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Exploring the Adoption of Financial Technology (FinTech) by Banking and Insurance Companies Customers in Ghana Using an Extended UTAUT2 Model

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Abstract

The rapid growth of financial technology (FinTech) has transformed the delivery of financial services globally, yet customer adoption remains uneven, particularly within developing economies. This study investigates the adoption of FinTech by banking and insurance company customers in Ghana using an extended Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model. A quantitative research approach was employed, adopting a descriptive cross-sectional survey design. Data were collected from 409 active FinTech users through a structured questionnaire administered using both online and face-to-face methods. Partial Least Squares Structural Equation Modelling (PLS-SEM) was utilised to analyse the data. The findings reveal that behavioural intention significantly predicts actual FinTech use behaviour. Effort expectancy, facilitating conditions, and hedonic motivation positively and significantly influence behavioural intention, while habit, perceived trust, and social influence exhibit significant negative effects. Performance expectancy and personal innovativeness show positive but statistically insignificant relationships with behavioural intention; however, personal innovativeness directly and significantly predicts use behaviour. Ethical perceptions strongly predict perceived trust, which in turn significantly influences both behavioural intention and actual use. The model explains a substantial proportion of variance in behavioural intention and use behaviour, demonstrating strong predictive relevance. The study contributes to the FinTech literature by extending the UTAUT2 model to include ethics and trust within the Ghanaian banking and insurance context. Practically, the findings provide insights for financial institutions and policymakers to design user-centred, trustworthy, and ethically grounded FinTech solutions that enhance customer adoption and sustained usage.

Introduction

The Fourth Industrial Revolution has intensified the demand for digital transformation across industries, with financial institutions experiencing some of the most profound changes. The convergence of intelligent automation, data-driven decision-making, and interconnected digital platforms has fundamentally altered how financial services are designed, delivered, and consumed. In the digital era, financial institutions increasingly rely on technology-enabled business models to enhance efficiency, expand service reach, and improve customer experience (Jünger & Mietzner, 2020). As a result, technology has become deeply embedded in all aspects of financial service provision, reshaping traditional banking and insurance operations (Bureshaid et al., 2021).

Within this evolving landscape, Financial Technology (FinTech) has emerged as a transformative force that integrates financial services with advanced information technologies. FinTech encompasses a wide range of technology-driven innovations, including mobile payments, digital banking, peer-to-peer transfers, and data-driven financial services, aimed at improving accessibility, convenience, and system efficiency (Hwang et al., 2021; Roh et al., 2021). Although FinTech remains in a relatively early stage of development, scholars and practitioners increasingly view it as a defining element of the future financial ecosystem. Its rapid diffusion has been supported by the widespread use of mobile technologies and cloud-based platforms, enabling customers to manage financial activities seamlessly across time and space.

Globally, investment in FinTech has expanded significantly, reflecting growing confidence in its disruptive potential. According to Statista (2021), global investment in FinTech firms rose dramatically from USD 9 billion to over USD 210 billion by 2021. Similarly, global awareness and usage of FinTech services have increased substantially, with EY Global (2021) reporting that 96% of individuals are familiar with at least one FinTech service and nearly two-thirds actively use such services. These trends underscore the mainstream acceptance of FinTech and its growing relevance across both developed and emerging economies.

The banking and insurance sectors have been particularly affected by FinTech-driven innovations. FinTech solutions have enabled financial institutions to improve operational efficiency, reduce transaction costs, and deliver personalized services that enhance customer satisfaction (Giglio, 2021; Hu et al., 2019). In emerging markets, digital banking adoption has accelerated rapidly, reaching levels comparable to those of developed economies (Ahmed & Sur, 2023). The integration of technologies such as artificial intelligence, big data analytics, blockchain, and mobile internet has further expanded the scope and functionality of FinTech services, challenging traditional financial service models and intensifying competition (Chikri & Kassou, 2024).

In Sub-Saharan Africa, FinTech has become a key driver of financial inclusion and economic participation. Ghana, in particular, has emerged as one of Africa's fastest-growing digital markets, alongside countries such as Nigeria, Kenya, and South Africa (Ayakwah et al., 2021; Geiger et al., 2019). FinTech firms and digital platforms have increasingly complemented and in some cases disrupted traditional banking and insurance services by offering customer-centric, technology-enabled financial solutions (Nelaturu et al., 2022). Despite these developments, the success of FinTech initiatives ultimately depends on customers' willingness to adopt and continuously use these technologies.

The COVID-19 pandemic further accelerated FinTech adoption by reinforcing the need for contactless, remote, and efficient financial services (Slawinski, 2021). While a growing body of research has examined FinTech adoption across different contexts, much of the existing literature focuses on developed economies or specific sectors such as banking, with limited attention to insurance services and emerging economies such as Ghana. Moreover, empirical studies rarely integrate ethical considerations, trust mechanisms, and behavioural continuance factors within a single explanatory framework. Against this backdrop, the present study investigates the adoption of FinTech by banking and insurance customers in Ghana by extending the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) to incorporate perceived ethics, trust, personal innovativeness, and use behaviour.

Empirical studies on FinTech adoption consistently demonstrate that behavioural intention is influenced by a combination of technological, social, and psychological factors, although findings vary across contexts and sectors. Research grounded in UTAUT, UTAUT2, and TAM has identified performance expectancy, effort expectancy, facilitating conditions, social influence, hedonic motivation, habit, and trust as significant predictors of FinTech adoption in emerging and developed economies (Bommer et al., 2023; Hassan et al., 2022; Mulyana et al., 2020; Sultana et al., 2023). Extensions of these models have further highlighted the roles of personal innovativeness, perceived risk, perceived security, and ethical

considerations in shaping adoption intentions and usage behaviour (Almashhadani et al., 2023; Chawla et al., 2023; Zhang et al., 2023).

However, empirical evidence remains fragmented, with inconsistent effects reported for core constructs such as social influence, performance expectancy, and perceived risk across different cultural and institutional settings (Hoang et al., 2021; Tang et al., 2020). Notably, most prior studies focus on single financial sectors, predominantly banking, while overlooking insurance services and the joint behaviour of banking and insurance customers. Furthermore, limited research integrates perceived ethics and trust as antecedents linking technological perceptions to actual use behaviour, particularly in Sub-Saharan African contexts. Consequently, there is a clear gap in the literature for a comprehensive, context-specific model that extends UTAUT2 by incorporating ethical perceptions, trust, personal innovativeness, and actual usage behaviour to explain FinTech adoption among banking and insurance customers in Ghana. Table 1 shows a summary of empirical studies and identified research gaps addressed by the current study.

Table 1
Summary of Empirical Studies on FinTech Adoption and Identified Research Gaps Addressed by the Current Study

Empirical Focus in Prior Studies	Key Evidence from Literature	Identified Limitation / Gap	How the Current Study Addresses the Gap
Core UTAUT / TAM constructs	Performance expectancy, effort expectancy, facilitating conditions widely examined (Mulyana et al., 2020; Sultana et al., 2023)	Inconsistent findings across sectors and contexts	Re-tests core UTAUT2 paths within Ghana's banking and insurance context
Sectoral focus	Predominantly banking or Islamic finance (Hassan et al., 2023; Hoang et al., 2021)	Insurance customers largely underrepresented	Integrates **banking and insurance customers** in a single model
Behavioural intention focus	Majority stop at BI as outcome (Bommer et al., 2023)	Limited explanation of actual use behaviour	Examines **BI → USE** and **PI → USE**, strengthening behavioural realism
Trust as mediator	Trust mediates risk–intention link (Al Nawayseh, 2020; Ali et al., 2021)	Trust often treated in isolation from ethics	Models **Perceived Ethics → Trust → BI / USE**
Perceived risk emphasis	Risk effects mixed and context-dependent (Tang et al., 2020; Zhang et al., 2023)	Overemphasis on risk, neglect of ethical perceptions	Shifts focus from risk dominance to **ethical trust-building mechanisms**
Personal innovativeness	Found significant in some contexts (Almashhadani et al., 2023)	Rarely linked to actual use behaviour	Tests **PI → BI** and **PI → USE** simultaneously
Social influence	Significant in emerging markets, insignificant elsewhere	Contextual inconsistency not well explained	Re-examines SI within **Ghana's collectivist-social environment**
Hedonic motivation & habit	Strong predictors in meta-analyses (Bommer et al., 2023)	Underexplored in African contexts	Includes **HM → BI** and **HT → BI** in Ghana
Ethical considerations	Rarely included in adoption models	Ethical perceptions overlooked in FinTech research	Introduces **Perceived Ethics (ET)** as a novel antecedent
Geographic coverage	Dominated by Asia & Middle East	Limited Sub-Saharan African evidence	Provides **context-specific empirical evidence from Ghana**
User groups	Students, Islamic bank users, tech-savvy consumers	General customers underrepresented	Focuses on **actual banking and insurance customers**

Theoretical Foundation and Hypotheses Development

This study is grounded in the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), an extension of the original UTAUT model developed by Venkatesh et al. (2003) and later refined to explain consumer technology adoption behaviour (Venkatesh et al., 2012). UTAUT2 synthesises constructs from foundational theories such as the Technology Acceptance Model (TAM) and the Theory of Reasoned Action (TRA), providing a comprehensive socio-psychological framework for explaining behavioural intention and technology use. UTAUT2 posits that performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit jointly influence behavioural intention and use behaviour. The model has been extensively validated across multiple technology contexts, including digital finance, mobile banking, and electronic payments (Chauhan & Jaiswal, 2016; Dowdy, 2020; Khalilzadeh et al., 2017). Its predictive robustness and adaptability make it particularly suitable for investigating FinTech adoption in emerging economies.

However, despite its strengths, UTAUT2 has been criticised for insufficiently accounting for trust-based and ethical considerations, which are particularly salient in financial technologies where perceived risk, data privacy, and transparency concerns remain prominent (Bagozzi, 2007; Raihan & Rachmawati, 2019). In response, this study extends UTAUT2 by incorporating perceived ethics, perceived trust, and personal innovativeness, thereby enhancing the model's explanatory power within the Ghanaian FinTech context.

Hypotheses Development

Use Behaviour (Actual Use of FinTech Services)

Use behaviour, also referred to as actual usage, represents the extent to which individuals translate their intentions into concrete actions through the sustained utilisation of FinTech services. Within technology adoption research, actual use is regarded as the ultimate behavioural outcome, reflecting not only acceptance but also the practical integration of technology into users' daily financial activities. Unlike behavioural intention, which captures users' motivational readiness, actual use provides empirical evidence of engagement with FinTech platforms in real-world settings.

Drawing from behavioural theories such as the Theory of Reasoned Action and the Unified Theory of Acceptance and Use of Technology, actual use behaviour is conceptualised as a direct consequence of behavioural intention (Sharma & Munjal, 2024; Venkatesh et al., 2003). This intention–behaviour linkage is critical in FinTech contexts, where favourable intentions do not always translate into sustained usage due to trust concerns, usability challenges, or ethical apprehensions. Examining actual use therefore enables a more comprehensive understanding of FinTech adoption beyond attitudinal dispositions.

Empirical evidence consistently supports a positive relationship between behavioural intention and actual use of FinTech services (Hassan et al., 2023; Senyo & Osabutey, 2020; Thusi & Maduku, 2020). These studies suggest that individuals who exhibit stronger intentions are more likely to engage in consistent FinTech usage. Consequently, this study incorporates actual use behaviour as a key endogenous construct, allowing for a more robust assessment of FinTech adoption among banking and insurance

customers in Ghana. Based on the foregoing theoretical and empirical evidence, it was therefore postulated that:

H1

“Behavioural intention has a positive and significant effect on actual use of FinTech services”.

Effort Expectancy and Behavioural Intention

Effort expectancy refers to the degree to which individuals perceive FinTech services as easy to use and free of complexity. When FinTech platforms are perceived as user-friendly, customers are more likely to develop favourable intentions towards adoption. Empirical studies consistently demonstrate that effort expectancy significantly influences behavioural intention, particularly in emerging economies where digital literacy varies widely (Mulyana et al., 2020; Sultana et al., 2023). Based on this reasoning, it was therefore formulated that:

H2

“Effort expectancy has a positive and significant effect on behavioural intention to use FinTech services”.

Performance Expectancy and Behavioural Intention

Performance expectancy reflects users’ beliefs regarding the extent to which FinTech services enhance efficiency, convenience, and financial management. In financial contexts, perceived usefulness remains a critical determinant of adoption, as users prioritise technologies that deliver tangible benefits. Several empirical studies report a positive association between performance expectancy and behavioural intention, although findings vary across sectors (Bommer et al., 2023; Mulyana et al., 2020; Parviz & Arthur, 2025). Accordingly, it was postulated that:

H3

“Performance expectancy has a positive and significant effect on behavioural intention to use FinTech services”.

Facilitating Conditions and Behavioural Intention

Facilitating conditions capture users’ perceptions of the availability of technical, organisational, and infrastructural support necessary for FinTech usage. Adequate internet connectivity, digital devices, and user support systems enhance customers’ confidence and readiness to adopt FinTech services. Prior studies have confirmed the importance of facilitating conditions in shaping adoption intentions (Acquah et al., 2024; Hassan et al., 2022; Sultana et al., 2023). Thus, it was formulated that:

H4

“Facilitating conditions have a positive and significant effect on behavioural intention to use FinTech services”.

Social Influence and Behavioural Intention

Social influence reflects the extent to which individuals perceive that “important others” believe they should use FinTech services (Hoque et al., 2024). Given the relatively novel nature of FinTech in many emerging economies, individuals often rely on social cues and peer experiences when forming adoption decisions (Chan et al., 2022; Firmansyah et al., 2022; Vardari & Hameli, 2025). Empirical findings provide mixed but context-dependent evidence regarding the role of social influence. Based on this perspective, it was proposed that:

H5

“Social influence has a positive and significant effect on behavioural intention to use FinTech services”.

Hedonic Motivation and Behavioural Intention

Hedonic motivation refers to the enjoyment or pleasure derived from using FinTech services (Amnas et al., 2023). Beyond functional benefits, enjoyable user experiences can strengthen emotional attachment and enhance adoption intentions. Meta-analytic evidence suggests that hedonic motivation is among the strongest predictors of FinTech usage intention (Bommer et al., 2023; Kashyap et al., 2026; Sharma et al., 2025). It was therefore postulated that:

H6

“Hedonic motivation has a positive and significant effect on behavioural intention to use FinTech services”.

Habit and Behavioural Intention

Habit represents the extent to which individuals perform behaviours automatically due to prior experience (Acquah et al., 2024). In digital finance, repeated exposure to FinTech platforms can lead to habitual usage patterns that reinforce adoption intentions. Empirical studies confirm habit as a significant predictor of behavioural intention in FinTech contexts (Bommer et al., 2023; Venkatesh et al., 2012). Accordingly, it was formulated that:

H7

“Habit has a positive and significant effect on behavioural intention to use FinTech services”.

Perceived Ethics and Perceived Trust

Perceived ethics refers to users' perceptions of fairness, transparency, and responsible conduct by FinTech service providers. Ethical practices play a critical role in trust formation, particularly in financial environments characterised by information asymmetry. Empirical studies highlight trust as a key mechanism through which ethical perceptions influence adoption decisions (Ali et al., 2021; Chawla et al., 2023). Based on this argument, it was postulated that:

H8

"Perceived ethics has a positive and significant effect on perceived trust in FinTech services".

Perceived Trust, Behavioural Intention, and Actual Use

Trust reflects users' confidence in the reliability, security, and integrity of FinTech services. Trust has been widely recognised as a central determinant of both intention and actual usage behaviour (Al Nawayseh, 2020; Hassan et al., 2022; Zhao et al., 2024). Users who trust FinTech platforms are more likely to intend to use them and translate these intentions into sustained usage. Thus, it was formulated that:

H9

"Perceived trust has a positive and significant effect on behavioural intention to use FinTech services".

H10

"Perceived trust has a positive and significant effect on actual use of FinTech services".

Personal Innovativeness, Behavioural Intention, and Actual Use

Personal innovativeness captures individuals' willingness to experiment with new technologies (Salifu et al., 2025). Highly innovative users are more inclined to adopt disruptive technologies such as FinTech earlier and more frequently (Almashhadani et al., 2023; Leong et al., 2020). Empirical evidence supports the direct influence of personal innovativeness on both intention and actual usage (Salifu et al., 2025). Accordingly, it was proposed that:

H11

"Personal innovativeness has a positive and significant effect on behavioural intention to use FinTech services".

H12

"Personal innovativeness has a positive and significant effect on actual use of FinTech services".

Conceptual Model

The conceptual model of the study based on the formulated hypotheses is displayed by Fig. 1.

Note

“BI = Behavioural Intention; EE = Effort Expectancy, ET = Perceived Ethics; FC = Facilitating Conditions; HM = Hedonic Motivation; HT = Habit; PE = Performance Expectancy; PI = Personal Innovativeness; PT = Perceived Trust; SI = Social Influence; and USE = Use behaviour”

Figure 1: Conceptual model

Source: Authors’ own work

Methodology

Research Design

The research design provides the methodological framework that guides how a study is systematically planned, executed, and analysed in order to address its stated objectives. In quantitative research, the choice of design is largely determined by the nature of the research problem, the theoretical orientation of the study, and the type of data required to test the proposed relationships among variables. Broadly, research designs may be classified as experimental or non-experimental. While experimental designs involve manipulation and control of variables to establish causality, non-experimental designs focus on observing existing phenomena without researcher intervention.

This study adopted a descriptive cross-sectional survey design to investigate the determinants of financial technology adoption among banking and insurance customers in Ghana. The choice of this design is consistent with the objective of capturing respondents’ perceptions, intentions, and usage behaviour at a single point in time, without manipulating any study variables (Abreh et al., 2025; Almashhadani et al., 2023). A cross-sectional approach is particularly appropriate for technology adoption studies, as it enables the examination of prevailing attitudes, behaviours, and relationships among constructs within a defined population (Hassan et al., 2023). Additionally, the cross-sectional survey approach supports the efficient collection of data from a large and diverse sample, thereby enhancing the external validity and generalisability of the findings (Hassan et al., 2022). Given the quantitative orientation of the study and the need to empirically test multiple hypotheses derived from the extended UTAUT2 framework, this design was deemed both methodologically appropriate and practically feasible.

Sample

The sample for this study consisted of customers of banking and insurance companies in Ghana who actively use financial technology (FinTech) services. The selection of this group was intentional, as the study sought to obtain insights from respondents with direct experience and sufficient familiarity with FinTech platforms used for banking and insurance transactions. Focusing on actual users ensured that responses reflected informed perceptions, behavioural intentions, and real usage behaviour rather than hypothetical adoption tendencies.

A purposive sampling approach was employed to identify respondents who met the inclusion criteria, namely individuals who had previously used or were currently using FinTech services offered by banking or insurance institutions. This approach is appropriate for FinTech adoption studies, as it allows researchers to target participants with relevant knowledge and practical exposure to digital financial services (Almashhadani et al., 2023; Sultana et al., 2023). Given the dispersed nature of FinTech users across Ghana, purposive sampling enabled efficient access to respondents most capable of providing meaningful and reliable data aligned with the objectives of the study. The minimum sample size was determined using G*Power software, which indicated a requirement of 172 respondents based on a model with a maximum of 10 predictors, an effect size of 0.15, a significance level of 0.05, and a statistical power of 0.95. To strengthen the robustness of the analysis and improve the generalisability of the findings, the study exceeded this minimum threshold by targeting a larger sample. Out of the 500 questionnaires administered, 409 were successfully retrieved, representing a response rate of 81.8%, which is considered adequate for quantitative survey research. This high return rate enhanced the reliability of the data and provided a sufficient basis for subsequent statistical analyses and interpretation. The expanded sample size enhanced the statistical power of the analysis and improved the reliability of the results, particularly for the application of Partial Least Squares Structural Equation Modelling.

Instrument

Data for the study were collected using a structured questionnaire, which served as the primary research instrument. The use of a questionnaire is well suited to quantitative research, as it enables the systematic collection of standardised data that can be readily quantified and subjected to statistical analysis. Questionnaires are particularly effective for technology adoption studies because they allow researchers to capture respondents' perceptions, attitudes, and behavioural intentions across a wide range of constructs within a relatively short period.

The questionnaire was adapted from previously validated instruments used in FinTech and technology adoption research to ensure content relevance, measurement accuracy, and contextual suitability. Adapting established scales allows researchers to retain the psychometric strengths of existing instruments while modifying item wording to reflect the cultural and institutional context of the study. This approach enhances both validity and reliability while ensuring alignment with the study's objectives.

The instrument was organised into two main sections. The first section collected demographic information, including gender, age, educational qualification, monthly income, and respondents' familiarity with FinTech services. This section provided background information necessary for profiling respondents and for testing the moderating effects of demographic variables. The second section consisted of items measuring the core study constructs: effort expectancy, social influence, perceived risk, behavioural intention, use behaviour, facilitating conditions, perceived trust, hedonic motivation, personal innovativeness, habit, and ethics. All items were measured using a "five-point Likert scale ranging from strongly disagree (1) to strongly agree (5)". Each construct was operationalised using multiple items to allow for a more comprehensive and nuanced assessment of respondents' perceptions and behaviours.

Data Collection

Data collection was carried out using a mixed-mode approach, combining face-to-face administration and online survey distribution. This approach was adopted to accommodate differences in geographical location, internet accessibility, and technological proficiency among respondents across Ghana. The online questionnaire was administered using Google Forms and distributed through digital platforms, including email and social media channels related to banking and financial services. This method enabled the researcher to reach respondents across multiple regions efficiently and cost-effectively.

In addition to the online survey, face-to-face data collection was conducted to improve response rates and to include respondents who may have limited access to digital platforms. This method also allowed for direct interaction with participants, providing opportunities to clarify questions where necessary and ensuring more complete responses. Trained research assistants supported the administration of questionnaires in selected locations, including banks, insurance companies, and public spaces.

Prior to data collection, introductory letters were submitted to the management of selected banking institutions and insurance companies to seek formal approval. These letters outlined the purpose of the study, assured confidentiality, and explained how the data would be used. Ethical considerations were strictly observed throughout the data collection process, including obtaining informed consent, ensuring voluntary participation, and maintaining respondent anonymity. The combination of online and face-to-face methods enhanced coverage, reduced sampling bias, and contributed to the robustness of the dataset.

Analysis Strategy

The data analysis process followed a structured and sequential approach. Initially, the collected data were entered into the Statistical Package for the Social Sciences (SPSS) for data screening, coding, and preliminary analysis. This stage involved checking for missing values, identifying outliers, and generating descriptive statistics to summarise respondents' demographic characteristics and overall response patterns.

Following data cleaning, the dataset was converted into a comma-separated values format and imported into SmartPLS 4 for further analysis. The primary analytical technique employed was "Partial Least Squares Structural Equation Modelling (PLS-SEM)". PLS-SEM is particularly appropriate for studies involving complex models with multiple latent constructs and indicators, as well as for predictive and theory-building research (Acquah et al., 2025; Arthur et al., 2025; Hair et al., 2021; Hair et al., 2022). The method allows for the simultaneous assessment of the measurement model and the structural model, providing comprehensive insights into both construct validity and hypothesised relationships.

The measurement model was evaluated by examining indicator reliability, internal consistency reliability, convergent validity, and discriminant validity using established criteria such as "factor loadings, Cronbach's alpha, composite reliability, Average Variance Extracted, and the HTMT ratio". The structural model assessment involved analysing path coefficients, significance levels, coefficients of determination, and predictive relevance. Bootstrapping procedures were applied to test the significance of hypothesised relationships. This analytical strategy enabled a rigorous examination of the determinants of FinTech

adoption, the role of behavioural intention in predicting actual use, and the moderating influence of demographic factors. By combining SPSS and SmartPLS, the study ensured both statistical precision and theoretical robustness in addressing the research objectives.

Results

Measurement model

The outer loadings of all indicators on their respective latent constructs met the recommended threshold of 0.70 (see Table 2 and Appendix A), with a few slightly below but still within acceptable limits (Hair et al., 2021). Table 2 presents the “outer loadings, Cronbach’s alpha (CA), composite reliability (CR), average variance extracted (AVE), and outer VIF values”. All CR values exceeded the 0.70 threshold, indicating good internal consistency reliability. Similarly, AVE values for all constructs were above 0.50, confirming convergent validity. Outer VIF values were below the critical value of 3.3 (Legate et al., 2023), indicating no multicollinearity concerns among indicators. The algorithm results of the PLS-SEM are displayed by Fig. 2.

Table 2
Measurement Model Results (Outer Loadings, CA, CR, AVE, and VIF)

Construct	Indicator	Loading	VIF	CA	CR	AVE
BI	BI1	0.660	1.385	0.714	0.823	0.539
	BI2	0.779	1.576			
	BI3	0.744	1.504			
	BI4	0.747	1.505			
EE	EE1	0.767	1.767	0.786	0.86	0.606
	EE2	0.825	2.216			
	EE3	0.801	1.933			
	EE4	0.717	1.206			
ET	ET1	0.843	1.961	0.864	0.906	0.707
	ET2	0.868	2.201			
	ET3	0.855	2.513			
	ET4	0.797	2.18			
FC	FC1	0.749	1.608	0.823	0.871	0.576
	FC2	0.821	1.864			
	FC3	0.75	1.998			
	FC4	0.709	1.923			
	FC5	0.761	2.128			
HM	HM1	0.644	1.284	0.76	0.847	0.583
	HM2	0.754	1.469			
	HM3	0.846	1.824			
	HM4	0.795	1.781			
HT	HT1	0.853	1.912	0.807	0.875	0.702
	HT2	0.93	1.833			
	HT3	0.718	1.603			
PE	PE1	0.853	2.074	0.818	0.878	0.644

Note: “BI = Behavioural Intention; EE = Effort Expectancy, ET = Perceived Ethics; FC = Facilitating Conditions; HM = Hedonic Motivation; HT = Habit; PE = Performance Expectancy; PI = Personal Innovativeness; PT = Perceived Trust; SI = Social Influence; and USE = Use behaviour”

Construct	Indicator	Loading	VIF	CA	CR	AVE
	PE2	0.72	1.57			
	PE3	0.779	1.543			
	PE4	0.849	1.914			
PI	PI1	0.848	1.802	0.771	0.868	0.687
	PI2	0.851	1.867			
	PI3	0.785	1.368			
PT	PT1	0.889	1.987	0.822	0.893	0.736
	PT2	0.812	1.707			
	PT3	0.871	1.908			
SI	SI1	0.782	1.8	0.834	0.882	0.601
	SI2	0.77	1.591			
	SI3	0.765	1.902			
	SI4	0.83	1.962			
	SI5	0.725	1.581			
USE	USE1	0.758	1.542	0.772	0.854	0.595
	USE2	0.745	1.502			
	USE3	0.829	1.952			
	USE4	0.75	1.672			

Note: “BI = Behavioural Intention; EE = Effort Expectancy, ET = Perceived Ethics; FC = Facilitating Conditions; HM = Hedonic Motivation; HT = Habit; PE = Performance Expectancy; PI = Personal Innovativeness; PT = Perceived Trust; SI = Social Influence; and USE = Use behaviour”

Discriminant Validity

Discriminant validity was evaluated using the HTMT ratio (see Table 3). All HTMT values among BI, EE, ET, FC, HM, HT, PE, PI, PT, SI, and USE were below the threshold of 0.90, indicating satisfactory discriminant validity (Hair et al., 2025). This confirms that the constructs are empirically distinct and do not exhibit multicollinearity concerns.

Table 3: HTMT ratio

	BI	EE	ET	FC	HM	HT	PE	PI	PT	SI	USE
BI											
EE	0.666										
ET	0.452	0.684									
FC	0.547	0.810	0.841								
HM	0.768	0.761	0.593	0.582							
HT	0.395	0.772	0.802	0.804	0.688						
PE	0.604	0.853	0.779	0.821	0.682	0.814					
PI	0.492	0.432	0.525	0.549	0.600	0.671	0.507				
PT	0.393	0.737	0.792	0.773	0.793	0.771	0.646	0.446			
SI	0.544	0.880	0.601	0.753	0.667	0.679	0.892	0.371	0.567		
USE	0.832	0.763	0.813	0.817	0.744	0.765	0.735	0.615	0.762	0.535	

Structural Model

Based on the results presented in Table 4, a structural model assessment was carried out to examine the hypothesized relationships among the latent constructs. The evaluation included the examination of “path coefficients (β), standard deviations (SD), t-statistics, p-values, confidence intervals, and effect sizes (f^2)”, as well as the “coefficient of determination (R^2)” for endogenous constructs. The analysis employed a bootstrapping procedure with 10,000 subsamples to assess the significance of path relationships, and multicollinearity diagnostics were conducted using VIF values. The VIF values across the paths ranged between 1.000 and 4.147, indicating that multicollinearity was not a concern, as all values were below the conservative threshold of 5.

The results indicated that BI significantly predicted USE ($\beta = 0.444$, $t = 12.325$, $p < 0.001$, $f^2 = 0.434$), accounting for 61.8% of the variance in USE ($R^2 = 0.618$). EE significantly influenced BI ($\beta = 0.324$, $t = 3.329$, $p < 0.001$, $f^2 = 0.053$), with a VIF of 3.722, suggesting no multicollinearity. Similarly, FC positively predicted BI ($\beta = 0.410$, $t = 3.761$, $p < 0.001$, $f^2 = 0.076$), and HM was also a strong predictor of BI ($\beta = 0.536$, $t = 7.971$, $p < 0.001$, $f^2 = 0.249$). Conversely, HT had a significant negative effect on BI ($\beta = -0.332$, $t = 3.696$, $p < 0.001$, $f^2 = 0.053$), as did PT ($\beta = -0.286$, $t = 4.768$, $p < 0.001$, $f^2 = 0.069$) and SI ($\beta = -0.157$, $t = 2.294$, $p = 0.011$, $f^2 = 0.014$).

Although PE ($\beta = 0.087$, $t = 1.077$, $p = 0.141$, $f^2 = 0.004$) and PI ($\beta = 0.097$, $t = 1.378$, $p = 0.084$, $f^2 = 0.012$) showed positive associations with BI, their effects were not statistically significant. However, PI had a significant direct effect on USE ($\beta = 0.165$, $t = 4.005$, $p < 0.001$, $f^2 = 0.057$). Moreover, ET showed a very strong and significant predictive effect on PT ($\beta = 0.702$, $t = 37.457$, $p < 0.001$, $f^2 = 0.970$), accounting for 49.2% of the variance in PT ($R^2 = 0.492$). PT also had a direct and significant influence on USE ($\beta = 0.428$, $t = 11.746$, $p < 0.001$, $f^2 = 0.407$), underscoring its importance as a predictor. Figure 3 shows the PLS-SEM bootstrapping results.

Table 4
Structural model

Path	β	M	SD	T Statistics	P Values	VIF	5.0%	95.0%	f^2	R^2
BI -> USE	0.444	0.445	0.036	12.325	0.000	1.189	0.381	0.500	0.434	0.618
EE -> BI	0.324	0.326	0.097	3.329	0.000	3.722	0.171	0.489	0.053	0.465
ET -> PT	0.702	0.703	0.019	37.457	0.000	1.000	0.668	0.730	0.970	0.492
FC -> BI	0.410	0.404	0.109	3.761	0.000	4.147	0.236	0.594	0.076	
HM -> BI	0.536	0.535	0.067	7.971	0.000	2.162	0.427	0.646	0.249	
HT -> BI	-0.332	-0.322	0.090	3.696	0.000	3.897	-0.482	-0.191	0.053	
PE -> BI	0.087	0.080	0.081	1.077	0.141	3.331	-0.044	0.220	0.004	
PI -> BI	0.097	0.098	0.070	1.378	0.084	1.502	-0.023	0.209	0.012	
PI -> USE	0.165	0.164	0.041	4.005	0.000	1.244	0.099	0.234	0.057	
PT -> BI	-0.286	-0.287	0.060	4.768	0.000	2.209	-0.384	-0.186	0.069	
PT -> USE	0.428	0.430	0.036	11.746	0.000	1.178	0.368	0.487	0.407	
SI -> BI	-0.157	-0.150	0.068	2.294	0.011	3.302	-0.278	-0.053	0.014	

Note: M = Sample mean, SD = Standard deviation; R^2 adjusted for BI, PT and USE are 0.454, 0.491 and 0.615 respectively.

Predictive Relevance

Table 5 presents the results of the “Stone–Geisser predictive relevance (Q^2)” assessment for the endogenous constructs in the proposed FinTech adoption model. The Q^2 values were obtained using the blindfolding procedure by comparing the “sum of squares observed (SSO)” with the “sum of squares error (SSE)”. A Q^2 value greater than zero indicates that the model has predictive relevance for a given endogenous construct, whereas values equal to zero suggest no predictive relevance.

As shown in Table 5, “behavioural intention (BI)” records a Q^2 value of 0.239, indicating that the model demonstrates acceptable predictive relevance for customers’ intention to adopt FinTech services. This

suggests that the explanatory constructs included in the extended UTAUT2 framework such as “effort expectancy, facilitating conditions, hedonic motivation, habit, personal innovativeness, perceived trust, social influence, and perceived ethics”, meaningfully predict customers’ behavioural intentions within the Ghanaian banking and insurance context.

Similarly, perceived trust (PT) yields a Q^2 value of 0.351, reflecting strong predictive relevance. This result underscores the central role of trust in FinTech adoption, particularly as influenced by ethical perceptions and related antecedents. The finding suggests that the model effectively explains variations in customers’ trust in FinTech services, reinforcing the importance of trust-building mechanisms in digital financial environments.

Furthermore, use behaviour (USE) records a Q^2 value of 0.358, indicating substantial predictive relevance of the model in explaining actual FinTech usage. This implies that behavioural intention and personal innovativeness meaningfully translate into real usage behaviour among customers of banking and insurance companies in Ghana. In contrast, constructs such as “effort expectancy (EE), perceived ethics (ET), facilitating conditions (FC), hedonic motivation (HM), habit (HT), performance expectancy (PE), personal innovativeness (PI), and social influence (SI)” report Q^2 values of zero, as they are modelled as exogenous constructs. Consequently, predictive relevance is not assessed for these variables.

The results confirm that the proposed extended UTAUT2 model exhibits adequate predictive relevance, particularly for behavioural intention, perceived trust, and use behaviour. This provides empirical support for the model’s suitability in predicting FinTech adoption among banking and insurance customers in Ghana.

Table 5
Predictive Relevance (Q^2) of Endogenous Constructs in the FinTech Adoption Model

Construct	SSO	SSE	Q^2 (= 1-SSE/SSO)
BI	1636	1245.572	0.239
EE	1636	1636	
ET	1636	1636	
FC	2045	2045	
HM	1636	1636	
HT	1227	1227	
PE	1636	1636	
PI	1227	1227	
PT	1227	795.78	0.351
SI	2045	2045	
USE	1636	1051.11	0.358

Discussion

The current study examined the adoption of FinTech by banking and insurance company customers in Ghana using an extended Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model. The findings of this study demonstrate that behavioural intention strongly predicts the actual use of FinTech services among banking and insurance customers in Ghana. This aligns with the theoretical propositions of UTAUT2 and the Theory of Reasoned Action, which posit that behavioural intention is the immediate antecedent of technology usage (Venkatesh et al., 2012; Sharma et al., 2020). In the Ghanaian context, the strong intention–use relationship may reflect growing awareness and familiarity with digital financial services, alongside increased reliance on mobile money and banking apps in everyday financial transactions. Empirical studies in other emerging economies similarly report that strong intentions translate into sustained adoption (Senyo & Osabutey, 2020; Thusi & Maduku, 2020), reinforcing the universal applicability of this relationship while highlighting its relevance in Ghana's FinTech landscape.

Effort expectancy positively influenced adoption intentions, suggesting that perceived ease of use is a key driver of FinTech adoption in Ghana. Customers appear more willing to adopt FinTech services when platforms are intuitive and require minimal technical skills. This finding corroborates earlier studies in emerging economies where digital literacy varies, such as those by Mulyana et al. (2020) and Sultana et al. (2023). In Ghana, where some users may have limited experience with digital finance, platforms that reduce cognitive load and simplify processes likely enhance users' willingness to engage.

Facilitating conditions and hedonic motivation were also significant predictors of adoption intentions. The availability of reliable infrastructure, internet connectivity, and supportive customer service appears crucial for fostering positive adoption behaviours. Similarly, the enjoyment and satisfaction derived from using FinTech services reinforce intentions to adopt, aligning with Bommer et al. (2023), who noted that hedonic experiences strengthen emotional attachment to financial technologies. In Ghana, where digital financial services increasingly compete for attention, enjoyable and seamless experiences can differentiate providers and encourage sustained usage.

Interestingly, certain constructs such as habit, social influence, and performance expectancy exerted weaker or negative effects on adoption intentions in the current study. This could reflect the context-specific dynamics of Ghanaian FinTech adoption. For example, habitual usage may be less influential because FinTech platforms are relatively new and customers are still exploring different services rather than relying on automatic routines. Similarly, social influence may be weaker as adoption decisions are often guided more by personal convenience and trust in the platform than by peers. Performance expectancy showed limited direct influence on intention, possibly because users in Ghana prioritise practical accessibility, security, and ethical practices over abstract efficiency gains, reflecting a contextual sensitivity to perceived risks in digital finance.

Perceived ethics emerged as a strong determinant of trust, which, in turn, influenced both adoption intentions and actual usage. This finding underscores the central role of ethical perceptions in financial technology adoption, particularly in Ghana where concerns about fraud, data privacy, and transparency are prevalent. Customers are more likely to adopt FinTech services when they perceive providers as ethical and trustworthy, corroborating the argument of Ali et al. (2021) and Chawla et al. (2023) that ethical practices directly shape trust and adoption behaviour.

Finally, personal innovativeness directly influenced actual use of FinTech services, highlighting the role of individual differences in shaping adoption. Customers who are more willing to experiment with new technologies are more likely to explore and maintain engagement with FinTech platforms, even in the absence of strong behavioural intentions. This finding aligns with prior studies (Leong et al., 2020; Almashhadani et al., 2023) and is particularly relevant in Ghana, where early adopters often pave the way for broader community acceptance of digital financial solutions.

The findings suggest that the UTAUT2 model, when extended with perceived ethics, perceived trust, and personal innovativeness, is a robust framework for explaining FinTech adoption in Ghana. While core constructs like behavioural intention, effort expectancy, facilitating conditions, and hedonic motivation significantly drive adoption, context-specific factors such as emerging usage patterns, trust concerns, and ethical perceptions shape the nuanced adoption behaviour observed among Ghanaian customers. These insights provide practical guidance for FinTech providers seeking to enhance adoption and sustained use in Ghana’s unique socio-economic and technological landscape.

Implications of the Study

The findings of this study offer important theoretical, practical, and policy implications. Theoretically, the study extends the UTAUT2 framework by incorporating perceived ethics, perceived trust, and personal innovativeness, demonstrating that these factors significantly enhance the model's explanatory power in the Ghanaian FinTech context. Practically, the results provide guidance for FinTech providers on strategies to improve adoption and sustained usage. Emphasizing user-friendly interfaces, reliable support systems, and ethical business practices can increase customer confidence and engagement. Additionally, the study highlights the importance of targeting innovative early adopters to encourage wider uptake. Policymakers and regulatory bodies such as the Bank of Ghana and the National Insurance Commission can leverage these insights to develop guidelines that enhance transparency, security, and ethical standards in digital financial services, thereby fostering greater trust among users.

Limitations and Future Studies

While this study provides valuable insights, it has several limitations. The cross-sectional research design restricts the ability to infer causal relationships, suggesting that longitudinal or experimental studies could provide stronger evidence of temporal effects. The study was conducted in selected urban areas in Ghana, which may limit the generalizability of the findings to rural communities or other emerging economies. Additionally, self-reported data may be subject to social desirability or response biases. Future studies could expand the scope by including diverse geographic regions, examining sector-specific FinTech adoption patterns, or integrating qualitative methods to capture deeper insights into user experiences. Researchers may also explore additional contextual factors such as financial literacy, risk perception, and cultural influences to further refine models of FinTech adoption in Ghana.

Conclusion

This study examined the adoption of FinTech services by banking and insurance customers in Ghana using an extended UTAUT2 model. The findings confirm that behavioural intention, effort expectancy, facilitating conditions, hedonic motivation, perceived ethics, perceived trust, and personal innovativeness play significant roles in predicting actual use of FinTech services. Contextual factors in Ghana, including trust concerns and ethical considerations, significantly shape customer adoption behaviour. The study contributes to both theory and practice by extending UTAUT2 and providing actionable recommendations for FinTech providers, regulators, and policymakers. Ultimately, enhancing usability, trust, and ethical standards can promote greater financial inclusion and technology adoption in Ghana.

Declarations

CRediT authorship contribution statement

Kwaku Okyere Danquah: Conceptualization, Data curation, Investigation, Writing – original draft, Writing – review & editing, Resources, Software, Supervision, Methodology, Validation, Visualization. The author reviewed the manuscript and approved it for final submission.

Ethics Statement

The study was conducted in accordance with ethical standards and all applicable institutional guidelines and regulations. Ethical approval letter was waived by the ethics committee of the Sumy State University. Informed consent was obtained from all participants. All procedures followed in the study complied with the principles outlined in the “Declaration of Helsinki”.

Clinical Trial Number:

Not Applicable

Consent of Participants

Informed consent was obtained from all participants before data collection.

Data Availability

Data will be made available upon request.

Conflict of interest

The author declare that they have no conflicts of interest.

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Figures

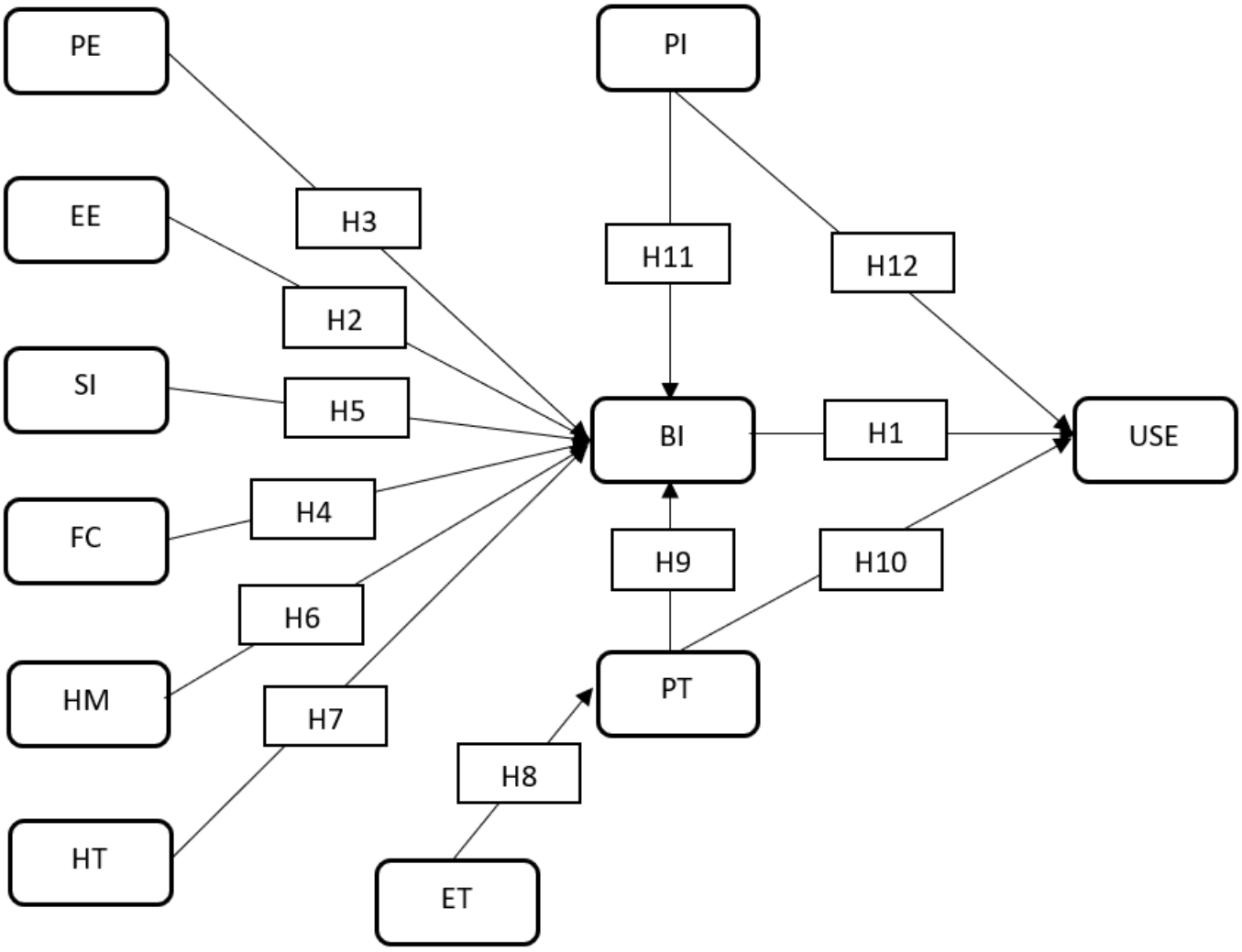


Figure 1

Conceptual model

Note: “BI = Behavioural Intention; EE = Effort Expectancy, ET = Perceived Ethics; FC = Facilitating Conditions; HM = Hedonic Motivation; HT = Habit; PE = Performance Expectancy; PI = Personal Innovativeness; PT = Perceived Trust; SI = Social Influence; and USE = Use behaviour”

Source: Authors’ own work

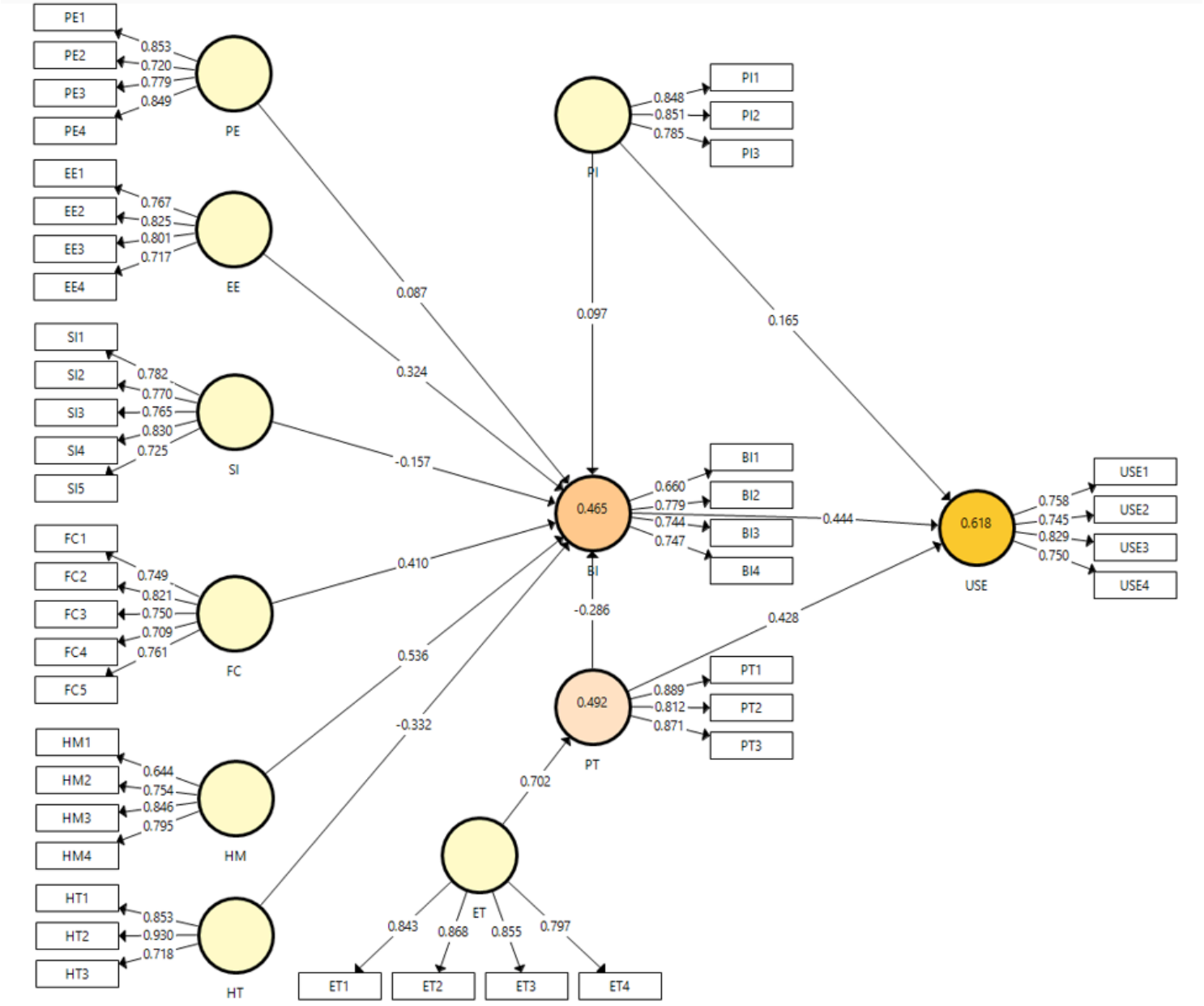


Figure 2

“Algorithm results of PLS-SEM”

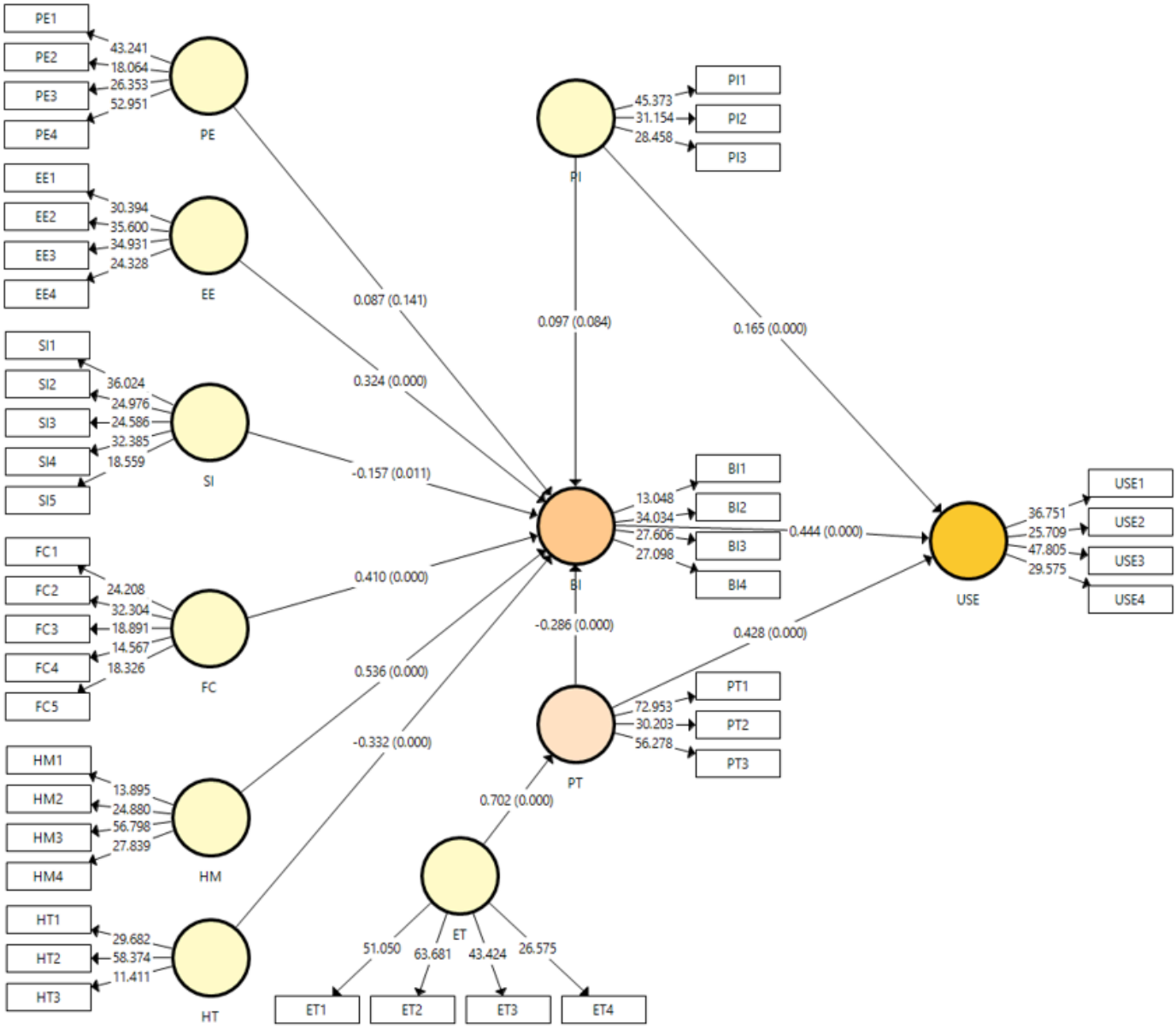


Figure 3

“Bootstrapping results of PLS-SEM”

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- AppendixA.docx