictor in the fully adjusted country model. Differences in coefficient magnitude or statistical significance are not interpreted as formal evidence that the underlying relationships differ across countries.

4.7 Summary of hypothesis testing and country-specific evidence

This section summarizes the overall hypothesis-testing results and presents the country-specific evidence to highlight similarities and differences in the observed relationships across Kosovo, Albania, and North Macedonia.

Table 18 consolidates the formal hypothesis decisions and shows that conclusions are derived from the adjusted

hierarchical regression rather than from zero-order correlations. H1 is not supported because the DM coefficient, although positive, does not reach the 0.05 threshold in the fully specified model ($\beta = 0.127$, $p = 0.076$). H2 is supported: BTF show the strongest positive adjusted association with PFI ($\beta = 0.438$, $p < 0.001$). H3 is also supported, with FL retaining a positive and statistically significant association after adjustment for controls and the other explanatory variables ($\beta = 0.287$, $p < 0.001$). H4 is supported because the DM $\times$ FL interaction is positive and significant ($\beta = 0.266$, $p = 0.004$), indicating that the DM association becomes stronger at higher levels of FL. H5 is not supported because the three-way interaction is not statistically significant ($\beta = -0.176$, $p = 0.083$). Robust covariance estimation leaves all five support decisions unchanged.

Table 19 shows that the country-specific evidence is heterogeneous and should be interpreted as descriptive within-country sensitivity evidence rather than as formal cross-country hypothesis testing. In Kosovo, H1 is not supported because DM is essentially null ($\beta = 0.004$, $p = 0.963$), whereas H2 and H3 are supported: BTF ($\beta = 0.523$, $p < 0.001$) and FL ($\beta = 0.192$, $p = 0.012$) are both positively associated with PFI. In Albania, H1 is also not supported ($\beta = -0.060$, $p = 0.705$), while H2 is supported through a strong positive BTF association ($\beta = 0.508$, $p = 0.003$). H3 is not supported in Albania because the FL coefficient is positive but non-significant ($\beta = 0.222$, $p = 0.147$). In North Macedonia, none of H1-H3 is supported at the 0.05 level. DM is positive but non-significant ($\beta = 0.437$, $p = 0.079$), while BTF and FL are also non-significant. This pattern indicates that the pooled findings are not reproduced uniformly in every national subsample. However, the smaller subgroup sizes, particularly for North Macedonia, and the absence of established measurement invariance mean that differences in significance cannot be interpreted as proof that the underlying associations differ statistically across countries.

Table 18. Summary of hypothesis testing results

H	Tested Relationship	β (p)	Decision
H1	DM $\rightarrow$ PFI	0.127 (0.076)	Not Supported
H2	BTF $\rightarrow$ PFI	0.438 (< 0.001)	Supported
H3	FL $\rightarrow$ PFI	0.287 (< 0.001)	Supported
H4	DM $\times$ FL	0.266 (0.004)	Supported
H5	DM $\times$ BTF $\times$ FL	-0.176 (0.083)	Not Supported

Note: Decisions are based on the fully specified four-block hierarchical OLS model. H4 is evaluated through the DM $\times$ FL interaction and H5 through the three-way interaction. Heteroskedasticity-robust covariance estimation produced the same decisions (robust p-values: H1 = 0.056; H2 < 0.001; H3 < 0.001; H4 = 0.002; H5 = 0.125).

Table 19. Country-specific evidence for H1–H3

Country	H1: DM	H2: BTF	H3: FL
Kosovo N = 156	$\beta = 0.004$ $p = 0.963$ Not Supported	$\beta = 0.523$ $p < 0.001$ Supported	$\beta = 0.192$ $p = 0.012$ Supported
Albania N = 55	$\beta = -0.060$ $p = 0.705$ Not Supported	$\beta = 0.508$ $p = 0.003$ Supported	$\beta = 0.222$ $p = 0.147$ Not Supported
North Macedonia N = 44	$\beta = 0.437$ $p = 0.079$ Not Supported	$\beta = -0.257$ $p = 0.300$ Not Supported	$\beta = -0.010$ $p = 0.962$ Not Supported

Note: These regressions are supplementary within-country sensitivity analyses. “Supported” denotes a positive coefficient significant at $p < 0.05$ within that country model. H4 and H5 were not estimated separately by country because the country-specific specifications did not include interaction terms. The table is not a formal test of cross-country coefficient differences.

The three countries are also examined through separate regressions, in which each national subsample is estimated independently and no country serves as a reference category. By contrast, in the pooled hierarchical model, Kosovo is the reference category for the country control because Albania_D and NMacedonia_D are entered as dummy variables while Kosovo is omitted. Consequently, the two country-dummy coefficients compare Albania and North Macedonia with Kosovo on the conditional outcome level, holding the remaining model terms constant. This coding does not test whether the slopes of DM, BTF, or FL differ between countries; such comparisons would require explicit country-by-predictor interaction terms.

Taken together, the two summaries provide a transparent bridge from formal hypothesis testing to the subsequent discussion. The pooled hierarchical model remains the primary basis for inference because it uses the largest common analytical sample and evaluates the focal predictors, controls, and interactions within one coherent specification. The country-specific models add useful sensitivity information by showing where similar or different within-country patterns appear, but they are not treated as evidence of statistically established national differences. This distinction preserves the strength of the supported findings while avoiding overinterpretation of subgroup results. The discussion that follows therefore emphasizes the pooled hypothesis decisions and uses country-level estimates only as supplementary contextual evidence.

5. DISCUSSION OF RESULTS

The pooled hierarchical results show that PFI is most strongly associated with BTF and FL. DM has a positive but non-significant direct coefficient in the fully adjusted model, while its interaction with FL is positive and significant. The dependent variable is the six-item PFI observed composite.

The strongest adjusted association is observed for BTF. This supports the argument that trust, perceived security, risk perception, attitudes toward innovation, preference for FinTech, and social influence are closely associated with how users experience digital financial services. This finding is strongly supported by Behavioral Finance theory. Kahneman and Tversky [33] and Thaler [34] argued that financial decisions are not purely rational, but are influenced by risk perception, confidence, attitudes, and behavioral evaluation. In the same direction, Jafri et al. [35] and Zhang et al. [36] emphasized that trust, data security, perceived usefulness, and perceived ease of use are important predictors of FinTech adoption in banking. Therefore, these studies largely support the results of the present study, because they confirm the importance of behavioral and trust-related factors. However, the present findings extend this literature by showing that BTF are also associated with the broader PFI on use-related benefits and financial-management outcomes.

FL also has a positive and statistically significant adjusted association with PFI. This result is strongly supported by Lusardi and Mitchell [9], who described FL as a form of human capital that improves financial decision-making. It is also consistent with Amnas et al. [37] and Ferilli et al. [38], who showed that digital FL is important for financial inclusion and for users' ability to benefit from FinTech services. These studies support the finding that users with stronger FL and better ability to assess financial risk are more likely to benefit

from digital financial services. The contribution of the present study is that it confirms this relationship in the Western Balkan context, where digital banking services are expanding but users may still differ in their ability to evaluate digital financial information, risks, and benefits.

DM has a positive but weaker direct coefficient than BTF and FL, and it does not reach the 0.05 significance threshold in the final hierarchical model ($\beta = 0.127$, $p = 0.076$). This suggests that digital exposure is better interpreted in conjunction with the other predictors and interaction structure rather than as an independently established direct association in the fully adjusted model.

The positive and significant interaction between FL and DM is one of the most important findings of this study. It indicates that the positive association between DM and PFI becomes stronger at higher levels of FL. This finding is supported by Amnas et al. [37] and Ferilli et al. [38], who emphasized that digital FL helps users understand, evaluate, and benefit from digital financial services. Therefore, the present study supports recent literature but adds a more specific contribution: DM should not be treated only as a direct promotional factor, but also as a conditional relationship whose magnitude varies with users' financial capability. The three-way interaction among DM, BTF, and FL is negative but not statistically significant ($\beta = -0.176$, $p = 0.083$). It is therefore not interpreted as evidence of information overload, selectivity, saturation, or diminishing returns. The supported two-way DM $\times$ FL interaction is probed with simple slopes and a Johnson-Neyman region-of-significance analysis. Holding BTF at its standardized mean, the positive DM association becomes statistically significant when standardized FL is approximately 0.07 SD above its sample mean; a second mathematical boundary occurs at approximately -2.28 SD and is treated as an extreme lower-tail result rather than the principal substantive finding.

The pooled findings can also be situated within regional evidence from the Balkan context. Miftari et al. [39] showed that FinTech is relevant for improving financial inclusion in Balkan countries. Similarly, Miftari et al. [40] emphasized the roles of institutional quality, digital infrastructure, data security, consumer protection, and FL in strengthening trust in digital financial services and supporting sustainable development. The present pooled evidence likewise highlights trust-related factors and FL in relation to PFI. Because measurement invariance was not established and the national subsamples are unequal, these regional parallels are interpreted at the pooled study level rather than as evidence of country-specific structural differences. Institutional quality, digital infrastructure, data security, and consumer protection are cited here as contextual findings from prior literature; they were not measured in the present empirical model and are not used to justify country-specific recommendations.

Recent studies provide broader contextual evidence on FinTech outcomes. He et al. [41] reported associations between FinTech development and bank performance, while Khalil [42] examined FinTech and financial performance in Egyptian banks. Rohaeni et al. [43] linked FL, FinTech, and inclusion to MSME growth, and Salem et al. [44] examined FinTech adoption in relation to bank financial performance. In the regional context, Shima and Tomorri [45] studied FinTech adoption and financial performance in Albanian agribusiness enterprises, while Iseni [46] discussed FinTech-enabled lending and alternative-data credit scoring for SMEs in North Macedonia. These studies concern outcomes and settings that

differ from the present user-level PFI measure; they are used as contextual literature rather than as direct validation of the present coefficients. This broader perspective suggests that FinTech outcomes are shaped not only by trust and FL, but also by the wider institutional, financial, and policy environment [47].

Overall, the pooled results are consistent with literature emphasizing trust-related factors and FL, while the direct DM coefficient is weaker and not significant in the fully adjusted model. The significant DM $\times$ FL interaction indicates that the association between DM and PFI varies with FL. The user-status sensitivity analysis shows that the substantive pattern is preserved after excluding respondents without recorded FinTech use: BTF, FL, and the DM $\times$ FL interaction remain significant, while DM and the three-way interaction remain non-significant.

The diagnostic sensitivity analysis strengthens this interpretation: although heteroskedasticity was detected, sandwich-robust covariance estimation produced the same hypothesis decisions as the conventional OLS output. BTF, FL, and the DM $\times$ FL interaction remained significant, while the direct DM term and the three-way interaction remained non-significant at the 0.05 level.

The inferential pattern therefore emphasizes the significant positive BTF and FL coefficients and the positive DM $\times$ FL interaction. The three-way interaction is not statistically significant in the fully specified hierarchical model ($p = 0.083$) and is not interpreted substantively.

The results extend previous literature by showing that PFI is associated with both direct and lower-order conditional relationships. BTF and FL remain significant, whereas the direct role of DM is weaker and the three-way interaction is not statistically supported.

Potential common-method variance, temporal ordering, and persistence are important limitations of the present design. All focal measures were obtained from the same respondents in one cross-sectional questionnaire, so the data provide a single-time-point assessment and cannot determine whether FinTech use, perceived benefits, or the observed associations persist, weaken, or strengthen over time. The study did not measure continuance intention, repeated-use frequency, retention, or responsible-use behavior as longitudinal outcomes. The forced one-factor PAF accounted for 34.759% of extracted variance and therefore did not reveal a dominant single general factor; however, this diagnostic cannot exclude source-related bias or establish temporal precedence. Accordingly, the reported coefficients describe contemporaneous adjusted and conditional associations within this sample and are not interpreted as evidence of causality, persistence, or sustained adoption.

6. CONCLUSIONS

Within the cross-sectional sample from Kosovo, Albania, and North Macedonia, PFI is associated with respondents' BTF, FL, and the conditional relationship between DM and FL. The dependent measure is an observed composite of use-related benefits, perceived financial-management outcomes, and recommendation/advocacy. These findings describe contemporaneous perceived associations at one point in time; they do not establish causal effects, persistence of use, retention, or long-term/sustainable adoption.

The final hierarchical model indicates that BTF have the

strongest positive standardized association with PFI ($\beta = 0.438$, $p < 0.001$), followed by FL ($\beta = 0.287$, $p < 0.001$). DM is positive but not independently significant at 0.05 ($\beta = 0.127$, $p = 0.076$). The significant DM $\times$ FL interaction ($\beta = 0.266$, $p = 0.004$) shows that the association involving DM varies with FL.

Because the residual-variance diagnostic indicated heteroskedasticity, inference was also checked with robust sandwich standard errors. This sensitivity analysis did not change the hypothesis conclusions: DM remained non-significant ($p = 0.056$), BTF and FL remained significant (both $p < 0.001$), DM $\times$ FL remained significant ($p = 0.002$), and the three-way term remained non-significant ($p = 0.125$).

A key conditional result is the positive DM $\times$ FL interaction. The three-way interaction is not statistically significant and is not used to support claims about overload, saturation, or diminishing returns. Simple-slope analysis shows that the DM association is non-significant at low FL ($B = -0.059$, $p = 0.456$) and at the mean ($B = 0.109$, $p = 0.076$), but positive and significant at high FL ($B = 0.277$, $p = 0.002$). Johnson-Neyman analysis further indicates that the positive conditional DM association with FL is approximately 0.07 SD above its sample mean, with BTF held at its standardized mean.

The country-specific regressions provide supplementary regional context only. BTF are significant in the Kosovo and Albania subsamples, FL is significant only in Kosovo, and the North Macedonia model is not statistically significant overall. These patterns are not interpreted as formal between-country differences because the national subsamples are unbalanced and measurement invariance was not established. The pooled hierarchical model remains the primary basis for inference, and country patterns describe within-sample associations rather than national population estimates.

Overall, the study extends TAM and UTAUT by integrating marketing, behavioral, and FL dimensions into a broader model of PFI. Future research should use longitudinal or panel designs to evaluate whether FinTech use and perceived benefits persist over time and should directly measure continuance intention, repeated-use frequency, retention, and responsible-use behavior. Such designs could distinguish short-term perceptions from sustained behavioral patterns and provide a stronger basis for evaluating persistence. Future studies should also expand the model by including institutional trust, regulatory awareness, and digital infrastructure. Survey designs should separate actual users from potential users at the screening stage and apply skip logic so that experience-dependent outcome items are administered only to respondents with relevant FinTech use. Longitudinal, temporally separated, or multi-source measurement would additionally reduce common-method concerns and strengthen causal and temporal inference. These additional constructs were not measured in the present model and are proposed strictly as future research directions rather than as evidence-based policy recommendations.

6.1 Recommendations

To distinguish evidence-based implications from broader policy proposals, the recommendations in this section are limited to constructs represented in the empirical model: DM, BTF, FL, and PFI. Based on the observed associations, practical implications for FinTech in Kosovo, Albania, and North Macedonia are limited to the measured user-level dimensions. Higher PFI was observed alongside stronger BTF

and FL, while the DM association varied with FL. These findings provide the empirical basis for the recommendations directed at FinTech providers, banks, public institutions, educational organizations, and users.

For banks and FinTech providers, the main implication is to combine DM with financial education and trust-building communication. Promotional campaigns should not only advertise services but also communicate potential user benefits such as time savings, expense monitoring, financial-management support, and reduced uncertainty. Mobile banking and FinTech applications can provide clear educational messages, transparent security information, and user-friendly design that supports informed decision-making.

For public institutions, regulators, and educational organizations, the empirical evidence most directly supports financial-literacy initiatives and clear communication that helps users understand digital financial services, evaluate perceived security, and make informed financial decisions.

For users, FinTech should be viewed not only as a convenient digital tool, but as part of responsible financial management. Users should understand how digital services work, compare information carefully, and use FinTech platforms for budgeting, expense monitoring, and financial planning.

Building directly on these evidence-based implications, several practical actions can be recommended. Banks and FinTech providers can integrate short financial-literacy explanations directly into mobile applications, online banking platforms, and digital campaigns, particularly when introducing new services or features. Promotional messages can be accompanied by concise explanations of service benefits, transaction procedures, perceived-security features, fees where relevant, and the ways in which digital tools can support budgeting and financial management. Providers can also offer short in-app tutorials, frequently asked questions, practical examples, and step-by-step guidance to help users understand digital financial products before making decisions.

Trust-related communication can be strengthened through transparent explanations of security procedures, authentication processes, transaction confirmation, and available customer-support channels. In addition, financial-literacy initiatives can include practical guidance on comparing digital financial products, monitoring expenses, evaluating financial information, and incorporating FinTech tools into regular budgeting and financial planning. Banks and FinTech providers can periodically assess users' perceptions of trust, financial understanding, digital communication, and perceived FinTech benefits in order to identify areas where user education and communication require improvement. These actions remain focused on the constructs measured in the present study and should not be interpreted as evidence of effects arising from unmeasured institutional or regulatory conditions.

Country-specific recommendations are not derived from subgroup coefficient differences. The subgroup regressions are exploratory and do not establish that different strategies are required in Kosovo, Albania, and North Macedonia. Evidence-based implications are restricted to the measured dimensions: FL, trust-related and perceived-security factors, DM/communication, and PFI. Institutional trust, regulatory quality, digital infrastructure, consumer-protection systems, and other macro-level conditions are reserved for future research rather than presented as findings of the current model. Future country-comparative research should use larger and

more balanced national samples and formally assess measurement invariance before testing differences in regression coefficients.

Overall, the findings support a user-centered FinTech environment in which digital financial services are understandable, trustworthy, and practically useful for users' financial well-being. Because sustainability and temporal persistence were not directly operationalized, these implications concern current PFI and should not be interpreted as evidence of sustainable, persistent, or long-term adoption. Such claims require direct longitudinal measures of continuance, repeated use, retention, and responsible FinTech behavior.

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APPENDIX

Appendix A. List of abbreviations

Abbreviation	Meaning / Definition
FinTech	Financial Technology
DM	Digital Marketing
BTF	Behavioral and Trust Factors
FL	Financial Literacy
PFI	Perceived FinTech Impact
TAM	Technology Acceptance Model
TAM3	Technology Acceptance Model 3
UTAUT	Unified Theory of Acceptance and Use of Technology
OLS	Ordinary Least Squares
SPSS	Statistical Package for the Social Sciences
UI	User Interface
UX	User Experience
VIF	Variance Inflation Factor
ANOVA	Analysis of Variance
SD	Standard Deviation
SE	Standard Error
CI	Confidence Interval
N	Sample Size / Number of Observations
R ²	Coefficient of Determination
Adj. R ²	Adjusted Coefficient of Determination
β	Regression Coefficient
p	Probability Value (p-value)
COVID-19	Coronavirus Disease 2019
ALB	Albania
XXK	Kosovo
MKD	North Macedonia
DM × FL	Interaction between Digital Marketing and Financial Literacy
DM × BTF × FL	Three-way interaction between Digital Marketing, Behavioral and Trust Factors, and Financial Literacy

Appendix B. Consumer FinTech questionnaire

Section A – Demographic and general information: Please tick (✓) one answer unless otherwise indicated

A1. Country of Residence	☐ Kosovo ☐ Albania ☐ North Macedonia
A2. Age	☐ Under 20 ☐ 21–30 ☐ 31–40 ☐ 41–50 ☐ 51 or above
A3. Gender	☐ Male ☐ Female ☐ Other ☐ Prefer not to answer
A4. Highest level of education completed	☐ Secondary/High school ☐ Bachelor's ☐ Master's ☐ Doctoral ☐ Other
A5. Employment status	☐ Employed ☐ Self-employed ☐ Student ☐ Unemployed ☐ Retired ☐ Other
A6. Approximate monthly personal income	☐ < €300 ☐ €300–€700 ☐ €700–€1,000 ☐ ≥ €1,000 ☐ Prefer not to answer
A7. Do you currently use any FinTech or digital financial services (e.g., mobile/online banking, digital wallets, digital payments, money-transfer applications)?	☐ Yes ☐ No

Section B – Response scale

For each statement below, please indicate the extent to which you agree or disagree by circling one number

1	2	3	4	5
Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree

Section C – Digital marketing

Please indicate your level of agreement with the following statements concerning the digital marketing activities of FinTech providers

Code	Statement	1	2	3	4	5
DM1	Social media advertising increases my interest in using FinTech services.	☐	☐	☐	☐	☐
DM2	Information communicated through the digital channels of FinTech providers is clear and useful.	☐	☐	☐	☐	☐
DM3	The professional presentation and design of FinTech providers' digital channels positively influence my perception of their services.	☐	☐	☐	☐	☐
DM4	Online promotions, incentives, or special offers encourage me to use FinTech services.	☐	☐	☐	☐	☐
DM5	Online communication by FinTech providers increases my confidence in their services.	☐	☐	☐	☐	☐

Section D – Behavioral and trust factors

Please indicate your level of agreement with the following statements concerning trust, perceived security, and attitudes toward FinTech

Code	Statement	1	2	3	4	5
BTF1	I trust FinTech platforms to provide secure financial transactions.	☐	☐	☐	☐	☐
BTF2	I am concerned about the possible loss or misuse of my personal or financial data when using FinTech services.	☐	☐	☐	☐	☐
BTF3	I consider FinTech an important innovation for managing modern financial activities.	☐	☐	☐	☐	☐
BTF4	I feel confident using FinTech services for routine financial transactions.	☐	☐	☐	☐	☐
BTF5	Recommendations or experiences shared by family members, friends, or other people influence my willingness to use FinTech services.	☐	☐	☐	☐	☐

Appendix C. Descriptive statistics of the study variables

Statement	N	Mini mum	Maxi mum	Mean	Std. Deviation
Social media advertisements influence my decision to use FinTech applications.	262	1	5	3.24	1.242
The information provided by FinTech platforms is clear and reliable.	262	1	5	3.60	1.048
The interface and design of the application (UI/UX) influence my satisfaction with using it.	262	1	5	3.56	1.152
Online promotions (cashback, offers) motivate me to use FinTech more frequently.	262	1	5	3.53	1.167
The online communication of FinTech companies increases my positive perception of them.	262	1	5	3.56	1.152
I trust FinTech platforms to be secure for conducting financial transactions.	262	1	5	3.78	1.102
I am concerned about the risk of losing data or funds when using FinTech services.	262	1	5	2.67	1.235
I consider FinTech a necessary innovation for modern financial management.	262	1	5	3.78	1.066
I have greater trust in financial technology than in traditional banks.	262	1	5	3.49	1.203
I use FinTech because my friends or family members also use it.	262	1	5	3.49	1.280
I have sufficient knowledge to understand basic financial concepts.	262	1	5	3.87	1.029
I feel capable of assessing the financial risk of digital investments.	262	1	5	3.71	1.141
Financial education helps me make careful decisions regarding the use of FinTech.	262	1	5	3.84	1.089
I have participated in training or read materials on personal financial management.	262	1	5	3.45	1.291
Using FinTech has helped me save time and manage my finances better.	262	1	5	3.92	1.038
I have improved the efficiency of my transactions through FinTech applications.	262	1	5	3.86	1.079
I have increased my use of digital financial services over the past year.	262	1	5	3.75	1.126
Using FinTech has helped me monitor my monthly expenses more effectively.	262	1	5	3.85	1.071
FinTech has had a positive impact on my personal financial management.	262	1	5	3.86	1.046
I would recommend the use of FinTech to others because of its benefits.	262	1	5	3.85	1.101
Valid N (listwise)	262				