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Moderating the role of the perceived security and endorsement on the relationship between perceived risk and intention to use the artificial intelligence in financial services

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A B S T R A C T

Advancement of banking and financial investment has led to the rapid expansion of services automation. The consistent increase of Artificial Intelligence (AI) usage in investment management implies the impending popularity of technology-based service. This study examined influencer endorsement and perceived security benefits as moderators to the relationship between perceived risk and financial AI services. Questionnaires were disseminated to 300 respondents who were customers with experience of using financial AI services in Jordan, and they were chosen through purposive sampling method. Structural equation modeling run using Smart-partial least squares (PLS 3.3.6) was employed in analyzing the data obtained from 220 completed questionnaires. The results show that perceived risk negatively affects financial AI services, while influencer endorsement and perceived security moderate the relationship between perceived risk and financial AI services. This study provides insight to companies on how to reduce perceived risk to encourage people to use business intelligence applications, as in the use of financial technology services.

1. Introduction

Artificial intelligence (AI) is a wide concept nowadays and has gradually entered the daily life of people, from being primarily associated with science fiction. Today, people use AI in various forms and manners, daily. AI was first introduced in 1956 but as mentioned by Fletcher (2018), the progress of AI had been slow, particularly in its revolution into a technological reality. AI is now accepted in the general society, and in the business field, AI has been extensively used, in all industries and at all stages. In fact, today, AI technologies are crucial for businesses in maintaining a competitive edge (AL-Rawashdeh & Mamat, 2019).

AI comprises the technologies of machine learning (ML) and deep learning (DL) that are used in combination (Dwivedi & Hughes, 2019), and the use of AI in the financial services industry worldwide has radically changed the industry. The investment on AI by this industry is substantial and through the use of AI, this industry has significantly expanded at a very fast pace (Buchanan & Wright, 2021). In the field of finance, the use of AI has been more common among firms involved in hedge funds and HFT. Meanwhile, other domains have started to follow suit, as can be observed among insurance firms, regulators, and banks that have begun to implement AI.

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Fintech companies are among AI users. According to Mhlanga (2020), these companies use AI to encourage the poor, women, small businesses, youths, and low-income earners to take part in the mainstream financial market. Fintech is a product or service used by non-financial institutions in providing their clients with innovative service technologies (Sweeney et al., 2015). Additionally, Fintech is associated with the formation of models, values, and processes of financial related items like contracts, money, bonds, and stocks (Freedman, 2006). It also can be perceived as a financial services reform by technology (Wonglimpiyarat, 2017).

Financial Stability Board (FSB) laid down the four categories of Fintech as follows: 1) Fintech that involves Payments, Clearing, and Settlement via electronic wallet or digital money, 2) Fintech that involves Deposits, Loans and Capital Raising via crowdfunding, P2P lending platforms, and payday loans on just one platform which enables the sharing of profit from the funds, 3) Fintech that involves Market Provisioning / Aggregators that accumulate various kinds of important market information for consumers to facilitate their purchasing decisions, and 4) Fintech that involves Investment and Risk Management with services for instance financial planning, online trading platforms, and insurance. Online trading platforms or e-trading allows direct investment via computers and other assets (Masnita, 2021).

In Jordan, the use of AI and its various applications have resulted in new prospects in the labor market (Salameh & Lutfi, 2021), and its usage (alongside its applications) in government institutions in this country has made the provided services more accessible and more efficient, while also increasing the quality (Hawamleh & Ngah, 2017). Also, the use of AI and its applications among government institutions decreases cost and increases the acceptance in the society. Furthermore, the economic development is sped up through AI. Additionally, the incorporation of AI to the systems and solutions for matters like big data management and cyber-attacks has led to the creation of an innovation and entrepreneurship friendly environment (MoDEE, 2020).

Jordan is in the process of turning into a strong regional tech hub and an entrepreneurial enabler, leveraging the disposal of eminent local talents, with AI as the national strategic priority for the country to achieve sustainable development goals by 2030. Through AI, innovative methodologies could be efficiently developed, leading to the efficient application of both conventional and modern data sources and new data frameworks (MoDEE, 2020). It is thus crucial to improve AI applications including technological financial services applications to reduce perceived risk (Alhawamleh & Ngah, 2017; Park et al., 2019; Al-Gasawneh et al., 2021).

Influencer endorsement affects financial artificial intelligence (AI) services (Hu et al., 2019; Pelau et al., 2021), and Perceived Risk (Anuar et al., 2020; Veissi, 2017). Relevantly, perceived Monetary Benefit affects financial AI services and Perceived Risk (Kim, 2020; Gansser & Reich, 2021; Susanto et al., 2020; Xia & Hou, 2016). In Jordan, the use of financial AI services is still low among customers. Hence, in this study, influencer endorsement and perceived monetary benefits are the factors investigated as moderators in the reduction of perceived risks.

2. Literature review

2.1 Intention to using Financial Artificial Intelligence Services

Artificial Intelligence (AI) entails a collection of theories and algorithms that allow computer systems to perform tasks that require human intelligence, and in some situations, AI supersedes humans (Pau, 1991). Among the computer tasks that require human intelligence in their execution include text interpretation, visual perception, and visual recognition (Alhawamleh, 2012). AI was first introduced in the 50s, but it wasn't until recently that AI caught the interest of scholars and users alike. AI today is highly sophisticated and is popularly used in various domains because of the following (Lui & Lamb, 2018): 1) the growing volume of accessible digital data, 2) the increase in data storage and computational processing capacity at smaller cost, and 3) the use of sophisticated algorithms.

Payment transactions today usually involve the use of financial technologies or Fintech, and so, AI is essential in both online buying and selling, making AI an important part of people's life (Nagy & Hajdú, 2021; Alghasawneh et al., 2021). Online shopping is initiated by shopping intention which refers to the level to which consumers show their willingness in using the Internet services to purchase products or services or to compare products cost-wise (Iqbal et al., 2012). Shopping intention may be considered as a basis for consumer behavior anticipation. Meanwhile, shopping intention is impacted by a number of factors, making it a difficult construct to quantify. Schlosser, White and Lloyd (2006) accordingly mentioned the importance of online shopping privacy because it can increase online shopping intention. Shopping intention could predict the real purchase of customers, it is thus investigated in this study as demonstrated in Halimi et al. (2021). The parameters included are as follows: likelihood of shopping for products online, recommending online shopping to others, and making the purchase again in the future after a positive first online shopping experience. The present study examined the intention to perform online shopping as demonstrated in Masnita et al. (2021). The work measurement follows Al-Gasawneh et al. (2020).

2.2 Perceived risk

Online purchasing process is still inundated by uncertainties (Masoud, 2013), and perceived risk has been found to significantly impact online shopping (Jordan et al., 2018) aside from being a major booster to consumer behavior (Hong & Cha, 2013). As described in Chen (2010), perceived risk theory helps marketers in understanding the opinions of consumers. Therefore, marketing decisions usually would include risk analysis (Mitchell, 1999). Mitchell (1999) stated that it is common for customers to prioritize averting mistakes over boosting their purchasing effectiveness. For this reason, perceived risk is effective in describing the behavior of customers. Perceived risk relates to how far the use of the Internet in purchasing something is considered as risky. Fraud and violation of information privacy are all potential risks associated with the Internet environment. Meanwhile, consumer behavior involves certain risk, causing consumers to feel uncertain, which, as indicated by Jordan et al. (2018), may lead to undesirable outcomes. Consumers will try to decrease perceived risk in their purchasing progression (Jordan et al., 2018), and consumers usually would look for information to support their actions when they feel uncertain. Framarz et al. (2016) accordingly stated that perceived risk relates to the amount of money to be gained or lost during a purchase. Equally, it relates to how consumers feel towards the certainty of the favorableness of purchase outcomes, focusing on loss and uncertainty mostly. Accordingly, the variables investigated in this study are those relevant to the consumers' perceived risks namely: price, product quality, time loss, lack of good feel, after-sale service, price value psychological health, and privacy information. Jordan et al. (2018) relevantly reported that the variables impede the intention of consumers to use Financial AI Services.

2.3 Perceived security

Perceived security is an issue faced by consumers when purchasing services or products online, and according to Suh and Han (2003) it results from the vulnerabilities of the internet site from which the product is purchased. Notably, encryption, guard, confirmation, and authentication have been reported as antecedents of perceived security, as these variables impact consumer's perceived security (Chellappa & Pavlou, 2002). Furthermore, people generally are unaware that their information is being recorded, stored and perhaps unlawfully utilized. People are increasingly wary about revealing their sensitive information on the internet (Hawamleh et al., 2020). In this context, perceived security may be understood as the subjective likelihood, as perceived by the customer, that his or her personal or financial information will not be revealed, kept, and/or appropriated during e-commerce and storage by the external parties (Flavian et al., 2006). In terms of privacy, Eastlick et al. (2006) described it as the capability of a person in controlling, managing, and cautiously revealing his/her private information. In online transactions, the safety of private information is essential, and according to Liu et al. (2008), privacy safety denotes transaction integrity that impacts transaction choices. Affirmation of privacy can increase the perceived trustworthiness of e-carriers (Belanger et al., 2002). Many online buying sites have accordingly improved their privacy regulations in an attempt to eradicate the issues associated with purchaser security. Transaction security and payment systems are elements of perceived security. Many online customers waver just at the last stage of the ordering process, just prior to clicking the 'order' button. Relevantly, Bunduchi (2005) described transaction risks as operational risks related to other parties in the transaction who purposely mishandle the transaction.

2.4 Influencer Endorsement

Influencer endorsement refers to the addition of fame to some reliable somebody in their respective field to disseminate awareness of the brand in question, and particularize the product and its usage, to drive sales. Aanchal (2020) mentioned that influencer endorsement leverages the Influencer's knowhow and fame.

2.5 Hypothesis developments

2.5.1 Relationship between Perceived Risk and Financial AI Services

Essentially, online buying and selling involve using financial technologies in payment transactions which implies the involvement of AI (Nagy & Hajdú, 2021). In a study on online purchasing behavior of consumers, Masoud (2013) discussed six dimensions of consumers' perceived risk which negatively affected online purchasing behavior, but the author also mentioned that time risk and social risk had no impact on online shopping. Meanwhile, Amirtha, Sivakumar and Hwang (2021) found that perceived risk and intention to perform online shopping were negatively correlated. In their study, Hasan, Shams and Rahman (2020) found that the inclination to use AI apps is significantly and negatively affected by perceived risk. The following hypothesis was hence formed:

H_1: *Perceived Risk has a negative impact on financial AI services.*

2.5.2 The moderating effect of Influencer Endorsement on the relationship between Perceived Risk and Financial AI Services

Influencer endorsement imparts fame to certain reliable personalities in their respective arenas to increase the public's awareness of a brand in question and detail the specifics of the product and its usage, to generate sales (Ki et al., 2020). Masoud (2013) and Nagy and Hajdu (2021) relevantly reported that Perceived Risk had a negative impact on financial AI services, while a negative correlation between Perceived Risk and financial AI services was concluded in Amirtha, Sivakumar and Hwang (2021). When the relationship status between the predictors and the dependent variables is inconsistent, a moderating variable has to be included (Baron & Kenny, 1986; Bibi et al., 2016). A moderating variable is thus included in this study, to the relationship between perceived risk and financial AI services. Specifically, the influence of influencer endorsement was the moderator variable in this study, because it was found to affect financial AI services in several related studies (e.g., Hu et al., 2019; Pelau et al., 2021). Additionally, Perceived Risk's impact was explored in several studies including Anuar et al. (2020) and Veissi (2017). The construct of influencer endorsement was therefore expected to moderate the relationship between Perceived Risk and financial AI services. The following hypothesis was hence formulated:

H$_2$: *Influencer Endorsement moderates the relationship between Perceived Risk and Financial AI Services.*

2.5.3 The moderating effect of Perceived Security on the relationship between Perceived Risk and Financial AI Services

Perceived security theory suggests subjective probability of a customer being confident that the personal or financial information he/she provided will not be revealed, saved, and/or appropriated during e-commerce and during storage by external parties. Perceived Risk was found to negatively affect the intention to use financial AI in Masoud (2013) and Nagy and Hajdu (2021). Meanwhile, Amirtha, Sivakumar and Hwang (2021) reported that Perceived Risk was negatively associated with financial AI services. Hence, moderator variables should be included in the relationship between these constructs (Baron & Kenny, 1986; Bibi et al., 2016), considering that the status of the relationship has been inconsistent. The relationship between Perceived Risk and financial AI services needs to be examined with moderator variables because perceived security has been found to affect intention to use the financial AI services (see: Kim, 2020; Gansser & Reich, 2021). Also, perceived security was also found to affect Perceived Risk (see: Susanto et al., 2020; Xia & Hou, 2016). In this study, perceived Monetary Benefit was conjectured to moderate the relationship between Perceived Risk and financial AI services. Hence, the established hypothesis is as follows:

H$_3$: *Perceived Security moderates the relationship between Perceived Risk and Financial AI Services.*

3. Research method

This study adopted research parameters from past studies. Accordingly, three items of financial AI services perception based on the uni-dimensionality model from Al-Gasawneh et al. (2020) were included. Further, perceived security construct included two dimensions namely payment system covered by five items and Transaction security covered by six items as in Amriel's (2018) multi-dimensionality model. Meanwhile, the construct of influencer endorsement involved four dimensions of trustworthiness (covered by three items), credibility (covered by three items), physical appearance (covered by one item), and expertise and experience (covered by two items). The use of influencer endorsement was based on Aanchal's (2020) multi-dimensionality model. For the construct of perceived risk, this study followed Jordan et al.'s (2018) uni-dimensionality model, and this construct was covered by four items. For ease of measurement, a five-point Likert scale was provided to each item.

3.1 Sampling

The study population comprised users of intelligent financial services like online shopping. Online survey was the method used in this study to gather data. Respondents were provided with the survey link which was sent through social media platforms (e.g., WhatsApp, Instagram and Facebook). Also, they were asked to forward the link to other users of intelligent financial services activities (e.g., online shopping). Convenience sampling was the method applied in choosing the study respondents and the sampling method was deemed appropriate because the purpose of this study was to assess the validity of theoretical effects. The analysis was performed using structural equation modelling run using SmartPLS, as recommended by Hair et al. (2019). Furthermore, the power analysis results showed that the minimum sample size for this study was 73 with the medium effect size (0.8), based on three research predictors (Gefen et al., 2011). However, to gain the highest possible response rate, 300 participants were selected.

4. Data analysis and findings

The three hypotheses proposed in this study were tested using a variance-based SEM namely Smart-PLS 3.3.6, as proposed by Hair et al. (2019). This allowed prediction of the relationship between variables to be made. Out of the 250 answered questionnaires, 30 were incomplete and thus excluded from the analysis. Hence, 220 responses were the final number of analyzed responses.

4.1 Moderating Analysis Approach

The use of the partial least squares method in this study provided several approaches to moderator analysis, and this study employed the two-stage approach that follows the current reflective-reflective constructs. According to Hair et al. (2019), the approach allows the implication of the moderator effect to be evaluated, for both formative and reflective construct. Hence, the moderator effect was examined without facing issues associated with substandard statistical power of the product indicator approach. As suggested by its name, the approach involves two stages. Specifically, the first stage involved the evaluation of convergent validity and discriminant validity with no consideration on the interaction term. The second stage involved the identification of the structural model details, leading to the determination of the product indicator, resulting in the union of the interaction term together with the predictor and moderator variables (see: Hair et al., 2017).

4.2 Assessment of Measurement Model

SEM analysis was performed in this study and there were two steps involved. The first step involved the verification of the measurement model through the verification of convergent validity and discriminant validity, while the second step involved the verification of the structural model or the hypothesis testing. Accordingly, perceived risk, perceived monetary benefits and financial AI services were the examined key variables of first order constructs. For the second order constructs to expand the knowledge of relevant logical and consensus functions, influencer endorsement made up the reflective-reflective composition involving the factors of trustworthiness, credibility, physical appearance, expertise, and experience. During the second stage, the authors reduced the quantity of interactions and assumptions in the structural model order (see: Hair et al., 2017) to simplify the PLS direction model and improve understanding. There were two phases involved in this strategy implementation. In the first phase, repetitive indicator technique was applied to attain the first-order scores for first-order constructs, while the second phase involved the calculation of CR. Further, the first-order variables were weighted to compute the AVE of the second-order constructs. For convergent validity determination, Hair et al.'s (2017) suggestion was followed. Hence, convergent validity of the model would be assumed if loading and AVE was higher than 0.5 while composite reliability was higher than 0.7. Details of construct validity evaluation can be viewed in Table 1 and Fig. 1. As shown, Table 1 is showing values higher than specified value. Therefore, the model has convergent validity.

Table 1
Measurement Model

First order Construct	Items	Factor loading	CR	AVE
Perceived risk (PR)	PR 1	0.792	0.910	0.560
	PR 2	0.797		
	PR 3	0.764		
	PR 4	0.703		
	PR 5	0.741		
	PR 6	0.730		
	PR 7	0.712		
	PR 8	0.745		
Perceived Monetary Benefits (PMB)	PMB 1	0.897	0.914	0.842
	PMB 2	0.938		
Trustworthiness	Tr 1	0.828	0.906	0.762
	Tr 2	0.912		
	Tr 3	0.877		
Credibility	Cr 1	0.877	0.946	0.780
	Cr 2	0.867		
	Cr 3	0.886		
Physical appearance	PH 1	0.872	0.889	0.728
	PH 2	0.841		
	PH 3	0.845		
Expertise and Experience	EX 1	0.805	0.887	0.724
	EX 2	0.865		
	EX 3	0.881		
Financial Artificial Intelligence Services	FAIS 1	0.910	0.926	0.808
	FAIS 2	0.923		
	FAIS 3	0.862		
Transaction security	TS 1	0.853	0.932	0.720
	TS 2	0.845		
	TS 3	0.821		
	TS 4	0.847		
	TS 5	0.833		
	TS 6	0.849		
Payment system	PS 1	0.834	0.855	0.863
	PS 2	0.844		
	PS 3	0.819		
	PS 4	0.821		
	PS 5	0.839		
Second Order Constructs				
Influencer Endorsement	Trustworthiness	0.892	0.921	0.752
	Credibility	0.830		
	physical appearance	0.844		
	Expertise and Experience	0.823		
Perceived security	Transaction security	0.864	0.911	0.712
	Payment system	0.887		

In determining the discriminant validity of the measurement model, this study followed Franke and Sarstedt (2019). Hence, Heterotrait-Monotrait ratio (HTMT) was computed, and the resultant values have to be smaller than 0.85 to achieve discriminant validity. The values are all displayed in Table 2, and as shown, all values of HTMT were lower than the proposed cut-off value. Therefore, discriminant validity of the model is affirmed.

Table 2
Discriminant Validity (HTMT)

	PR	PS	Tr	Cr	PH	EX	IE	FAIS
PR								
PS	0.574							
Tr	0.836	0.533						
Cr	0.167	0.106	0.141					
PH	0.083	0.557	0.794	0.151				
EX	0.765	0.812	0.622	0.415	0.675			
IE	0.776	0.578	0.791	0.641	0.65	0.788		
FAIS	0.795	0.759	0.613	0.054	0.654	0.86	0.776	

4.3 Structural Model

The structural model was checked to see if it had a collinearity issue. From the obtained VIF value for all its constructs, all was lower than the cut-off value of 5 (see: Diamantopoulos & Siguaw, 2006). Hence, the model can be assumed to be free from collinearity issues. A bootstrapping procedure was executed with a resample of 5,000 in the evaluation of the model's standard beta (*B*) and t-values. Based on Hair et al. (2017), the model was also evaluated in terms of its effect sizes (f^2).

The results show a negative significant relationship between perceived risk and Financial AI Services (*B* = -0.533, t = 3.416, p < 0.01). This shows that H1 is supported. In determining the effect size (f^2), Cohen (1988) suggested that: 0.02 means small effect size, 0.15 means medium effect size, and 0.35 means large effect size. Hence, in this study, the variable supporting the hypothesis is showing large effect size. As for the coefficient value or R^2, it was 0.429, which means that the exogenous variables, namely cost, perceived benefits, readiness and customer pressures, with top management attitude, have the ability to explain 42.9% of variances. Additionally, the Q^2 value correlating with online shopping intention was larger than 0, specifically, 0.540. Therefore, it can be said that predictive power is present in the model. The details can be observed in Table 3 and Fig. 2.

Table 3
Hypotheses testing for direct relationships

	Path	St, β	St. d	R^2	Q^2	F^2	VIF	T-value	P-value
H1	PR >FAIS	-0.533	0.156	0.506	0.521	0.530	2.187	3.416	0.000

4.3.1 Moderation Analysis

The results of the moderating effect of Influencer Endorsement on the relationship between perceived risk and Financial AI Services are as follows: *B* = 0.402, t = 3.757: p < 0.05. This denotes that Influencer Endorsement moderated the negative relationship between perceived risk and Financial AI Services. Table 4 can be referred to. Next, the results of the moderating effect of Perceived security on the relationship between perceived risk and Financial AI Services are as follows: *B*=0.418, t = 2.235: p < 0.0.05. This shows that perceived security moderated the negative relationship between both constructs. The details of moderation analysis are provided in Fig. 3 and Fig. 4, and the non-parallel lines in each Dawson plot show that the relationship between perceived risk and Financial AI Services will be moderated by high-level influencer endorsement, and by high-level perceived security.

Table 4
Hypotheses testing for moderating variable

	Path	St, β	St. d	R^2	T-value	P-value
H3	PR-FAIS*IE	0.402	0.107		3.757	0.031
H2	PR-FAIS *PS	0.418	0.187	0.541	2.235	0.002

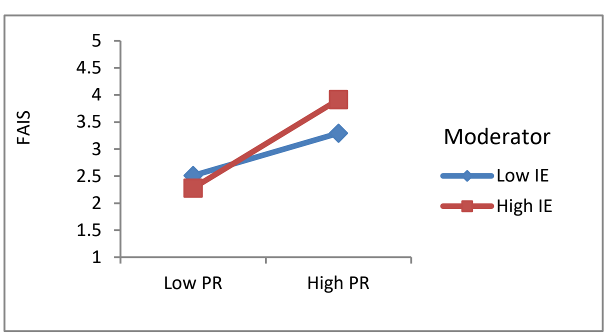

Fig. 3. Dawson's plot (moderating of IE)

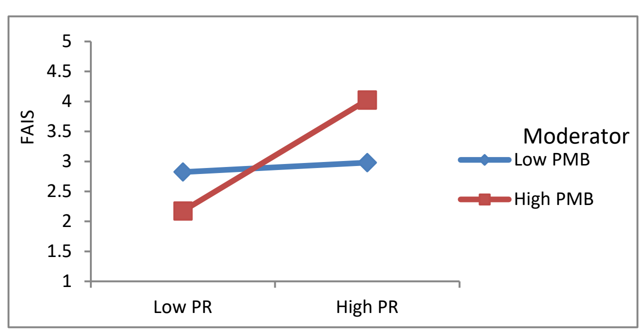

Fig. 4. Dawson's plot (moderating of PMB)

5. Discussion and conclusion

The influence of perceived risk on Financial AI Services was examined in this study, and the relationship between both constructs was examined further through the inclusion of two moderators namely influencer endorsement and perceived security. There were three hypotheses established in this study, based on past findings. Specifically, H1 as the first hypothesis supposed that perceived risk would have a negative impact on Financial AI Services. This hypothesis was supported. This result was in agreement with Amirtha, Sivakumar and Hwang (2021) who indicated that perceived risks will make people reluctant to use technological financial services because they do not want to face losses, and because they are not competent to use it.

H2 as the second hypothesis conjectured the moderating effect of influencer endorsement on the relationship between perceived risk and Financial AI Services. In other words, the use of influencers in promoting technology use and in expanding and improving the use process is expected to increase user intention to use financial technology services. The chosen influencer is a physically fitting expert with credibility, expertise, and trustworthiness. The results proved that influence endorsement moderated the relationship.

H3 as the third hypothesis, conjectured the moderating effect of perceived security on the relationship between Perceived Risk and Financial AI Services, and this hypothesis was supported as well. This means that if the customer feels that his private information provided to the shopping site will not be revealed, saved, and/or stolen during e-commerce and during storage by outside parties, the perceived risk from financial AI services will be decreased.

6. Future work

Customers made up the unit of analysis in this study. Hence, the moderating impact of influencer endorsement was determined by customer perception. This study could be replicated with companies as a unit of analysis. This will enrich the findings further, as the moderating impact of influencer endorsement can be understood from the viewpoint of companies. Next, different approaches could be used in the next studies, specifically the use of longitudinal and qualitative approaches or other approaches except quantitative approach which was applied in this study. This will deepen the understanding of the subject. Also, the probable change in consumer perspectives could be identified. Also, for the purpose of expanding the knowledge reservoir of the subject matter, other constructs, aside from influencer endorsement and perceived security, could also be used as moderating variables to the relationship between perceived risk and financial AI services.

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