Journal of Organizational and End User Computing
Volume 35 • Issue 2

Predicting the Intention to Adopt Innovation in Supply Chain Finance:
Determinants of Brazilian FinTech

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ABSTRACT

Based on the mixed model unified technology acceptance and utilization theory (UTAUT) and spinner innovation model (SPINNER), a theoretical model is suggested to explain the determinant of behavioral intention to predict innovation in the context of a financial sector firm. A questionnaire was developed to collect primary data, which was subsequently processed through the artificial intelligence technique (deep learning). The constructs (performance expectancy, effort expectancy, social influence, facilitating conditions, behavioral intention, public knowledge, private knowledge, and innovation) supported the model, including mediating hypotheses. It was observed that the mixed methodological approach (SEM and ANN) can help to find the linear and non-linear relationships better, being that the error of the predicted model is 0.104, that is, 10.4% relatively low, which evidences that ANN can be used to predict the dependent variable innovation safely.

KEYWORDS

Deep Learning, Innovation, Spinner Innovation, Supply Chain Financing

INTRODUCTION

Supply chain financial services have been growing in literature. For instance, a robust Supply Chain Financial Logistics Supervision System was constructed by harnessing the power of Internet of Things (IoT) technology to examine the practical implementation of IoT technology in enabling customers to

DOI: 10.4018/JOEUC.333689

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supervise the logistics process effectively (Liu et al., 2023). Also, a comprehensive supply chain finance (SCF) framework introducing two novel coordinating contracts that leverage trade credit financing was designed to address different problem settings within the supply chain (Emtehani et al., 2023).

FinTech has gained popularity as it refers to innovative technologies adopted by financial service institutions. The emergence of online peer-to-peer (P2P) lending platforms has introduced a promising FinTech business model that connects investors with capital recipients within supply chains (SCs) (Taleizadeh et al., 2022). Recent advancements in financial technology, known as FinTech, have emerged as solutions to various challenges. These FinTech-driven business models, including crowdfunding, peer-to-peer lending, invoice trading, mobile wallets and payments, and platform-driven SCF, are reshaping the landscape for small businesses (Chang et al., 2021; Chen, Li et al., 2021; Leung, Cho, & Wu, 2022; Liu Panfilova et al., 2022; Liu, Sakulyeva et al., 2022; Malaquias et al., 2021; Shankar, 2022; Sharma et al., 2023; Wamba et al., 2021). The effects of dynamic employee capabilities, FinTech, and innovative work behavior on employee and supply chain performance in the Vietnamese financial industry were analyzed in terms of impact (Phan et al., 2022).

The "prediction" and "adoption" approaches have been gaining cult in the FinTech market. Using structural modeling equations and neural networks has become popular in the financial sector by researchers aiming to identify users' behavior intentions of digital services. The "single" methods have a fundamental difference in relation to the mixed approach, as they are based on a single approach and depend on a single model built based on the acquired knowledge. For example, partial least squares structural equation modeling was used to understand the intention of behavioral use of the FinTech services by companies, a causal-predictive analysis (Irimia-Diéguez et al., 2023). A correlation-regression analysis scenario method for forecasting was used to describe the number of FinTech companies in the finance sector (Taujanskaitė & Kuizinaitė, 2022). In addition, a deep learning-based prediction model is implemented to predict the price movement of fund classes based on the classification results in China FinTech (Chen et al., 2021).

The unified technology acceptance and utilization theory (UTAUT) model has been used to investigate behavioral intentions in several contexts. Recently, studies examined the behavioral intentions of extension professionals from two extension systems to foster the adoption of precision farming (Lee et al., 2023). Prior studies have examined the factors that impact the acceptance of mobile learning technology for 21st-century skills-based training among teachers in Saudi Arabia and Pakistan (Dahri et al., 2023).

In addition, Sulistyaningrum et al. (2023) focus on integrating three theories, including the UTAUT model, to determine factors that could influence people's behavior toward adopting telepharmacy services. Also, another application of the model was developed to investigate the main factors influencing users' intention to accept e-wallets in Jordan (Hammouri et al., 2023). Conversely, the Spinner Innovation Model (SPINNER) has been used to predict small and medium enterprises (SMEs) innovations. Prior studies explore the prediction of innovation in SMEs applying the data mining technique - cross-industry standard process for data mining (CRISP-DM) (Figueiredo et al., 2023). Recently, Figueiredo et al. (2023) explored the integration between SPINNER and the Triple Helix Model to analyze the influence to improve system innovation in SMEs. Equally important, Figueiredo and Ferreira (2020) applied SPINNER to explore Brazil's innovation propensity in the service sector. The model integrated the variable knowledge creation, knowledge transfer, and innovation. Figueiredo et al. (2020) explored the innovation and co-creation in KIBS with the Spinner Innovation Model application. They found that SPINNER explained the propensity for innovation in KIBS and demonstrated that the innovation process was based on the knowledge integrated with co-creation and knowledge transfers. The study contributes to the literature by addressing a new model to predict the intention to adopt innovation in SCF in the Brazilian financial sector, specifically FinTech. However, previous studies may show non-representative results because they were applied in isolated ways in different economic sectors and countries. For example, Zhong and Hitchcock (2021) sought a new predictive model for stock price forecasting to solve the problem of insufficient data for machine learning models. In addition, Wang et al. (2022) addressed the credit risk prediction in small firms in SCF, showing that financial-based information (e.g., TOC and NIR) are more useful in predicting the credit risk of SMEs in SCF. Erfanian et al. (2022) investigated macroeconomic and microeconomic indicators in the SCF and defined that the BTC price prediction is feasible by means of economic theories.

To address the research gaps, our study explores the following question: *How do we predict the intention to adopt innovation in SCF in the Brazilian FinTech*?

The motivation for the study to explain the determinant of behavioral intention to predict innovation in the context of a financial sector firm is based on the following factors: i) the financial sector, especially FinTech, has grown in several markets, including Latin America; thus, it is interesting to investigate the application of a predictive mixed model, including two analysis techniques, since they are considered of high capacity of exploration and analysis of data applied in the scientific literature; ii) when compared to traditional data analysis techniques, the application of mixed models in predicting the intention to innovate in the financial sector is still in its early stages.

Even though many researchers have addressed the two models in several different studies, the accuracy of the mixed model presented in our study can help to find the linear and non-linear relationships better, being that the error of the predicted model is 0.104, that is, 10.4% relatively low, which evidences that Artificial Neural Network (ANN), can be used to predict the dependent variable innovation safely; iii) when it comes to predicting the intention to innovate in finance, the proposed model becomes an important tool.

The prediction of the adoption of innovation in the financial sector, FinTech, is extremely relevant because it collaborates with the premise of the market, innovation as a factor of competitiveness and exponential growth (Talay et al., 2017). In addition, the study addresses the contribution of the variables of the UTAUT and SPINNER models, considering the prediction of innovation adoption in the Brazilian market, which grows exponentially. Our approach developed for the model presents significant accuracy in predicting innovation considering future scenarios, thus being unprecedented in the international literature.

The presented study is organized as follows. In the next section, we present a literature review on innovation and SCF, taking an initial approach, reviewing previous studies, and summarizing the empirical results from the adopted models. Then, we discuss how the conceptual modeling was developed from two scientific models, the UTAUT and the SPINNER models, applied respectively to technology adoption and innovation forecasting and includes the variables used in the ANN model. Next, we show the results based on the empirical model and discuss the findings with the previous literature. Finally, we present the main conclusions, limitations, and future research.

LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

Predict Innovation and Supply Chain Financing in FinTech Firms

FinTech firms serve a pivotal function as intermediaries in signaling, enabling interactions between pertinent stakeholders, expediting the exchange of information, and mitigating information disparities stemming from data overload (Song et al., 2023). Furthermore, the advancement of financial technology (FinTech) has bolstered the embrace of SCF by utilizing information technologies (IT) to provide financial services and streamline lending and transaction procedures for SMEs (Soni et al., 2022).

Furthermore, previous studies have applied and developed various traditional prediction methods for innovation in the financial sector. For example, Figueiredo et al. (2023) investigate the potential impact of integrating Spinner Innovation and Triple Helix models on enhancing systemic innovation. Li et al. (2022) explained the correlation between operational capabilities and investment components to aid firm managers and investors in comprehending the innovation process in SCF.

Among them, many are applied to FinTech to determine the main factors determining the change in FinTech's behavior, considering the economic sector's prediction and future development in digital services (Taujanskaitė & Kuizinaitė, 2022). For instance, Abou-Shouk and Soliman (2021) used the Unified Theory of Acceptance and Use of Technology model to explore the factors that lead to and result from the intention of tourism organizations to adopt gamification in customer engagement.

An earlier study developed a forecasting model based on machine learning to predict credit risk in SMEs in China using financial information, operation information, innovation information, and negative events as predictors (Wang et al., 2022). In addition, Horvát et al. (2023) found that Heckman's two-variable model (speed and diversity of opinion) predicts who is funded and who repays the financial outcome. Using correlation analysis, Li and Tan (2021) described that the ARIMA model predicts the actual value using the "Operating income growth rate" indicator.

The Taskforce on Nature-related Financial Disclosures (TNFD Framework) is another traditional approach to predicting better risk management from health firms. Deweerdt et al. (2022) discovered that many factors can stifle innovation because companies cannot predict the return, and innovation is complex and unclear to achieve. Moreover, Erfanian et al. (2022) included ordinary least squares (OLS) and multilayer perceptron (MLP) to predict the BTC price. Wu (2023) explored the influence of big data technology on the innovation enterprise economic mode, showing that the company's planned deployment of staff deviates only slightly from the actual deployment of staff.

In addition, Zhong and Hitchcock (2021) used the variables, weekly historical prices, finance reports, and text information to apply a predictable model for stock prices. Also, Liu et al. (2021) conclude that blockchain crowdfunding, FinTech, encryption currency, and SCF are the key research directions in the study. Regarding how stock market reactions to marketing actions affect subsequent marketing decisions, Talay et al. (2017) describe that the available literature on marketing finance, especially on innovation, affects the predictive power of immediate actions. However, the literature review shows the importance of FinTech´s studies to financial sector products, including innovative methods to engage clients (Garg et al., 2023). Considering SCF to support baking systems, Mahmoudi et al. (2023) applied a multiple-criteria decision-making (MCDM) problem and proposed a model based on the Ordinal Priority Approach (OPA).

Looking at the E-commerce SCF for SMEs in the role of green innovation, Guo et al. (2023) used regression analysis techniques to have the results. In addition, numerous financial institutions are keen on embracing technological solutions to bolster operational efficiency in managing SCF. This intricate process involves multiple participants and encompasses many complex financial activities (Kao et al., 2022). Regarding future research, Sharma et al. (2023) considered that FinTech addresses some challenges regarding platform-driven SCF in the ecosystem context.

However, traditional models have been used to describe some results in the context of the SCF Business Model, bringing mixed theoretical analysis of the Business Model Canvas (BMC) to the perspective of competitive advantages (Zhou & Lee, 2023). In contrast, advanced technology (blockchain) has been used to address current challenges in supply chain financing processes (Tsai, 2023). This means that academics and professionals urgently need accurate and up-to-date knowledge of FinTech (Phan et al., 2022).

One more method is decision-making used for different scales in the ARDL long-term coefficients and AHP to financial investment decisions (Atmaca & Karadaş, 2020), and the accurate forecasts for investment decision-making could be used in terms of market returns as the most effective tools for risk management (Mallikarjuna & Rao, 2019).

To investigate how financial literacy and behavioral traits affect the adoption of electronic payment (ePayment) services, Long et al. (2023) used the instrumental variable approach. In addition, (VARFIMA) model was used by Oral and Unal (2019) to model and extract the time series to estimate the forecasting process. Also, the grey system theory was used to predict the Bitcoin price changes (Faghih Mohammadi Jalali & Heidari, 2020). In addition, Big data analytic techniques associated with machine learning algorithms were an important application in the stock market investment field (X. Zhong & Enke, 2019).

Finally, the Group Method of Data Handling (GMDH) neural network has exhibited strong performance in data mining, prediction, and optimization (Zhang et al., 2023).

HYPOTHESES

Performance Expectancy

Performance expectancy can be defined as a belief related to the ability to succeed in an action (Wu & Kang, 2021). Performance expectancy refers to how much technology aids consumers in accomplishing specific tasks (Fedorko et al., 2021). Also, the level of performance expectancy associated with open data (OD) plays a crucial role in the user technology acceptance models, especially concerning the future implementation of OD in Industry 4.0 and its potential impact on Society 5.0.(Sołtysik-Piorunkiewicz & Zdonek, 2021). In addition, performance expectancy can be described as the anticipated influence of a technology's functional advantage, even when operating in uncertain conditions (Sewandono et al., 2023).

Hypothesis 1. Performance Expectancy (PEXP) positively influences the intention to predict innovation.

Effort Expectancy

Performance expectancy represents how much technology assists consumers in carrying out specific actions. On the other hand, effort expectancy pertains to the ease with which consumers can utilize the technology (Fedorko et al., 2021). In addition, The relationship between digital competence and effort expectancy concerning work engagement has not been adequately explored or understood (Sang et al., 2023). Effort expectancy refers to the level of ease experienced by individuals while using technology (Venkatesh, 2022). Moreover, studies have revealed a significant impact of effort expectancy on the elderly's intention to use technology (Ramírez-Correa et al., 2023).

Hypothesis 2. Effort Expectancy (EEXP) positively impacts the intention to predict innovation for supply chain financing.

Social Influence

Social influence is a means of getting more useful information about the target product (Yang et al., 2023). In the medical field, social influence can be considered one-factor affecting therapy retention (Knight et al., 2023). According to Zareie and Sakellariou (2023), social influence is formed through human interactions and can significantly impact shaping opinions, facilitating the rapid and extensive dissemination of specific messages or news, and expediting the formation of collective viewpoints. Also, social influence plays a crucial role in developing call comprehension abilities (Garcia-Nisa et al., 2023).

Hypothesis 3. Social Influence (SIN) positively explains the intention to predict innovation for supply chain financing.

Knowledge

Private knowledge can extract local knowledge from data distributed in a decentralized way to collectively develop an intelligent model with differentiated privacy guarantees (Qi et al., 2023). In this configuration, each client retains its training data locally, without sharing it externally, while a central server maintains the intelligent model and provides a local copy to each client. However, public and private knowledge in product development has introduced new collaboration arrangements in which existing resources and knowledge combine with those traditionally retained by local and global companies (Ferpozzi, 2023). In addition, at certain times, the private sector, with limited knowledge, leads the search for new partners to develop available services based on confidentiality and a desire for personalized service (V et al., 2022). Finally, numerous studies in knowledge management suggest that enterprises and organizations can reap significant benefits by establishing systematic sharing, transfer, and reuse of knowledge. While knowledge sharing and transfer require effective mechanisms for capturing and transferring information, little research has been conducted to explore the various techniques used for knowledge reuse within organizations (Sandkuhl & Smirnov, 2018).

Hypothesis 4. Private Knowledge (PVRKM) positively influences the intention to predict innovation for supply chain financing.
Hypothesis 5. Public Knowledge (PUBKM) positively influences the intention to predict innovation for supply chain financing.

Facilitating Conditions

Yabutani and Yamada (2023) identify the conditions required to motivate residents to engage in community activities, considering their individual characteristics. In addition, Nuseir & Elrefae (2022) incorporated within the context are facilitating conditions, customer experience, and brand loyalty, all of which influence the utilization of social media marketing, ultimately enhancing consumer-based brand equity. Also, facilitating conditions significantly impact students' intention to interact with one another (Wut et al., 2022). While the influence of facilitating conditions on the success of information system implementation is crucial, there is a lack of empirical research in the literature concerning the relationship between facilitating conditions and continuance intention in private higher learning institutions (Kamarozaman & Razak, 2021). Furthermore, the predictive role of facilitating conditions, perceived ease of use, and perceived usefulness in Iranian EFL learners' perceptions of mobile-assisted language learning (MALL) were examined by Ebadi and Raygan (2023). In addition, facilitating conditions emerged as the primary factor influencing their dynamic mathematics software usage behavior (Yuan et al., 2023).

Hypothesis 6. Facilitating Conditions (FCON) positively influence the intention to predict innovation for supply chain financing.
Hypothesis 7. Facilitating Conditions (FCON) positively explain the innovation use behavior.

Innovation

Numerous studies have demonstrated that technological innovation has significantly reduced energy intensity (Wen et al., 2023). According to Li et al. (2023), the integration of digital finance with conventional finance and information technology (IT) holds great importance as it opens up new opportunities for green technology innovation and transformation within polluting industries Also, Chen and Liu (2023) used an innovation Spatial analysis, spatial Durbin models, and other methods are employed to analyze collaborative innovation between the logistics industry and manufacturing industry. Also, Irimia-Diéguez et al. (2023) focus on predicting FinTech innovation adoption, specifically examining the mediator role of social norms and attitudes in the innovation process. Finally, the relationship between embedding digital technology innovation networks and innovation behavior remains to be clarified and requires further investigation (Ge et al., 2023).

Hypothesis 8. Innovation (INN) positively influences innovation use behavior.

Figure 1 shows the theoretical model for the study based on the literature.

METHODS

Sample and Data

Primary data was collected from a Brazilian FinTech in the digital services sector in Rio de Janeiro, Brazil. The total valid data from the online questionnaire application was 124 respondents. The respondents work directly in digital services (digital accounts). The variables are defined from valid models of technology adoption and innovation prediction.

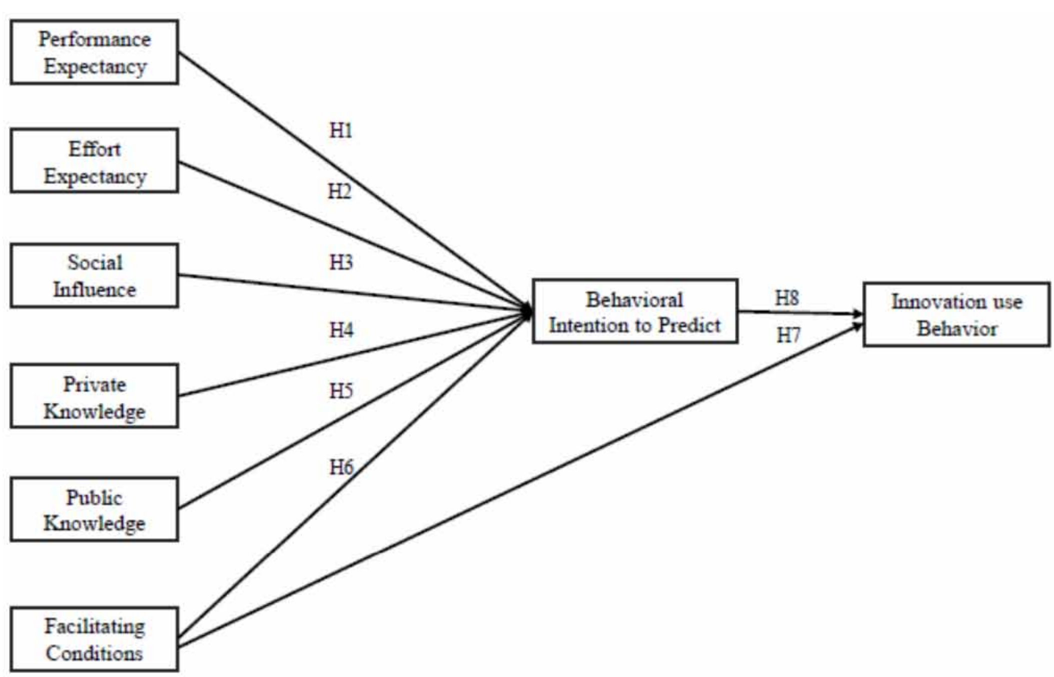
The sampling period for the collected data is from May 10 to June 30, 2023. The number of training and test samples is controlled to investigate prediction in the financial sector innovation context. The number of training cases was 96 (77,4%), and 28 (22,6,0%) cases were used for the test. The sample is a contextual benchmark, considering a specific time of data collection. A 7-point Likert scale was used (i.e., strongly disagree, slightly disagree, disagree, neutral, slightly agree, agree, strongly agree).

Procedures of Data Analysis

The structural equation modeling (SEM) (Hassan & Soliman, 2021) technique was used to analyze the data, with the partial least squares (PLS) (Hair Jr et al., 2020) method and ANN. The software used for the structural equation modeling analyses was "SmartPLS 4" (Ringle, Wende, & Becker, 2015), and for the neural networks (ANN), we used the Statistical Package for the Social Sciences (SPSS). The ANN used was the Multistrate Perceptron (MLP) type.

The following steps were applied for the structural equation modeling analysis:

Figure 1. Theoretical model



- Internal consistency and convergent validity were assessed using Cronbach's alpha and Composite Reliability (CR), respectively (Fornell & Larcker, 1981; Hair Jr. et al., 2009).
- Three tests were used to analyze the discriminant validity of the model. The first was the Cross Factor Loadings (CFC), which is the correlation of the Observed Variables (OV) with the Latent Variables (LV) (Ringle; Silva; Bido, 2014). Another test was the Fornell-Larcker Criterion, which compares the square roots of the SEMs with the Pearson correlations (Fornell; Larcker, 1981). The third test was the Heterotrait-Monotrait Ratio Criterion (HTMT), confirmed by the Bootstrapping method, which is a more efficient criterion than Fornell-Larcker and is a kind of estimation of the correlation between the Latent Variables (Netemeyer; Bearder; Sharma, 2003).
- Five tests were used to assess the criteria for evaluating the structural model. The Variance Inflation Factor (VIF) Collinearity Assessment verifies the existence of strong correlations between the variables, indicating collinearity problems (Hair et al., 2017). The Effect Size (f2) assesses the usefulness of each endogenous variable for adjusting the model (Cohen, 1988; Hair et al., 2014).

For the application of artificial neural networks (ANN):

- Neural network analysis (ANN) was used to complement the findings of PLS-SEM in capturing non-linear links (Lee, Hew, Leong, Tan & Ooi, 2020; Wong, Tan, Ooi, Lin & Dwivedi, 2022) due to the limitations of PLS-SEM, which can only identify corrective and linear investigations (Lim, Lee, Foo, Ooi & Wei - Han Tan, 2021).

MEASURES

Variables Used in the ANN Model

The variables used in the model are described in Table 1: Performance Expectancy (PEXP), Effort Expectancy (EEXP), Social Influence (SIN), Private Knowledge (PRVKM), Public Knowledge (PUBKM), Facilitating Conditions (FCON), and Behavioral Intention to Predict (BINP) as independent variables and the dependent variable Innovation (Inn) (Venkatesh, 2006, 2022) (Figueiredo et al., 2023; Figueiredo & Ferreira, 2020). All variables are of scalar type.

Model Specification

This section discusses how conceptual modeling Table 2 was developed from two scientific models, the UTAUT Model and the SPINNER Model, applied respectively to technology adoption and

Table 1. List of variables used on the model neural network

Abbreviation	Variable	Description	References
(PEXP)	Performance Expectancy	Dependent	(Venkatesh, 2006, 2022)
(EEXP)	Effort Expectancy	Dependent	(Venkatesh, 2006, 2022)
(SIN)	Social Influence	Dependent	(Venkatesh, 2006, 2022)
(FCON)	Facilitating Conditions	Dependent	(Venkatesh, 2006, 2022)
(BINP)	Behavioral Intention to Predict	Dependent	(Venkatesh, 2006, 2022)
(PRVKM)	Private Knowledge	Dependent	(Figueiredo, et al., 2023; Figueiredo & Ferreira, 2020)
(PUBKM)	Public Knowledge	Dependent	(Figueiredo, et al., 2023; Figueiredo & Ferreira, 2020)
(INN)	Innovation	Independent	(Figueiredo, et al., 2023; Figueiredo & Ferreira, 2020)

innovation prediction. It presents the variables associated with the model estimated using SEM and ANN. The traditional UTAUT Model is known for evaluating the adoption of new technologies, and the SPINNER Model is known for its application in predicting innovation in SMEs. The results of the association between the two models are presented throughout the study, showing the gain of effectiveness in the integration.

The first model was SEM, which was used to explain the antecedents of Behavioral Intention to Predict (BINP) (Hair Jr. et al., 2009). In addition, to assess convergent validity, the analysis of the model's internal consistency through Cronbach's alpha was performed, and the composite reliability (CR), including the average variance extracted (AVE) (Soliman et al. 2021). Considering the discriminant validity of the model, the average variance derived from the individual indicators was compared with the shared variance between the variables, including the Fornel-Larcker and HTMT criteria for the proposed model (Fornell & Larcker, 1981). The model evaluation was performed using variance inflation factor (VIF), coefficient, effect size indicator values (f2) or Cohen's indicator, model explanation coefficient R2, and predictive validity (Q2) or Stone-Geisser indicator. Table 2 shows the structural coefficients used in the model SEM for the dependent variable Innovation (Inn), with the Performance Expectancy (PEXP), Effort Expectancy (EEXP), Social Influence (SIN), Private Knowledge (PRVKM), Public Knowledge (PUBKM), Facilitating Conditions (FCON) and Behavioral Intention to Predict (BINP). This model was built based on Structural Equation Modeling, whose parameters were estimated using the SmartPLS® program.

The second model, ANN, was used to train and test the model Tabachnick & Fidell, (1991). The model explains the network training sample was equivalent to 96 (77.4%), while the test sample was 28 survey participants (22.6%). A total of 124 elements were considered valid. However, the processing in each neuron was done by the hyperbolic tangent and identity activation functions, as they are standard functions. In the tests performed with the other functions, these were the ones that presented the lowest root mean square error (RMSE) for training and testing.

RESULTS

Measurement Model (Internal Consistency and Convergent Validity)

The result of Cronbach's alpha indicates that all variables are within the acceptable range, demonstrating the reliability of the questionnaire (Table 3). It is recommended that Cronbach's alpha is greater than 0.7 (Hair Jr. et al., 2009), ranging from 0.791 to 0.944. The AVE value is acceptable because it has reached an average value greater than 0.5 and Composite Reliability (CR) (>0.7), according to Fornell and Larcker (1981) and Hair Jr. et al. (2009).

Table 2. Analysis of structural coefficients

Hypotheses	Relationship	β	S. D.	T Stat (|β / S. D.|)	p-Value
H_1	PEXP → BINP	-0,061	0,137	0,446	0,656
H_2	EEXP → BINP	0,039	0,128	0,304	0,761
H_3	SIN → BINP	0,042	0,083	0,512	0,609
H_4	PRVKM → BIP	0,348	0,096	3,623	0,000
H_5	PUBKM → BIP	0,312	0,106	2,927	0,003
H_6	FCON → BINP	0,206	0,136	1,513	0,130
H_7	FCON → IB	0,383	0,094	4,083	0,000
H_8	BINP → IB	0,555	0,069	7,993	0,000

Note: SD = *Standard Deviation*

Table 3. Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE)

Variables	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
Behavioral Intention to Predict (BINP)	0.864	0.907	0.709
Effort Expectancy (EEXP)	0.894	0.926	0.758
Facilitating Conditions (FCON)	0.870	0.921	0.795
Innovation use Behavior (INN)	0.967	0.971	0.753
Performance Expectancy (PEXP)	0.878	0.926	0.806
Private Knowledge (PRVKM)	0.791	0.863	0.611
Public Knowledge ((PUBKM)	0.859	0.904	0.706
Social Influence (SIN)	0.944	0.964	0.899

DISCRIMINANT VALIDITY (CROSS LOADINGS)

Table 4 presents the cross-correlation coefficients assessing the variables' discriminant validity. All the variables analyzed return a higher correlation with their latent variables of origin in relation to the other latent variables of the model. Thus, it can be concluded that the results meet the parameters defined for discriminant validity analysis (Henseler et al., 2015).

FORNELL-LARCKER AND HETEROTRAIT-MONOTRAIT RATIO CRITERIA

Two approaches were used to confirm discriminant validity, i.e., the Fornell-Larker (F-L) discriminant validity assessment and the Heterotrait-Monotrait ratio (HTMT) criterion using the bootstrapping method) (see Table 4). For the F-L criterion, the square root of the AVEs is larger than the correlations of the other variables (r_{ij} for $i \neq j$). As for the HTMT criterion, using the bootstrapping method for 5,000 subsamples, it is observed that the upper limits for 95% confidence are less than 1, except for the PEXP variable, which presented a value of 1.010 concerning the FCON variable. As the two criteria had their assumptions confirmed, the model presents convergent validity (Table 5).

Model Assessment (Variance Inflation Factor, Coefficient, Effect, and Predictive Relevance)

Table 6 shows the multicollinearity through the Variance Inflation Factor (VIF), whose values must be less than 5, thus confirming the non-multicollinearity between the variables (Hair et al., 2017).

The values of the effect size indicator (f^2) or Cohen's d indicator, the model explanation coefficient $R^{2,}$ and the predictive validity (Q^2) or Stone-Geisser indicator are presented in Table 7.

Regarding the effect size values (f^2) presented in Table 8, it is considered that the BINP → INN effect presents a significant value ($p < 0.05$); that is, some of the other relationships may not be confirmed the relationship between the variables (Hair Jr et al., 2017), while the FCON → INN effect was not significant ($p>0.05$). The degree of explanation of the independent variable Innovation use Behavior (INN) in the model $R^2 = 0.733$ with $p<0.05$, while for the variable Behavioural Intention to Predict (BINP) was $R^2 = 0.572$ with $p<0.05$), considered as strong effect (Cohen, 1988; Hair Jr et al., 2017).

Another indicator of model fit quality is the Predictive Relevance or Stone-Geisser indicator, where $Q^2 > 0$ is indicative of predictive relevance; $0.01 \leq Q^2 \leq 0.075$ weak degree, $0.075 < Q^2 \leq 0.25$ moderate degree and $Q^2 > 0.25$ strong degree (Chin, 2010; Hair Jr. et al., 2017). The Q^2 for the independent variables Behavioral Intention to Predict (BINP) and Innovation use Behavior (INN)

Table 4. Sets out the cross loadings

Indicators	Variables							
	BINP	EEXP	FCON	INN	PEXP	PRVKM	PUBKM	SIN
BINP_ 01	**0.811**	0.390	0.509	0.552	0.393	0.542	0.405	0.393
BINP_ 02	**0.862**	0.475	0.478	0.648	0.462	0.514	0.535	0.432
BINP_ 03	**0.851**	0.417	0.451	0.638	0.416	0.552	0.467	0.328
BINP_ 04	**0.841**	0.546	0.708	0.821	0.645	0.610	0.695	0.504
EEXP_ 01	0.412	**0.849**	0.638	0.524	0.800	0.555	0.427	0.679
EEXP_ 02	0.430	**0.916**	0.681	0.500	0.778	0.491	0.454	0.642
EEXP_ 03	0.443	**0.910**	0.633	0.556	0.749	0.510	0.477	0.531
EEXP_ 04	0.583	**0.801**	0.655	0.576	0.689	0.499	0.544	0.599
FCON_ 01	0.598	0.626	**0.856**	0.650	0.753	0.491	0.645	0.600
FCON_ 02	0.533	0.629	**0.875**	0.625	0.666	0.611	0.528	0.530
FCON_ 03	0.609	0.757	**0.942**	0.714	0.759	0.654	0.619	0.640
INN_ 01	0.744	0.501	0.603	**0.780**	0.497	0.633	0.473	0.407
INN_ 02	0.650	0.524	0.637	**0.881**	0.632	0.439	0.580	0.416
INN_ 03	0.679	0.551	0.609	**0.835**	0.566	0.536	0.509	0.428
INN_ 04	0.747	0.564	0.592	**0.887**	0.614	0.532	0.590	0.400
INN_ 05	0.747	0.496	0.661	**0.919**	0.605	0.471	0.597	0.444
INN_ 06	0.670	0.530	0.690	**0.883**	0.638	0.458	0.583	0.424
INN_ 07	0.690	0.541	0.586	**0.846**	0.619	0.445	0.574	0.438
INN_ 08	0.692	0.594	0.712	**0.891**	0.612	0.565	0.600	0.572
INN_ 09	0.705	0.535	0.661	**0.868**	0.550	0.579	0.542	0.518
INN_ 10	0.636	0.555	0.675	**0.842**	0.581	0.570	0.545	0.555
INN_ 11	0.716	0.598	0.681	**0.906**	0.646	0.591	0.612	0.427
PEXP_ 01	0.567	0.754	0.769	0.666	**0.934**	0.498	0.674	0.511
PEXP_ 02	0.530	0.750	0.767	0.613	**0.932**	0.522	0.637	0.525
PEXP_ 03	0.473	0.842	0.656	0.567	**0.823**	0.621	0.464	0.656
PRKM_ 01	0.371	0.346	0.440	0.358	0.325	**0.728**	0.354	0.349
PRKM _ 02	0.493	0.422	0.483	0.450	0.472	**0.798**	0.381	0.410
PRKM_ 03	0.516	0.507	0.536	0.454	0.513	**0.819**	0.401	0.476
PRKM_ 04	0.632	0.535	0.568	0.593	0.530	**0.779**	0.531	0.425
PUBKM_ 01	0.324	0.401	0.399	0.344	0.369	0.342	**0.641**	0.324
PUBKM_ 02	0.477	0.426	0.484	0.463	0.533	0.404	**0.851**	0.276
PUBKM_ 03	0.660	0.508	0.637	0.646	0.623	0.530	**0.927**	0.467
PUBKM_ 04	0.613	0.532	0.682	0.657	0.654	0.522	**0.912**	0.462
SIN_ 01	0.497	0.704	0.657	0.521	0.625	0.534	0.480	**0.942**
SIN_ 02	0.465	0.668	0.631	0.511	0.602	0.515	0.471	**0.973**
SIN_ 03	0.459	0.635	0.599	0.465	0.538	0.473	0.365	**0.929**

Source: Software SmartPLS® v. 3.3.9 (INGLE, WENDE; BECKER, 2015).

Table 5. Analysis of discriminant validity using the Fornel-Larcker and HTMT criteria for the proposed model

Variables		Pearson's Correlation Matrix							
		BINP	EEXP	FCON	INN	PEXP	PRVKM	PUBKM	SIN
BINP	0.842	1.000							
EEXP	0.871	0.552	1.000						
FCON	0.892	0.652	0.755	1.000					
INN	0.868	0.705	0.628	0.745	1.000				
PEXP	0.898	0.585	0.766	0.716	0.687	1.000			
PRVKM	0.782	0.663	0.593	0.657	0.611	0.603	1.000		
PUBKM	0.840	0.641	0.557	0.672	0.651	0.665	0.546	1.000	
SIN	0.948	0.500	0.707	0.664	0.527	0.621	0.536	0.464	1.000
			UL $(HTMT)_{97,5\%}$						
EEXP		0,769							
FCON		0,876	0,953						
INN		0,946	0,817	0,945					
PEXP		0,821	0,928	1,010	0,910				
PRVKM		0,914	0,848	0,911	0,842	0,876			
PUBKM		0,878	0,828	0,945	0,893	0,936	0,859		
SIN		0,701	0,874	0,858	0,701	0,821	0,775	0,691	

Table 6. Variance inflation factor (VIF)

Variable Exogenous	Variable Endogenous	
	Behavioral Intention to Predict (BINP)	Innovation Use Behavior (INN)
BINP		1.740
EEXP	3.998	
FCON	3.950	1.740
PEXP	3.820	
PRVKM	1.907	
PUBKM	2.048	
SIN	2,237	

presented $Q^2 = 0.496$ and $Q^2 = 0.577$, respectively, demonstrating predictive relevance with a strong degree (Chin, 2010; Hair Jr et al., 2017). Table 8 shows the results obtained between the latent variables in the model.

Figure 2 shows the PLS-SEM model.

MULTILAYER PERCEPTRON NETWORK

Table 9 shows the RNA case processing summary, and Table 10 shows the network information dealing with its construction characteristics.

Table 7. Value of f^2, R^2, and Q^2 for model variables

Variables	f^2	
	Behavioral Intention to Predict (BINP)	**Innovation Use Behavior (INN)**
BINP		0.663 (0.002)
EEXP	0.001 (0.958)	
FCON	0.025 (0.513)	0.316 (0.165)
PEXP	0.001 (0.908)	
PRVKM	0.149 (0.084)	
PUBKM	0.111 (0.183)	
SIN	0.002 (0.882)	
R^2	0.572 (0.000)	0.733 (0.000)
Q^2	0.496	0.577

Table 8. The structural model and hypotheses testing

Hypotheses	Path Coeficiente (β)	p - Value	Effect Size (f^2)	VIF	Results
$H_{1:}$ PE → BIP	-0,061	0,656	0,001 (0,908)	3,820	No Supported
H_2: EE → BIP	0,039	0,761	0,001 (0,958)	3,998	No Supported
$H_{3:}$ SI → BIP	0,042	0,609	0,002 (0,882)	2,237	No Supported
$H_{4:}$ PrK → BIP	0,348	0,000	0,149 (0,084)	1,907	Supported
$H_{5:}$ PuK → BIP	0,312	0,003	0,111 (0,183)	2,048	Supported
$H_{6:}$ FC → BIP	0,206	0,130	0,025 (0,513)	3,950	No Supported
$H_{7:}$ FC → IB	0,383	0,000	0,316 (0,165)	1,740	Supported
$H_{8:}$ BIP → IB	0,555	0,000	0,663 (0,002)	1,740	Supported

* Standard Deviation

Excluding the Bias Unit

The seven independent variables form the input layer or covariates: Performance Expectancy (PEXP), Effort Expectancy (EEXP), Social Influence (SIN), Private Knowledge (PRVKM), Public Knowledge (PUBKM), Facilitating Conditions (FCON), and Behavioral Intention to Predict (BINP). The covariates were rescaled by the standardized method, in which the mean is subtracted and divided by the standard deviation. The hidden layer contains unobservable network nodes. In this study, we worked with a hidden layer whose activation function was the hyperbolic tangent characteristic of using arguments with real values and transforming them in the interval (-1,1).

The rescaling method was standardized, and the activation function was identity, i.e., it uses real values and returns them identically. To measure the quality of the predicted ANN, the sum of squares was used as the error function.

The predicted values in the input layer were treated in a standardized way, so their values oscillate between -1 and 1, while the values of the output layer were treated by the identity function, thus representing the determined association values (Table 11). To ensure that the constructed model can be used in other opportunities, there is the possibility to save and store the 'trained' ANN.

Table 12 shows that the error of the predicted model is 0.104, that is, 10,4% relatively low, which evidences that ANN can be used to predict the dependent variable innovation safely.

Figure 2. PLS-SEM model

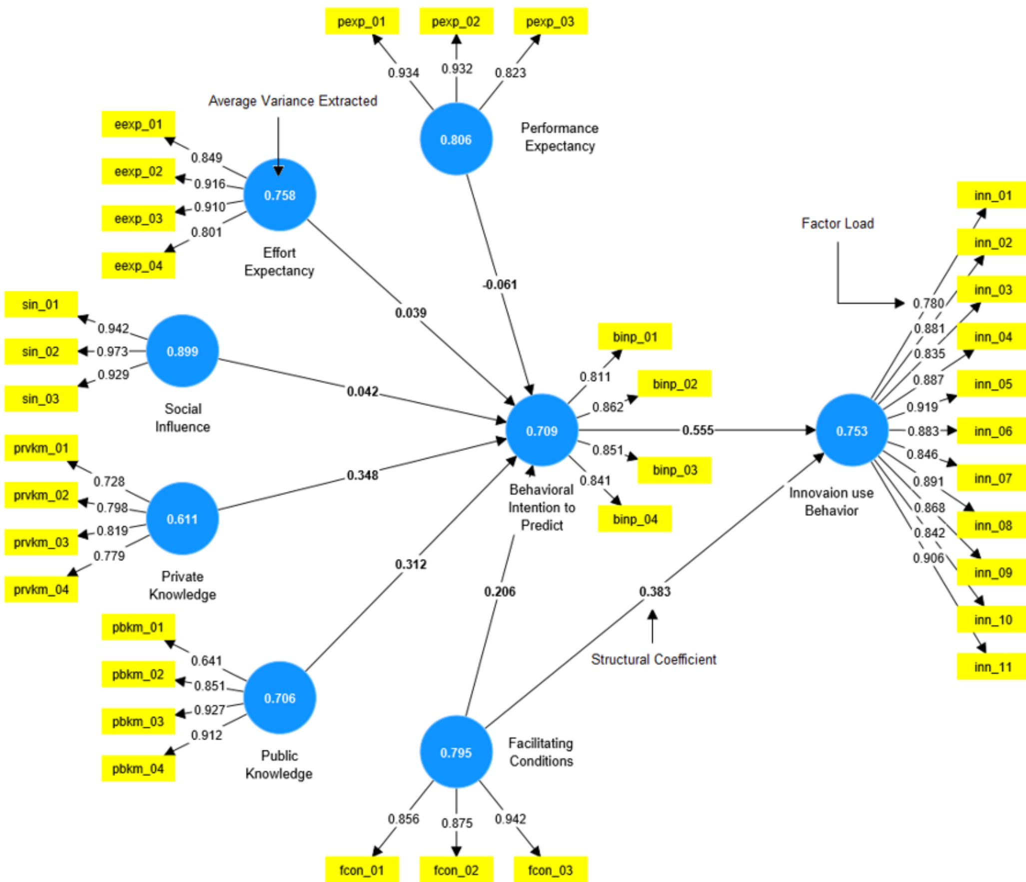


Table 9. Outcomes of persistence modeling for test and training sets

		n	Percent
Sample	Training	96	77,4%
	Testing	28	29,0%
Valid		124	100,0%
Excluded		84	
Total		208	

Source: SPSS program

The validation of the ANN estimated in this study is presented in Figures 3 and 4, which show the behavior of the predicted value for each observed value and the graph of the value of the residuals for each predicted value of the dependent variable, respectively. The behavior of the predicted values by the observed values is expected to present linearity.

In Figure 1, the analysis of the residuals shows that the normality hypothesis was met since the graph shows a behavior around the horizontal line centered at zero without characterizing a positive or negative trend.

Table 10. Network information

Network Information			
Input Layer	Covariates	1	PRVKM
		2	PUBKM
		3	PEXP
		4	EEXP
		5	SIN
		6	FCON
		7	BINP
	Number of Units[a]		7
	Rescaling Method for Covariates		Standardized
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		3
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	INN
	Number of Units		1
	Rescaling Method for Scale Dependents		Standardized
	Activation Function		Identity
	Error Function		Sum of Squares

Table 11. Parameter estimates

Predictor		Predicted			
		Hidden Layer 1			Output Layer
		H(1:1)	H(1:2)	H(1:3)	INN
Input Layer	(Bias)	-0.295	-0.792	-0.089	
	PRVKM	0.445	-0.439	0.502	
	PUBKM	0.466	-0.487	0.317	
	PEXP	0.379	-0.212	-0.154	
	EEXP	-0.130	-0.477	0.387	
	SIN	-0.034	-0.291	0.401	
	FCON	-0.077	0.068	-0573	
	BINP	-0.323	0.206	-1.113	
Hidden Layer 1	(Bias)				-0.456
	H(1:1)				0.306
	H(1:2)				-0.819
	H(1:3)				-0.944

In Figure 2, the analysis of the residuals shows that the normality hypothesis was met since the graph shows a behavior around the horizontal line centered on zero without characterizing a positive or negative trend.

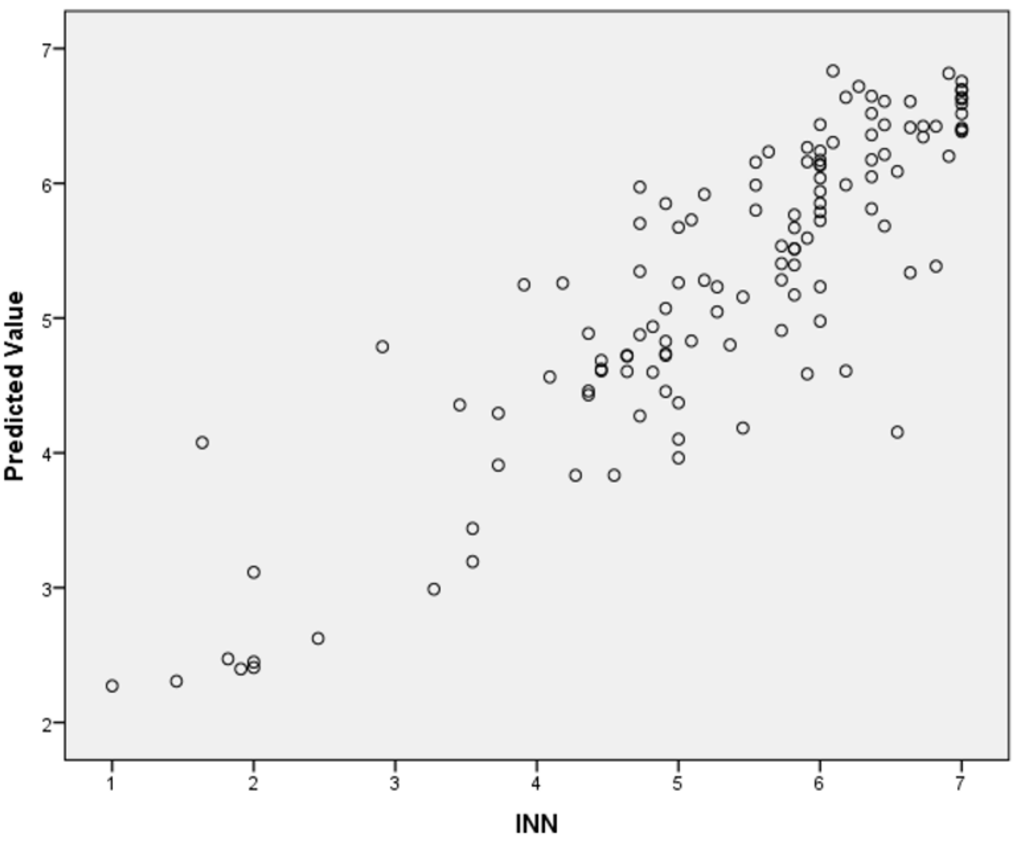
Table 13 and Figure 5 show information regarding the analysis of the importance of the independent variables in the construction of the ANN. It is observed that the variable Behavioral Intention Predict (BINP) is the one that contributes most to the prediction of RNA, that is, 100%,

Table 12. Model summary

Training	Sum of Squared Errors	13.873
	Relative error	0.292
	Stop rule used	1 consecutive step(s) without any decrease in error[a]
	Training Time	0:00:00.04
Testing	Sum of Squared Errors	1.993
	Relative error	0.104

Dependent variable: Inn; a: Error calculations are based on the test sample.

Figure 3. Graph of predicted value by observed value



followed by the variables Performance Expectancy (PEXP) that contributed with 85.6%, Facilitating Conditions (FCON) with 83.9%, Public Knowledge (PUBKM) with 53.5%, Private Knowledge (PRVKM) with 40.4%, Effort Expectancy (EEXP) with 39.4 and Social Influence (SIN) with 39.1.

DISCUSSION

The results support hypotheses 4, 5, 7, and 8 that the mixed model meets the prediction of the innovation behavior in the digital services sector, FinTech's. For these reasons, the ANN predicts the intention to

Figure 4. Graph of residuals per prediction

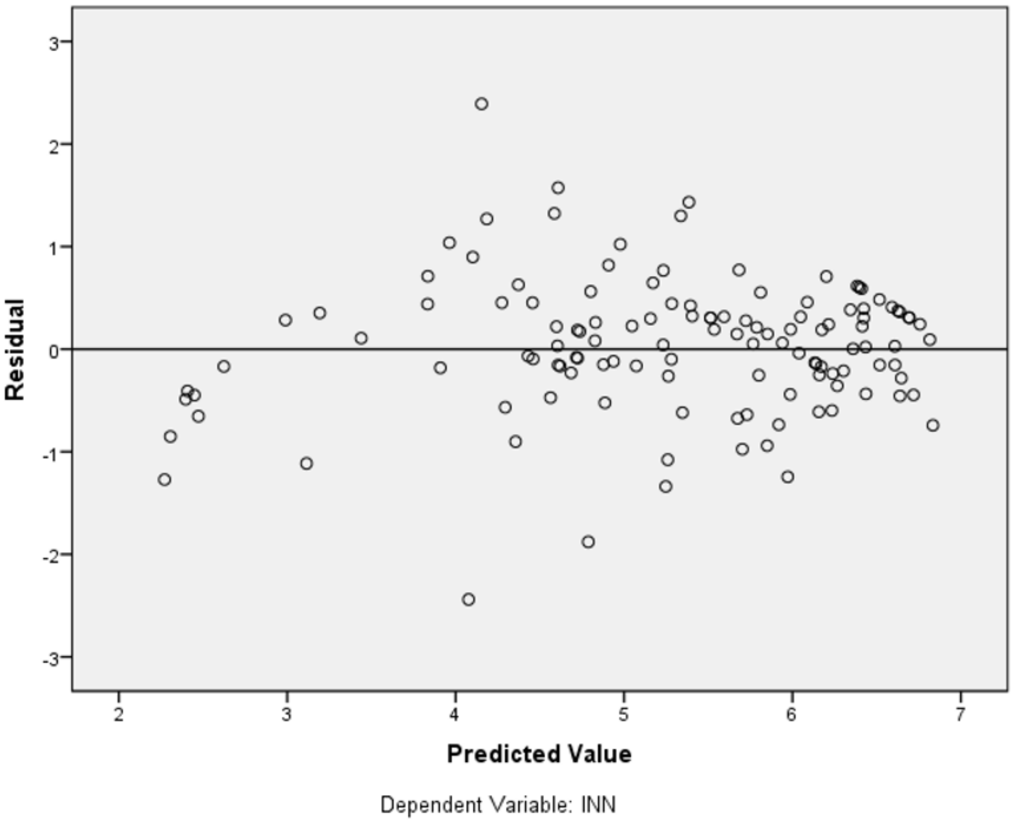


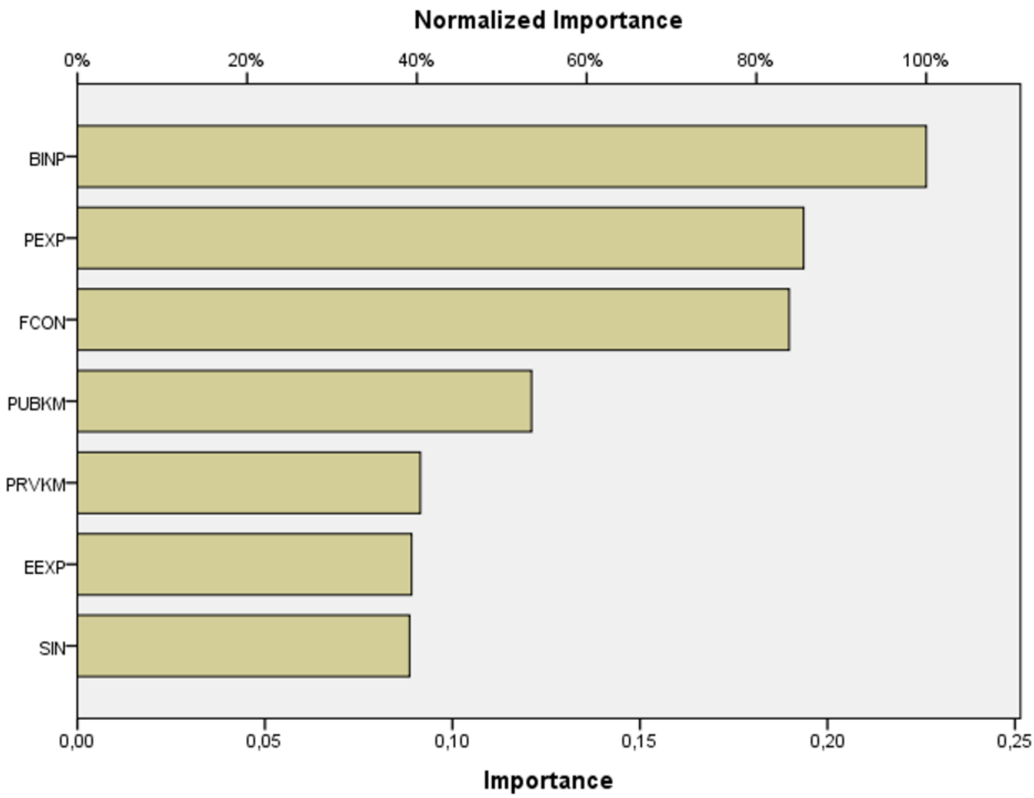
Table 13. Importance of the independent variable (innovation)

Variable	Importance	Normalized Importance (%)
Private Knowledge (PRVKM)	0.091	40.4
Publick Knowledge (PUBKM)	0.121	53.5
Performance Expectancy (PEXP)	0.194	85.6
Effort Expectancy (EEXP)	0.089	39.4
Social Influence (SIN)	0.089	39.1
Facilitating Conditions (FCON)	0.190	83.9
Behavioral Intention to Predict (BINP)	0.226	100.0

innovate in the Brazilian market. First, 74.4% of the network is oriented to training the model (with a relative error of 0,292), while 29.0% is oriented to testing the model. The ANN case processing summary and the network information deal with its construction characteristics.

Second, we observed that the mixed methodological approach, SEM, and ANN could help to find the linear and non-linear relationships better, being that the error of the predicted model is 0.104, that is, 10.4% relatively low, which evidences that ANN, can be used to predict the dependent variable

Figure 5. Graph representing the importance of the innovation variable



innovation safely. The importance of innovation variables' Behavioral Intention to Predict (BINP) to the study was 100%, followed by Performance Expectancy (PEXP) and Facilitating Conditions (FCON), both with more than 80%.

Considering *hypothesis 4*, our study supports that PVRKM (Private Knowledge) positively influences the intention to predict innovation for supply chain financing. This corroborates with Emtehani et al. (2023) that a comprehensive SCF framework by introducing two novel coordinating contracts that leverage trade credit financing was designed to address different problem settings within the supply chain. This is an example of an internal solution provided according to internal knowledge (Private Knowledge) to support the innovation process.

In terms of *hypothesis 5,* PUBKM (Public Knowledge) positively influences the intention to predict innovation for supply chain financing*;* our findings are consistent with Taleizadeh et al. (2022) in that the emergence of online peer-to-peer (P2P) lending platforms has introduced a promising FinTech business model that connects investors with capital recipients within supply chains (SCs). It means that the model is open to receiving external (public) knowledge to predict the sector's innovation through a digital platform.

H*ypothesis 7,* FCON (Facilitating Conditions), positively explains the innovation use behavior; according to Tsai (2023), advanced technology (blockchain) has been used to address current challenges in supply chain financing processes. This means that academics and professionals urgently need accurate and up-to-date knowledge of FinTech (Phan et al., 2022). In addition, Long et al. (2023) reinforce that to investigate how financial literacy and behavioral traits affect the adoption of electronic payment (ePayment) services, it was necessary to have an instrumental variable approach to facilitate the conditions to innovate.

Bringing *hypothesis 8,* INN (Innovation) positively influences innovation use behavior; it supports our empirical results according to Kao et al. (2022), where numerous financial institutions are keen on embracing technological solutions to bolster operational efficiency in managing SCF. This intricate process involves multiple participants and encompasses many complex financial activities. To conclude, our study brought value to the FinTech company, showing a mixed model that could be applied to predict the intention to innovate in the financial sector. Furthermore, the model showed accuracy using 50% of the proposed variables, being part of the UTAUT model and part of the SPINNER model, creating a balance in terms of hypotheses proposed and tested.

THEORETICAL IMPLICATIONS

The study results from applying the mixed method provide important theoretical and practical implications. Theoretically, we can extend the theory on digital services from FinTechs by considering some determinants. First, we understand which variables determine the intention to adopt innovation in FinTech's digital services by applying the hybrid model. Previous literature points to the use and relevance of the UTAUT model in several sectors, with greater relevance in the technology sector regarding technology adoption. In the case of the SPINNER model, its application in predicting innovation in SMEs was perceived. Second, we found that the behavioral determinant affects the intention to predict innovation (BINP) by 100%, regardless of the digital financial service developed by FinTech. Third, our findings advance theories on behavioral biases in decisions related to financial innovation in general and in technology adoption and digital service innovation prediction of FinTechs. In general, theories related to FinTechs broadly consider the context of investment and risk and avoid considering behavioral factors.

PRACTICAL IMPLICATIONS

This study has significant practical implications for startup entrepreneurs, FinTechs, and other financial sector institutions looking to deliver digital innovation products. This initial approach reinforces the importance of knowing and understanding the determinant variables of behavior related to financial innovation.

Innovation in the financial sector requires the consideration and knowledge of certain innovation-related behaviors, such as the relationship between effort expectancy and social influence, which may constitute a barrier to adopting innovation in FinTechs. On the other hand, knowledge of the relationship between public and private knowledge can mediate innovation in the financial sector. In addition, knowledge of the enabling conditions, the expectation of effort, and especially the intention to foresee innovation can be perceived as facilitators of the innovation process of FinTechs. In conclusion, including behavioral programs can help improve innovation prediction in FinTechs. Contributing a set of internal and external knowledge to the business can mitigate behavioral resistance to innovation. This, carrying out a co-creation process and interacting with different financial system actors to develop intensive digital solutions.

CONCLUSION

Over time, models based on artificial intelligence applications, such as artificial neural networks and deep learning, have been highlighted in various scientific studies and applications in different sectors (Chang, Wang, & Chuang, 2022; Du et al., 2022; Du & Shu, 2022; Feng & Chen, 2022; Hossain et al., 2022; Hou et al., 2022; Li, Wang et al., 2022; Li, Shang et al., 2022; Liu & Li, 2022; Paul, Riaz, & Das, 2022; Qiu, 2022; Rashidin et al., 2022; Shrivastav, 2022; Sun et al., 2022; Varsha et al., 2021; Wu, Qiao et al., 2022; Wu, Zhu et al., 2022; Xu, Xiang, & He, 2022; Yang & Wu, 2022; Zhao, 2022). However, the financial sector - FinTech, has shown strong growth in using this method to provide financial solutions.

This study aims to verify the application of determinants for SCF in Brazil. The accuracy of the mixed model, SEM, and ANN can help to find the linear and non-linear relationships better, being that the error of the predicted model is 0.104, that is, 10.4% relatively low, which evidences that ANN can be used to predict the dependent variable innovation safely. The application of the mixed model allowed significant results to be identified. The number of training and test samples is controlled to investigate prediction in the financial sector innovation context. The number of training cases was 96 (77,4%), and 46 (29,0%) cases were used for the test.

Although this study found that the mixed approach, including SEM and ANN, can help to find the linear and non-linear relationships better, reliably predicting the dependent variable innovation - this research shows some limitations. First, even though ANN is considered an excellent data analysis method, it is a model that finance professionals may probably find difficult to apply. Second, data from a FinTech based in Brazil was used in the study. Although the FinTech market in Latin America has been growing exponentially, influenced by the advancement of digitalization, the results cannot be generalized. The result of the study cannot represent a global view of the sector, as it lacks a more detailed and extended analysis to address a global market in terms of financial innovation.

Future studies can consider a few approaches: First, they can test the variables with new statistical approaches and compare them with the current model. Second, they can consider other digital services, regions, and countries. Third, researchers can compare the accuracy of other methods or mixed models in predicting innovation. Fourth, future studies can consider samples from various markets and compare the results against a single market or digital service. Finally, another future suggestion is exploring which artificial neural network approaches can be used to predict predictive behavior better.

REFERENCES

Abou-Shouk, M., & Soliman, M. (2021). The impact of gamification adoption intention on brand awareness and loyalty in tourism: The mediating effect of customer engagement. *Journal of Destination Marketing & Management*, *20*, 100559. doi:10.1016/j.jdmm.2021.100559

Atmaca, S., & Karadaş, H. A. (2020). Decision making on financial investment in Turkey by using ARDL long-term coefficients and AHP. *Financial Innovation*, *6*(1), 30. doi:10.1186/s40854-020-00196-z

Chang, T., Wang, N., & Chuang, W. (2022). Stock Price Prediction Based on Data Mining Combination Model. *Journal of Global Information Management*, *30*(7), 1–19. doi:10.4018/JGIM.296707

Chang, V., Chen, W., Xu, Q. A., & Xiong, C. (2021). Towards the Customers' Intention to Use QR Codes in Mobile Payments. *Journal of Global Information Management*, *29*(6), 1–21. doi:10.4018/JGIM.20211101.oa37

Chen, C., Li, G., Fan, L., & Qin, J. (2021). The Impact of Automated Investment on Peer-to-Peer Lending: Investment Behavior and Platform Efficiency. *Journal of Global Information Management*, *29*(6), 1–22. doi:10.4018/JGIM.20211101.oa36

Chen, X., & Liu, H. (2023). Collaborative innovation evolution of the logistics and manufacturing industry in China. *PLoS One*, *18*(6), e0287060. doi:10.1371/journal.pone.0287060 PMID:37319280

Chen, X., Ye, S., & Huang, C. (2021). Cluster-Based Mutual Fund Classification and Price Prediction Using Machine Learning for Robo-Advisors. *Computational Intelligence and Neuroscience*, *2021*, 1–14. doi:10.1155/2021/4984265 PMID:34956347

Chin, W. W. (2010). How to Write Up and Report PLS Analyses. In Handbook of Partial Least Squares: Concepts, Methods and Applications. Springer. doi:10.1007/978-3-540-32827-8_29

Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences* (Vol. 2). Psychology Press.

Dahri, N. A., Al-Rahmi, W. M., Almogren, A. S., Yahaya, N., Vighio, M. S., Al-maatuok, Q., Al-Rahmi, A. M., & Al-Adwan, A. S. (2023). Acceptance of Mobile Learning Technology by Teachers: Influencing Mobile Self-Efficacy and 21st-Century Skills-Based Training. *Sustainability (Basel)*, *15*(11), 8514. doi:10.3390/su15118514

Deweerdt, T., Caltabiano, K., & Dargusch, P. (2022). Original Research: How Will the TNFD Impact the Health Sector's Nature-Risks Management? *International Journal of Environmental Research and Public Health*, *19*(20), 13345. doi:10.3390/ijerph192013345 PMID:36293926

Du, P., & Shu, H. (2022). Exploration of Financial Market Credit Scoring and Risk Management and Prediction Using Deep Learning and Bionic Algorithm. *Journal of Global Information Management*, *30*(9), 1–29. doi:10.4018/JGIM.293286

Du, X., Zhao, X., Wu, C., & Feng, K. (2022). Functionality, Emotion, and Acceptance of Artificial Intelligence Virtual Assistants: The Moderating Effect of Social Norms. *Journal of Global Information Management*, *30*(7), 1–21. doi:10.4018/JGIM.290418

Ebadi, S., & Raygan, A. (2023). Investigating the facilitating conditions, perceived ease of use and usefulness of mobile-assisted language learning. *Smart Learning Environments*, *10*(1), 30. doi:10.1186/s40561-023-00250-0

Emtehani, F., Nahavandi, N., & Rafiei, F. M. (2023). Trade credit financing for supply chain coordination under financial challenges: A multi-leader–follower game approach. *Financial Innovation*, *9*(1), 6. doi:10.1186/s40854-022-00401-1

Erfanian, S., Zhou, Y., Razzaq, A., Abbas, A., Safeer, A. A., & Li, T. (2022). Predicting Bitcoin (BTC) Price in the Context of Economic Theories: A Machine Learning Approach. *Entropy (Basel, Switzerland)*, *24*(10), 1487. doi:10.3390/e24101487 PMID:37420506

Faghih Mohammadi Jalali, M., & Heidari, H. (2020). Predicting changes in Bitcoin price using grey system theory. *Financial Innovation*, *6*(1), 13. doi:10.1186/s40854-020-0174-9

Fedorko, I., Bačik, R., & Gavurova, B. (2021). Effort expectancy and social influence factors as main determinants of performance expectancy using electronic banking. *Banks and Bank Systems*, *16*(2), 27–37. doi:10.21511/bbs.16(2).2021.03

Feng, Z., & Chen, M. (2022). Platformance-Based Cross-Border Import Retail E-Commerce Service Quality Evaluation Using an Artificial Neural Network Analysis. *Journal of Global Information Management*, *30*(11), 1–17. doi:10.4018/JGIM.306271

Ferpozzi, H. (2023). Public-Private Partnerships and the Landscape of Neglected Tropical Disease Research: The Shifting Logic and Spaces of Knowledge Production. *Minerva*. Advance online publication. doi:10.1007/s11024-023-09496-x PMID:37359299

Figueiredo, R., & de Matos Ferreira, J. J. (2020). Spinner Model: Prediction of Propensity to Innovate Based on Knowledge-Intensive Business Services. *Journal of the Knowledge Economy*, *11*(4), 1316–1335. doi:10.1007/s13132-019-00607-2

Figueiredo, R., Ferreira, J. J. M., Silveira, R. G., & Villarinho, A. T. (2020). Innovation and co-creation in knowledge intensive business services: The Spinner model. *Business Process Management Journal*, *26*(4), 909–923. doi:10.1108/BPMJ-10-2019-0424

Figueiredo, R., Magalhães, C., & Huber, C. (2023). How to Predict the Innovation to SMEs? Applying the Data Mining Process to the Spinner Innovation Model. *Social Sciences (Basel, Switzerland)*, *12*(2), 75. doi:10.3390/socsci12020075

Figueiredo, R., Soliman, M., Al-Alawi, A. N., & Fatnassi, T. (2023). Could the 'Spinner Innovation'and 'Triple Helix'Models Improve System Innovation? *Applied System Innovation*, *6*(2), 42. doi:10.3390/asi6020042

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *JMR, Journal of Marketing Research*, *18*(1), 39–50. doi:10.1177/002224378101800104

Garcia-Nisa, I., Evans, C., & Kendal, R. L. (2023). The influence of task difficulty, social tolerance and model success on social learning in Barbary macaques. *Scientific Reports*, *13*(1), 1176. doi:10.1038/s41598-022-26699-6 PMID:36670123

Garg, G., Shamshad, M., Gauhar, N., Tabash, M. I., Hamouri, B., & Daniel, L. N. (2023). A Bibliometric Analysis of Fintech Trends: An Empirical Investigation. *International Journal of Financial Studies*, *11*(2), 79. doi:10.3390/ijfs11020079

Ge, C., Lv, W., & Wang, J. (2023). The Impact of Digital Technology Innovation Network Embedding on Firms' Innovation Performance: The Role of Knowledge Acquisition and Digital Transformation. *Sustainability (Basel)*, *15*(8), 6938. doi:10.3390/su15086938

Guo, J., Jia, F., Yan, F., & Chen, L. (2023). E-commerce supply chain finance for SMEs: The role of green innovation. *International Journal of Logistics Research and Applications*, 1–20. 10.1080/13675567.2023.2167959

Hair, J. F. Jr, Babin, B. J., & Krey, N. (2017). Covariance-Based Structural Equation Modeling in the *Journal of Advertising*: Review and Recommendations. *Journal of Advertising*, *46*(1), 163–177. doi:10.1080/00913367.2017.1281777

Hair, J. F., Jr., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2009). Análise multivariada de dados (6.a ed.). Bookman.

Hair, J. F. Jr, Howard, M. C., & Nitzl, C. (2020). Assessing measurement model quality in PLS-SEM using confirmatory composite analysis. *Journal of Business Research*, *109*, 101–110. doi:10.1016/j.jbusres.2019.11.069

Hammouri, Q., Aloqool, A., Saleh, B. A., Aldossary, H., Frejat, S. Y. A., Halim, M., Almajali, D. A., Al-Gasawneh, J. A., & Darawsheh, S. R. (2023). An empirical investigation on acceptance of e-wallets in the fintech era in Jordan: Extending UTAUT2 model with perceived trust. *International Journal of Data and Network Science*, *7*(3), 1249–1258. doi:10.5267/j.ijdns.2023.4.013

Hassan, S. B., & Soliman, M. (2021). COVID-19 and repeat visitation: Assessing the role of destination social responsibility, destination reputation, holidaymakers' trust and fear arousal. *Journal of Destination Marketing & Management*, *19*, 100495. doi:10.1016/j.jdmm.2020.100495

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. doi:10.1007/s11747-014-0403-8

Horvát, E.-Á., Dambanemuya, H. K., Uparna, J., & Uzzi, B. (2023). Hidden Indicators of Collective Intelligence in Crowdfunding. *Proceedings of the ACM Web Conference 2023*, 3806–3815. doi:10.1145/3543507.3583414

Hossain, M. A., Akter, S., Yanamandram, V., & Gunasekaran, A. (2022). Operationalizing Artificial Intelligence-Enabled Customer Analytics Capability in Retailing. *Journal of Global Information Management*, *30*(8), 1–23. doi:10.4018/JGIM.298992

Hou, H., Tang, K., Liu, X., & Zhou, Y. (2022). Application of Artificial Intelligence Technology Optimized by Deep Learning to Rural Financial Development and Rural Governance. *Journal of Global Information Management*, *30*(7), 1–23. doi:10.4018/JGIM.289220

Irimia-Diéguez, A., Velicia-Martín, F., & Aguayo-Camacho, M. (2023). Predicting Fintech Innovation Adoption: The Mediator Role of Social Norms and Attitudes. *Financial Innovation*, *9*(1), 36. doi:10.1186/s40854-022-00434-6 PMID:36687792

Kamarozaman, Z., & Razak, F. Z. A. (2021). The role of facilitating condition in enhancing user's continuance intention. *Journal of Physics: Conference Series*, *1793*(1), 012022. doi:10.1088/1742-6596/1793/1/012022

Kao, Y.-C., Shen, K.-Y., Lee, S.-T., & Shieh, J. C. P. (2022). Selecting the Fintech Strategy for Supply Chain Finance: A Hybrid Decision Approach for Banks. *Mathematics*, *10*(14), 2393. doi:10.3390/math10142393

Knight, D., Nkya, I. H., West, N. S., Yang, C., Kidorf, M., Latkin, C., & Saleem, H. T. (2023). Economic, social, and clinic influences on opioid treatment program retention in Dar es Salaam, Tanzania: A qualitative study. *Addiction Science & Clinical Practice*, *18*(1), 19. doi:10.1186/s13722-023-00374-1 PMID:36973794

Lee, C.-L., Strong, R., Briers, G., Murphrey, T., Rajan, N., & Rampold, S. (2023). A Correlational Study of Two US State Extension Professionals' Behavioral Intentions to Improve Sustainable Food Chains through Precision Farming Practices. *Foods*, *12*(11), 2208. doi:10.3390/foods12112208 PMID:37297453

Lee, K. H., & Min, B. (2015). Green R&D for eco-innovation and its impact on carbon emissions and firm performance. *Journal of Cleaner Production*, *108*, 534–542. doi:10.1016/j.jclepro.2015.05.114

Leung, G. S., Cho, V., & Wu, C. H. (2021). Crowd Workers' Continued Participation Intention in Crowdsourcing Platforms: An Empirical Study in Compensation-Based Micro-Task Crowdsourcing. *Journal of Global Information Management*, *29*(6), 1–28. doi:10.4018/JGIM.20211101.oa13

Li, G., Wang, X., Bi, D., & Hou, J. (2022). Risk Measurement of the Financial Credit Industry Driven by Data: Based on DAE-LSTM Deep Learning Algorithm. *Journal of Global Information Management*, *30*(11), 1–20. doi:10.4018/JGIM.308806

Li, J., He, Z., & Wang, S. (2022). A survey of supply chain operation and finance with Fintech: Research framework and managerial insights. *International Journal of Production Economics*, *247*, 108431. doi:10.1016/j.ijpe.2022.108431

Li, J., Zhang, G., Ned, J. P., & Sui, L. (2023). How does digital finance affect green technology innovation in the polluting industry? Based on the serial two-mediator model of financing constraints and research and development (R&D) investments. *Environmental Science and Pollution Research International*, *30*(29), 74141–74152. doi:10.1007/s11356-023-27593-y PMID:37202633

Li, M., Shang, X., Liu, N., Pan, X., & Han, F. (2022). Knowledge Management in Relationship Among Abusive Management, Self-Efficacy, and Corporate Performance Under Artificial Intelligence. *Journal of Global Information Management*, *30*(11), 1–26. doi:10.4018/JGIM.307067

Li, Q., & Tan, S. (2021). Innovative Development Path of State-owned Economy—Evidence Based on The Impact of COVID-19 on The Development of Chinese State-owned Industrial Enterprises and Their Post-epidemic Recovery from Financial Perspective. *E3S Web of Conferences, 275*, 01002. 10.1051/e3sconf/202127501002

Lim, A. F., Lee, V. H., Foo, P. Y., Ooi, K. B., & Wei–Han Tan, G. (2022). Unfolding the impact of supply chain quality management practices on sustainability performance: An artificial neural network approach. *Supply Chain Management*, *27*(5), 611–624. doi:10.1108/SCM-03-2021-0129

Liu, Q., & Li, J. (2022). The Progress of Business Analytics and Knowledge Management for Enterprise Performance Using Artificial Intelligence and Man-Machine Coordination. *Journal of Global Information Management*, *30*(11), 1–21. doi:10.4018/JGIM.302642

Liu, X., Wang, Y., Wang, J., & Xu, W. (2023). Supply chain financial logistics supervision system based on blockchain technology. *Journal of Ambient Intelligence and Humanized Computing*, *14*(8), 11059–11069. doi:10.1007/s12652-022-04452-1

Liu, Y., Zhang, S., Chen, M., Wu, Y., & Chen, Z. (2021). The Sustainable Development of Financial Topic Detection and Trend Prediction by Data Mining. *Sustainability (Basel)*, *13*(14), 7585. doi:10.3390/su13147585

Liu, Z., Panfilova, E., Mikhaylov, A., & Kurilova, A. (2022). Assessing Stability in the Relationship Between Parties in Crowdfunding and Crowdsourcing Projects During the COVID-19 Crisis. *Journal of Global Information Management*, *30*(4), 1–18. doi:10.4018/JGIM.297905

Liu, Z., Sakulyeva, T., Mikheev, A., & Stepanova, D. (2022). Management Problems in Global Crowdsourcing. *Journal of Global Information Management*, *30*(3), 1–15. doi:10.4018/JGIM.20220701.oa3

Long, T. Q., Morgan, P. J., & Yoshino, N. (2023). Financial literacy, behavioral traits, and ePayment adoption and usage in Japan. *Financial Innovation*, *9*(1), 101. doi:10.1186/s40854-023-00504-3 PMID:37325238

Mahmoudi, A., Sadeghi, M., & Naeni, L. M. (2023). Blockchain and supply chain finance for sustainable construction industry: Ensemble ranking using Ordinal Priority Approach. *Operations Management Research*. 10.1007/s12063-023-00374-z

Malaquias, R. F., Malaquias, F. F., Ha, Y. M., & Hwang, Y. (2021). A Cross-Country Study on Intention to Use Mobile Banking: Does Computer Self-Efficacy Matter? *Journal of Global Information Management*, *29*(2), 102–117. doi:10.4018/JGIM.2021030106

Mallikarjuna, M., & Rao, R. P. (2019). Evaluation of forecasting methods from selected stock market returns. *Financial Innovation*, *5*(1), 40. doi:10.1186/s40854-019-0157-x

Netemeyer, R. G., Bearden, W. O., & Sharma, S. (2003). *Scaling procedures: issues and applications*. Sage. doi:10.4135/9781412985772

Nuseir, M. T., & Elrefae, G. (2022). The effects of facilitating conditions, customer experience and brand loyalty on customer-based brand equity through social media marketing. *International Journal of Data and Network Science*, *6*(3), 875–884. doi:10.5267/j.ijdns.2022.2.009

Oral, E., & Unal, G. (2019). Modeling and forecasting time series of precious metals: A new approach to multifractal data. *Financial Innovation*, *5*(1), 22. doi:10.1186/s40854-019-0135-3

Paul, S. K., Riaz, S., & Das, S. (2022). Adoption of Artificial Intelligence in Supply Chain Risk Management: An Indian Perspective. *Journal of Global Information Management*, *30*(8), 1–18. doi:10.4018/JGIM.307569

Phan, X. T., Ngo, H. N., Nguyen, T. L., Pham, D. T., Truong, N. C., Pham, N. A., & Do, T. K. T. (2022). The effects of dynamic employee capabilities, fintech and innovative work behavior on employee and supply chain performance: Evidence from Vietnamese financial industry. *Uncertain Supply Chain Management*, *10*(4), 1305–1314. doi:10.5267/j.uscm.2022.7.009

Qi, T., Wu, F., Wu, C., He, L., Huang, Y., & Xie, X. (2023). Differentially private knowledge transfer for federated learning. *Nature Communications*, *14*(1), 3785. doi:10.1038/s41467-023-38794-x PMID:37355643

Qiu, J. (2022). Analysis of Human Interactive Accounting Management Information Systems Based on Artificial Intelligence. *Journal of Global Information Management*, *30*(7), 1–13. doi:10.4018/JGIM.294905

Ramírez-Correa, P., Grandón, E. E., Ramírez-Santana, M., Arenas-Gaitán, J., & Rondán-Cataluña, F. J. (2023). Explaining the Consumption Technology Acceptance in the Elderly Post-Pandemic: Effort Expectancy Does Not Matter. *Behavioral Sciences (Basel, Switzerland)*, *13*(2), 87. doi:10.3390/bs13020087 PMID:36829316

Rashidin, M., Gang, D., Javed, S., & Hasan, M. (2022). The Role of Artificial Intelligence in Sustaining the E-Commerce Ecosystem: Alibaba vs. Tencent. *Journal of Global Information Management*, *30*(8), 1–25. doi:10.4018/JGIM.304067

Sandkuhl, K. E. D., & Smirnov, A. V. (2018). Knowledge Management in Production Networks: Classification of Knowledge Reuse Techniques. *SPIIRAS Proceedings, 1*(56), 5. doi:10.15622/sp.56.1

Sang, G., Wang, K., Li, S., Xi, J., & Yang, D. (2023). Effort expectancy mediate the relationship between instructors' digital competence and their work engagement: Evidence from universities in China. *Educational Technology Research and Development*, *71*(1), 99–115. doi:10.1007/s11423-023-10205-4 PMID:36785812

Sewandono, R. E., Thoyib, A., Hadiwidjojo, D., & Rofiq, A. (2023). Performance expectancy of E-learning on higher institutions of education under uncertain conditions: Indonesia context. *Education and Information Technologies*, *28*(4), 4041–4068. doi:10.1007/s10639-022-11074-9 PMID:36247027

Shankar, A. (2022). Impact of Mobile Banking Application Interactivity on Consumer Engagement: An Experiment-Based Investigation. *Journal of Global Information Management*, *30*(5), 1–18. doi:10.4018/JGIM.290368

Sharma, S. K., Ilavarasan, P. V., & Karanasios, S. (2023). Small businesses and FinTech: A systematic review and future directions. *Electronic Commerce Research*. Advance online publication. doi:10.1007/s10660-023-09705-5

Shrivastav, M. (2022). Barriers Related to AI Implementation in Supply Chain Management. *Journal of Global Information Management*, *30*(8), 1–19. doi:10.4018/JGIM.296725

Soliman, M., Di Virgilio, F., Figueiredo, R., & Sousa, M. J. (2021). The impact of workplace spirituality on lecturers' attitudes in tourism and hospitality higher education institutions. *Tourism Management Perspectives*, *38*, 100826. doi:10.1016/j.tmp.2021.100826

Sołtysik-Piorunkiewicz, A., & Zdonek, I. (2021). How Society 5.0 and Industry 4.0 Ideas Shape the Open Data Performance Expectancy. *Sustainability (Basel)*, *13*(2), 917. doi:10.3390/su13020917

Song, H., Han, S., Liu, W., & Ganguly, A. (2023). What role do FinTech companies play in supply chain finance? A signaling intermediary perspective. *Journal of Business and Industrial Marketing*, *38*(6), 1279–1294. doi:10.1108/JBIM-12-2021-0587

Soni, G., Kumar, S., Mahto, R. V., Mangla, S. K., Mittal, M. L., & Lim, W. M. (2022). A decision-making framework for Industry 4.0 technology implementation: The case of FinTech and sustainable supply chain finance for SMEs. *Technological Forecasting and Social Change*, *180*, 121686. doi:10.1016/j.techfore.2022.121686

Sulistyaningrum, I. H., Pribadi, P., & Sari, S. (2023). Adaptation and validation of the telepharmacy service adoption behavior questionnaire during the COVID-19 pandemic crisis. *International Journal of Public Health Science*, *12*(2), 699. doi:10.11591/ijphs.v12i2.22518

Sun, K., Tan, A., Wang, Y. X., & Wickramasekera, R. (2022). Exploring Performance Management in China's Family SMEs Based on Structural Equation Modelling and Back-Propagation Neural Network. *Journal of Global Information Management*, *30*(11), 1–18. doi:10.4018/JGIM.301613

Tabachnick, B. G., & Fidell, L. S. (1991). Software for advanced ANOVA courses: A survey. *Behavior Research Methods, Instruments, & Computers*, *23*(2), 208–211. doi:10.3758/BF03203365

Talay, M. B., Akdeniz, M. B., & Kirca, A. H. (2017). When do the stock market returns to new product preannouncements predict product performance? Empirical evidence from the US automotive industry. *Journal of the Academy of Marketing Science*, *45*(4), 513–533. doi:10.1007/s11747-016-0507-4

Taleizadeh, A. A., Safaei, A. Z., Bhattacharya, A., & Amjadian, A. (2022). Online peer-to-peer lending platform and supply chain finance decisions and strategies. *Annals of Operations Research*, *315*(1), 397–427. doi:10.1007/s10479-022-04648-w

Taujanskaitė, K., & Kuizinaitė, J. (2022). Development of fintech business in Lithuania: Driving factors and future scenarios. *Business Management and Economics Engineering*, *20*(01), 96–118. doi:10.3846/bmee.2022.16738

Tsai, C.-H. (2023). Supply chain financing scheme based on blockchain technology from a business application perspective. *Annals of Operations Research*, *320*(1), 441–472. doi:10.1007/s10479-022-05033-3

v, V., Munjal, S. K., Jain, S., Abdullah V, Y., M, A., & Iyer, S. S. (2022, September 5). To investigate the knowledge, attitude and practices regarding tuberculosis case notification among public and private doctors practicing of modern medicine in South Delhi. *Monaldi Archives for Chest Disease*. Advance online publication. doi:10.4081/monaldi.2022.2374

Varsha, P. S., Akter, S., Kumar, A., Gochhait, S., & Patagundi, B. (2021). The Impact of Artificial Intelligence on Branding: A Bibliometric Analysis (1982-2019). *Journal of Global Information Management*, *29*(4), 221–246. doi:10.4018/JGIM.20210701.oa10

Venkatesh, V. (2006). Where To Go From Here? Thoughts on Future Directions for Research on Individual-Level Technology Adoption with a Focus on Decision Making. *Decision Sciences*, *37*(4), 497–518. doi:10.1111/j.1540-5414.2006.00136.x

Venkatesh, V. (2022). Adoption and use of AI tools: A research agenda grounded in UTAUT. *Annals of Operations Research*, *308*(1–2), 641–652. doi:10.1007/s10479-020-03918-9

Wamba, S. F., Queiroz, M. M., Blome, C., & Sivarajah, U. (2021). Fostering Financial Inclusion in a Developing Country: Predicting User Acceptance of Mobile Wallets in Cameroon. *Journal of Global Information Management*, *29*(4), 195–220. doi:10.4018/JGIM.20210701.oa9

Wang, L., Jia, F., Chen, L., & Xu, Q. (2022). Forecasting SMEs' credit risk in supply chain finance with a sampling strategy based on machine learning techniques. *Annals of Operations Research*. Advance online publication. doi:10.1007/s10479-022-04518-5

Wen, H., Shi, J., & Lu, P. (2023). Can Green Technology Innovation Reduce the Operational Risks of Energy-Intensive Enterprises? *Systems*, *11*(4), 194. doi:10.3390/systems11040194

Wong, L. W., Tan, G. W. H., Ooi, K. B., Lin, B., & Dwivedi, Y. K. (2022). Artificial intelligence-driven risk management for enhancing supply chain agility: A deep-learning-based dual-stage PLS-SEM-ANN analysis. *International Journal of Production Research*, 1–21. doi:10.1080/00207543.2022.2063089

Wu, Y. (2023). Retracted: Exploring the Influence of Big Data Technology on the Innovation of the Enterprise Economic Management Mode. *Security and Communication Networks*, *2023*, 1–1. doi:10.1155/2023/6560747

Wu, Y., & Kang, X. (2021). A Moderated Mediation Model of Expectancy-Value Interactions, Engagement, and Foreign Language Performance. *SAGE Open*, *11*(4). doi:10.1177/21582440211059176

Wu, Y., Zhu, D., Liu, Z., & Li, X. (2022). An Improved BPNN Algorithm Based on Deep Learning Technology to Analyze the Market Risks of A+H Shares. *Journal of Global Information Management*, *30*(7), 1–23. doi:10.4018/JGIM.313188

Wu, Z., Qiao, Y., Huang, S., & Liu, H. (2022). CVaR Prediction Model of the Investment Portfolio Based on the Convolutional Neural Network Facilitates the Risk Management of the Financial Market. *Journal of Global Information Management*, *30*(7), 1–19. doi:10.4018/JGIM.313188

Wut, T. M., Lee, S. W., & Xu, J. (2022). How do Facilitating Conditions Influence Student-to-Student Interaction within an Online Learning Platform? A New Typology of the Serial Mediation Model. *Education Sciences*, *12*(5), 337. doi:10.3390/educsci12050337

Xu, Z., Xiang, D., & He, J. (2022). Data Privacy Protection in News Crowdfunding in the Era of Artificial Intelligence. *Journal of Global Information Management*, *30*(7), 1–17. doi:10.4018/JGIM.286760

Yabutani, Y., & Yamada, N. (2023). Conditions facilitating the participation of residents of older apartment complexes in community activities in Japan: Basic study on community support measures. *Journal of Asian Architecture and Building Engineering*, *22*(1), 32–49. doi:10.1080/13467581.2021.2008399

Yang, K., Fujisaki, I., & Ueda, K. (2023). Social influence makes outlier opinions in online reviews offer more helpful information. *Scientific Reports*, *13*(1), 9625. doi:10.1038/s41598-023-35953-4 PMID:37369696

Yang, S., & Wu, H. (2022). The Global Organizational Behavior Analysis for Financial Risk Management Utilizing Artificial Intelligence. *Journal of Global Information Management*, *30*(7), 1–24. doi:10.4018/JGIM.296723

Yuan, Z., Liu, J., Deng, X., Ding, T., & Wijaya, T. T. (2023). Facilitating Conditions as the Biggest Factor Influencing Elementary School Teachers' Usage Behavior of Dynamic Mathematics Software in China. *Mathematics*, *11*(6), 1536. doi:10.3390/math11061536

Zareie, A., & Sakellariou, R. (2023). Influence maximization in social networks: A survey of behaviour-aware methods. *Social Network Analysis and Mining*, *13*(1), 78. doi:10.1007/s13278-023-01078-9

Zhang, W., Li, B., Liew, A. W.-C., Roca, E., & Singh, T. (2023). Predicting the returns of the US real estate investment trust market: Evidence from the group method of data handling neural network. *Financial Innovation*, *9*(1), 98. doi:10.1186/s40854-023-00486-2

Zhao, Y. (2022). Risk Prediction for Internet Financial Enterprises by Deep Learning Algorithm and Sustainable Development of Business Transformation. *Journal of Global Information Management*, *30*(7), 1–16. doi:10.4018/JGIM.300741

Zhong, S., & Hitchcock, D. (2021). S&P 500 Stock Price Prediction Using Technical, Fundamental and Text Data. *Statistics, Optimization & Information Computing*, *9*(4), 769–788. doi:10.19139/soic-2310-5070-1362

Zhong, X., & Enke, D. (2019). Predicting the daily return direction of the stock market using hybrid machine learning algorithms. *Financial Innovation*, *5*(1), 24. doi:10.1186/s40854-019-0138-0

Zhou, L., & Lee, H. (2023). Supply Chain Finance Business Model Innovation: Case Study on a Chinese E-Commerce-Centered SCF Adopter. *Systems*, *11*(6), 278. doi:10.3390/systems11060278

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