

Uncertain Supply Chain Management

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Avoiding uncertainty by measuring the impact of perceived risk on the intention to use financial artificial intelligence services

Jassim Ahmad Al-Gasawneh^{a*}, Amjed Alfityani^b, Saleh Al-Okdeh^b, Bisan Almasri^b, Hasan Mansur^b, Nawras M. Nusairat^a and Yousef Abu Siam^b

^aDepartment of Marketing, Faculty of Business, Applied Science Private University, Amman, Jordan

^bDepartment of Accounting, Faculty of Business, Applied Science Private University, Amman, Jordan

ABSTRACT

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The moderating role of influencer endorsement and perceived monetary benefits on the relationship between perceived risk and financial artificial intelligence services was explored in this study. Data were obtained through questionnaires distributed to 200 respondents who were selected using a purposive sampling method. The respondents were customers receiving financial artificial intelligence services in Jordan. Analysis was performed using a structural equation modeling approach run by Smart-partial least squares (PLS) 3.2.9 involving data from 138 returned questionnaires. The results show a negative impact of perceived risk on financial artificial intelligence services, and a moderation effect of influencer endorsement and perceived monetary benefits on the relationship between perceived risk and financial artificial intelligence services. The findings can assist companies in their strategies of decreasing perceived risks that individuals could be encouraged to utilize business intelligence applications, for instance, financial technology services.

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1. Introduction

For many, the concept of artificial intelligence (AI) is associated with science fiction dystopias. However, such belief has gradually diminished with the development of AI into a more common tool in today's daily life. AI is now accepted in general society, but AI is actually not a foreign concept. AI dates back to its introduction in 1956, but its progress was slow, especially in its transformation into a technological reality (Fletcher, 2018; Barakat, & AlZagheer, 2021). Within the domain of business, the use of AI has been vast, and people in fact have been interacting using AI every day, in one form or another. AI has permeated all layers of business processes, in all business industries. The explosion of AI technologies has made it integral in the preservation of competitive edge for businesses today (AL-Rawashdeh & Mamat, 2019).

The global financial services industry has dramatically been transformed by AI. AI encompasses a group of technologies comprising machine learning (ML) and deep learning (DL), and this gives AI ability to transform the current financial services industry (Dwivedi & Hughes, 2019). As reported by Buchanan & Wright (2021), the financial services industry spends considerably on AI services and this industry is expanding very swiftly. At present time, primary AI users in the finance domain have been hedge funds and HFT firms. However, other domains have begun AI application, as can be seen among banks, insurance firms, regulators, so forth. Aside from these institutions, Fintech companies have also been utilizing AI and its many applications. The use of AI by Fintech companies is for assuring participation of youths, women, low-income earners, the poor, and small businesses in the mainstream financial market (Mhlanga, 2020).

* Corresponding author

E-mail address j_algasawneh@asu.edu.jo (J. A. Al-Gasawneh)

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Fintech, as described by Sweeney et al. (2015), entails a product or service that non-financial institutions utilize to innovative and disruptive service technologies. In Freedman (2006), the concept was described as the construction of models, values, and processes of financial products, for instance, money, bonds, stocks, and contracts. Meanwhile, Ernst and Young perceive Fintech as a revolution in financial services made possible by technology. There are four categories of Fintech as mentioned in Financial Stability Board (FSB): The first category of Fintech includes Payments, Clearing, and Settlement which involves online payment system services via electronic wallet or digital money. The second category of Fintech includes Deposits, Loans and Capital Raising, and this category involves the use of crowdfunding, P2P lending platforms, and payday loans within a single platform and this allows profit sharing from the funds. The third category involves Market Provisioning / Aggregators that collect different types of necessary market information that consumers utilize. This service allows customers to make comparisons between products in terms of their prices, features and benefits, facilitating their decision making as they do not have to search for information separately. The fourth category, as the last category, involves Investment and Risk Management with services like financial planning, online trading platforms, and insurance. Through online trading platforms or e-trading, people could directly invest, using computers and other assets (Masnita, 2021; Alnaser et al., 2020).

AI has been employed in Jordan, and its many applications have generated new opportunities in the labor market. Also, the use of AI and its applications among government institutions in Jordan has increased the availability, quality and also efficiency of the provided services, leading to cost reduction while increasing their take-up across all divisions of society. Such use speeds up the economic development of the country. Also, through the development of applications with AI in addition to the systems and solutions for issues like cyber-attacks and big data management, an environment that stimulates innovation and entrepreneurship can be created (Ministry of Digital Economy and Entrepreneurship, 2020).

The government of Jordan has been striving to turn the country into a solid regional tech hub and an entrepreneurial enabler, leveraging the availability of distinguished local talents. Meanwhile, AI remains the country's national strategic priority as a way of accomplishing its sustainable development goals by 2030. AI adoption facilitates the formation of novel methodologies for achieving superior usage of traditional and non-traditional data sources and new data frameworks (Ministry of Digital Economy and Entrepreneurship, 2020). As such, applications of AI including the use of technological financial services must be improved through the reduction of perceived risk (Park et al., 2019; Al-Gasawneh, et al., 2021).

The effect of influencer endorsements on financial artificial intelligence services was reported by Hu et al. (2019) and Pelau et al. (2021), while the effect of influencer endorsements on Perceived Risk was reported in Anuar et al. (2020) and Veissi (2017). Further, the impacts of perceived Monetary Benefit on financial artificial intelligence services and Perceived Risk were reported by Kim (2020), Gansserand Reich (2021), Susanto et al. (2020) and Xia and Hou (2016). The above findings denote a literary gap, justifying the execution of the present study. Specifically, within Jordan, the use of financial artificial intelligence services should be increased among customers, and therefore, factors that reduce perceived risk using Influencer endorsements and perceived monetary benefits should become moderators.

2. Literature review

2.1 Intention to using Financial Artificial Intelligence Services

Artificial Intelligence (AI) can be described as a set of theories and algorithms through which, computer systems are able to carry out tasks that otherwise call for human intelligence, like visual recognition, text interpretation and visual perception, and in certain situations, the computer systems could perform the tasks better than humans can (Pau, 1991). AI dates to the 50s, but the concept did not receive much due attention until recently. The popularity of AI today was attributed to three factors. The first factor was the expanding volume of available digital data, the second factor was the increase in data storage and computational processing ability at lower cost and the third factor was the advancement of the applied algorithms. The factors have also led to the progression of AI, increasing its feasibility in use in various sectors including that of finance (Lui & Lamb, 2018).

Considering that payment transactions generally employ financial technologies (Fintech), AI is now integral in online buying and selling, and consequently in the life of people today (Nagy & Hajdú, 2021; Alghasawneh, et al., 2021). In online shopping, it begins with shopping intention, and in Iqbal, Hunjira and Rehman (2012), online shopping intention is the degree to which consumers demonstrate their readiness to utilize the Internet services to make purchases of products or services or to make comparisons of various products in terms of cost.

It is reasonable to consider shopping intention a basis for expecting consumer behavior. Equally, there are several factors found to impact shopping intention. For this reason, shopping intention is challenging to measure. In their study, Schlosser, White and Lloyd (2006) mentioned that focusing on privacy and security can increase the promotion of online shopping intention. Hence, there exists other aspects that determine the confidence of consumers in satisfying their needs and desires through businesses and good will.

Shopping intention has been frequently used to predict the actual purchasing habits of customers. As such, this study investigated online shopping intentions (Halimi et al., 2021; Hanandeh, 2017). In doing so, the parameters considered include: possibility of shopping for products online, suggesting online shopping to others, and making future purchases following a

positive first online shopping experience. The present study accordingly adopted one form of financial artificial intelligence services, namely the intention to perform online shopping, and the use of this construct was based on Masnita et al. (2021). As for the work measurement, it was based on Al-Gasawneh et al. (2020).

2.2 Perceived Risk

Despite the countless benefits of the Internet, consumers are faced with uncertainties in the online purchasing process (Masoud, 2013). Perceived risk is a significant factor that affects online shopping (Jordan et al., 2018). And it also could become a main motivator in consumer behavior (Hong & Cha, 2013). Perceived risk theory facilitates the understanding of marketers of the viewpoint of consumers of the world (Chen, 2010; Chen et al., 2015). Hence, risk analysis is usually included in marketing decisions (Mitchell, 1999). Customers are often compelled to prevent mistakes rather than optimizing their purchasing efficacy (Mitchell, 1999) and this makes perceived risk a potent tool in describing their behavior. Perceived risk entails the level to which using the Internet to make purchases is regarded as risky as exemplified by the incidences of credit card fraud, the issue of information privacy and the general feeling of doubt towards the Internet environment. Considering that consumer behavior involves certain risk, consumers may experience some level of uncertainty, and this leads to projected outcomes, some of which, can be undesirable (Jordan et al., 2018).

During purchasing transactions, consumers will make efforts to reduce perceived risk (Jordan et al., 2018). In dealing with uncertainty, consumers will usually search for information that could boost their confidence in their actions. Perceived risk entails the amount of money at stake during a purchase (Framarz et al., 2016) and it is also a subjective feeling of consumer with respect to the certainty of the favorableness of purchase consequences, focusing on loss and uncertainty. The discussed findings become the building blocks of the present study and the employed variables are those commonly used in studies that examined perceived risks of consumers. Specifically, these variables have been found to hinder the intention of consumers to use financial Artificial Intelligence Services. These variables are (Jordan et al., 2018) price, product quality, time loss, lack of good feel, after-sale service, price value, psychological health, and privacy information.

2.3 Perceived Monetary Benefit

People generally strive to achieve some monetary benefits from a new program or innovation (Amriel, 2018), and therefore, via advertisements, financial artificial intelligence services may create value.

2.4 Influencer endorsements

Influencer endorsements involve the attachment of fame to some trusted personalities in their corresponding domain with the purpose of spreading awareness of the associated brands and describing in detail the product and its usage. This can drive company sales. Influencer endorsement hence leverages the popularity and expertise of the Influencer (Aanchal, 2020; Nusairat et al., 2021; Ahmad et al., 2020).

2.5 Hypothesis developments

2.5.1 Relationship between perceived risk and financial artificial intelligence services

Online buying and selling generally involve the use of financial technologies in payment transactions, and therefore, involve artificial intelligence (AI) (Nagy & Hajdú, 2021). Masoud (2013) relevantly investigated six dimensions of consumers' perceived risk in studying online consumers' purchasing behavior, and concluded that it had an adverse impact on online consumers' purchasing behavior. However, the author found no impact of time risk, and social risk on online shopping. In their study, Amirtha, Sivakumarand Hwang (2021) concluded a negative relationship between perceived risk and intention to perform online shopping. Hasan, Shams and Rahman (2020) similarly reported a significant and negative impact imparted by perceived risk on the behavior change inclination to use artificial intelligence apps. Considering the aforementioned findings, the hypothesis below was therefore proposed:

H₁: *Perceived Risk has a negative impact on financial artificial intelligence services.*

2.5.2 The moderating effect of influencer endorsements on the relationship between perceived risk and financial artificial intelligence services

Influencer endorsements place fame to some trusted personalities in their corresponding domains for the purpose of spreading awareness of people of the related brands and describing the particulars of the product in addition to its usage, all of which could drive the company sales (Ki et al., 2020). The relationship between Perceived Risk and financial artificial intelligence services was also delineated. In their study, Masoud (2013) and Nagy and Hajdu (2021) concluded the negative impact of Perceived Risk on financial artificial intelligence services. Similarly, Sivakumarand Hwang (2021) found a negative linkage between Perceived Risk and financial artificial intelligence services.

The inconsistency between the predictors and the dependent variables means that there should be an inclusion of a moderating variable, as proposed in studies including Baron and Kenny (1986), Bibi, Pangil, and Johari (2016). For this reason, the present study has decided to include a moderating variable to the relationship between perceived risk and financial artificial intelligence services. Hence, the construct of influencer endorsements was included in this study as a moderator variable, as it has been found to impact financial artificial intelligence services in studies including Hu et al. (2019) and Pelau et al. (2021). Relevantly, the impact of Perceived Risk was examined in Anuar et al. (2020) and Veissi (2017). In essence, the variable of influencer endorsements was chosen as moderator to the relationship between Perceived Risk and financial artificial intelligence services. With consideration towards past related findings, the hypothesis below was therefore proposed:

H₂: *Influencer endorsements moderate the relationship between Perceived Risk and financial artificial intelligence services.*

2.5.3 *The moderating effect of perceived Monetary Benefit on the relationship between perceived risk and financial artificial intelligence services*

As posited by the concept of perceived monetary benefit, value in the use of financial artificial intelligence services can be created, particularly by way of advertisements. In fact, people are generally interested in getting certain monetary benefits from any new program or innovation like financial artificial intelligence services. Pertinently in their study, Masoud (2013) and Nagy and Hajdu (2021) concluded a negative impact of Perceived Risk on financial artificial intelligence services. A negative link between Perceived Risk and financial artificial intelligence services was reported by Sivakumar and Hwang (2021). In this regard, the inclusion of moderator variables was proposed in several studies including Baron and Kenny (1986), Bibi, Pangil, and Johari (2016), when there is consistency in the relationship between the predictors and the dependent variables.

A moderator was thus necessary in the present study's scrutiny of the relationship between Perceived Risk and financial artificial intelligence services, considering the impact of perceived Monetary Benefit on financial artificial intelligence services as was reported in past studies including Kim (2020) and Gansser and Reich (2021). The impact of perceived monetary benefits on Perceived Risk (e.g., Susanto et al., 2020; Xia & Hou, 2016) was also considered. The construct of perceived Monetary Benefit was therefore included as moderator variable to the link between Perceived Risk and financial artificial intelligence services. The following hypothesis was accordingly established:

H₃: *Perceived Monetary Benefit moderates the relationship between Perceived Risk and financial artificial intelligence services.*

3. Method

The research parameters of the present study were established from past relevant studies. Where the current study listed down three items of financial artificial intelligence services perception, these three items which follow the uni-dimensionality model from Al-Gasawneh et al. (2020), perceived monetary benefit includes two items following the uni-dimensionality model created by Amriel (2018), while influencer endorsement includes four dimensions of trustworthiness alongside its three items, credibility alongside its three items, and physical appearance that has one items, expertise and experience alongside two items following the multi-dimensionality model created by Aanchal (2020), while perceived risk as the third item includes four items following the uni-dimensionality model from Jordan et al. (2018). Each parameter was supplemented with a five-point Likert scale for measurement purposes.

3.1 Sampling

In this study, the population of research comprises those utilizing intelligent financial services such as online shopping, and data were gathered through a survey distributed online. where Respondents could gain access to the survey by clicking a link provided on platforms of social media such as Facebook, Instagram and WhatsApp. The respondents were also asked to forward the link to those involved in technological financial services activities like online shopping. The study respondents were selected using the convenience sampling method, and this method was deemed appropriate because the purpose of the study was to evaluate the validity of theoretical effects. Structural equation modelling with Smart PLS was applied for analysis (Hair et al., 2019). Power analysis was performed, and the smallest size of study participants for this study was 73 with the medium effect size (0.8) according to three research predictors (Gefen et al., 2011). Accordingly, this study has chosen to employ 200 participants to attain the highest rate of response possible.

4. Data analysis and findings

Smart-PLS 3.2.9, a variance-based SEM, was used in this study for hypothesis testing. This method was appropriately chosen as it could predict the relationship between variables (Hair et al., 2019). There were 160 responses received, but 22 had to be excluded from analysis as they were considered as incomplete, and therefore, there were 138 responses usable for. From the 138 responses: Majority (61.2%) were male participants, majority (59.6%) were single, majority (59.2%) were in the age group of 40-44 years of age, and 54.1% of the respondents had at least one degree. Multi-variate skewness and kurtosis were used in evaluating data normality, as proposed in Hair et al. (2019). The results show that the data were not multivariate

normal with the following details: Mardia's multivariate skewness ($B = 9.003$, $p < 0.01$) and Mardia's multivariate kurtosis ($B = 61.777$, $p < 0.01$). Hence, Smart-PLS which is a non-parametric analysis software could be used.

4.1 Moderating analysis approach

Partial least squares method was used in data analysis. The method allows several approaches to moderator analysis, that is, the product indicator approach with reflective-reflective construction. However, as discussed in Fassott et al. (2016), it lacks substantial statistical power, and an approach comprising two stages with formative indicators. As the more fitting approach, the latter approach, allows the evaluation of the significance of the moderator effect regardless of the used construct, formative or reflective (Hair et al., 2019). Utilizing a two-stage approach based on current reflective-reflective constructs, the present study examined the moderator effect. In doing so, problems of inferior statistical power of the product indicator approach can be averted. In the first stage, convergent validity and discriminant validity were evaluated, but during this stage, the interaction term was not taken into account. The structural model specifications were identified during the second stage. Here, the product indicator was determined, and this resulted in the unification of the interaction term alongside the predictor and moderator variables, as proposed in Hair et al. (2017).

4.2 Assessment of measurement model

SEM analysis was executed in two steps. During the first step, the measurement model was affirmed, and this involved the affirmation of convergent validity and discriminant validity. The next step involved the affirmation of the structural model or the testing of hypotheses. In this study, the examined key variables of first order constructs are perceived risk, perceived monetary benefits and financial artificial intelligence services. Meanwhile, the second order constructs are influencer endorsement as reflective-reflective structures, comprising the factors of trustworthiness, credibility, physical appearance, expertise and experience. The choice of influencer endorsements as second-order constructs was to enrich the knowledge of relevant logical and consensus functions. In the second stage, the number of interactions and assumptions in the structural model order was reduced, as proposed in Hair et al. (2017). Hence, the PLS direction model was simplified, and this facilitated understanding. The implementation of the strategy involved two phases, and the first phase involved the use of repetitive indicator technique, for the purpose of obtaining the first-order scores for first-order constructs. During the second phase, the CR was computed. Meanwhile, AVE of the second-order constructs was computed using the weighting of the first-order variables. The determination of convergent validity was based on Hair et al. (2017), that is, loading and AVE greater than 0.5 and composite reliability greater than 0.7 mean that the model has convergent validity. Table 1 and Fig. 1 accordingly display the construct validity evaluation through the measurement of all values. As shown, the values in Table 1 are all greater than the set minimum value. Convergent validity was thus affirmed.

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	Cr1	0.877	0.946	0.780
	Cr2	0.867		
	Cr3	0.886		
Physical appearance	PH1	0.872	0.889	0.728
	PH2	0.841		
	PH3	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		
Second Order Constructs				
Influencer Endorsement	Trustworthiness	0.892	0.921	0.752
	Credibility	0.830		
	physical appearance	0.844		
	Expertise and Experience	0.823		

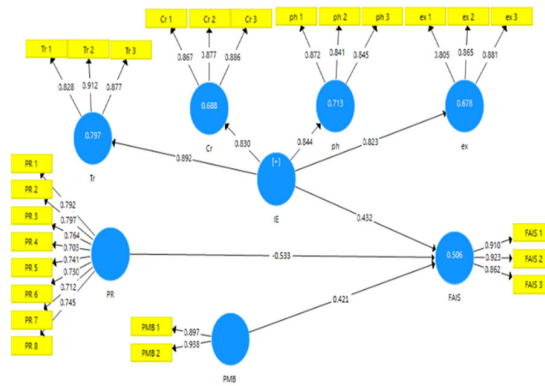


Fig. 1. Measurement Model

The following step after the affirmation of the convergent validity, is to affirm the discriminant validity. Following the recommendation of Franke and Sarstedt (2019), the achieved values of Heterotrait-Monotrait ratio (HTMT) have to be less than 0.85 in order that the discriminant validity can be confirmed. As can be observed Table 2, all obtained HTMT values were smaller than the cut-off value proposed by Franke and Sarstedt (2019). Hence, the model had discriminant validity.

Table 2
Discriminant validity (HTMT)

	PR	PMB	Tr	Cr	PH	EX	IE	FAIS
PR	0.797							
PMB	0.574	0.792						
Tr	0.836	0.533	0.797					
Cr	0.167	0.106	0.141	0.794				
PH	0.083	0.557	0.794	0.151	0.794			
EX	0.765	0.812	0.622	0.415	0.675	0.765		
IE	0.776	0.578	0.791	0.641	0.65	0.788	0.776	
FAIS	0.795	0.759	0.613	0.054	0.654	0.86	0.776	0.795

4.3 Structural model

The structural model was evaluated after it was affirmed that collinearity issue does not exist in the model. In this study, the obtained VIF value for all constructs is smaller than the cut-off value of 5 as recommended in Diamantopoulos and Siguaw (2006). Therefore, the researcher concluded that the model was free from collinearity problems. Further, standard beta (*B*) and t-values of the model were evaluated using a bootstrapping procedure with a resample of 5,000. The effect sizes (*f*²) of the model were examined as well following the recommendation of Hair et al. (2017). Also, as can be observed in Table 3 and Figure 2, perceived risk has a significant negative relationship with Financial Artificial Intelligence Services (*B* = -0.533, *t* = 3.416, *p* < 0.01), demonstrating support to H1. In terms of effect size (*f*²), this study follows the recommendations of Cohen (1988) as follows: 0.02 denotes small effect size, 0.15 denotes medium effect size, and 0.35 denotes large effect size. From the results, the variable supporting the hypothesis appears to have large effect size. Meanwhile, the obtained determination coefficient value or *R*² is 0.429. This shows that the exogenous variables (i.e., cost, perceived benefits, readiness and customer pressures, with top management attitude) could elucidate 42.9% of variances in intention. In addition, the *Q*² value correlated with online shopping intention was 0.540 (larger than zero). As such, the model has predictive power.

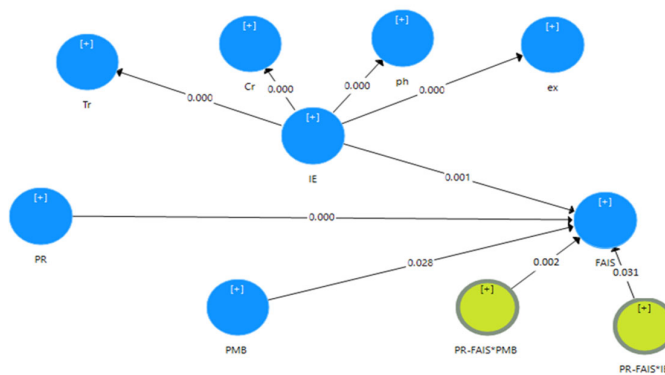


Fig. 2. Hypotheses testing of the relationships

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

Table 4 displays the details of the moderating effect of Influencer Endorsement on the negative relationship between perceived risk and Financial Artificial Intelligence Services ($B = 0.402, t = 3.757; p < 0.05$). The results show that the negative link between perceived risk and Financial Artificial Intelligence Services was moderated by Influencer Endorsement. Further, the results show that the negative relationship between perceived risk and Financial Artificial Intelligence Services was moderated by Perceived Monetary Benefits ($B=0.418, t = 2.235; p < 0.005$). The details of moderation analysis can be viewed in Figs. (3-4). Based on the non-parallel lines in each Dawson plot, it was clear that the relationship between perceived risk and Financial Artificial Intelligence Services will be moderated with a high level of influencer endorsement. The relationship will also be moderated with a high level of perceived benefits.

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 *PMB	0.418	0.187	0.541	2.235	0.002

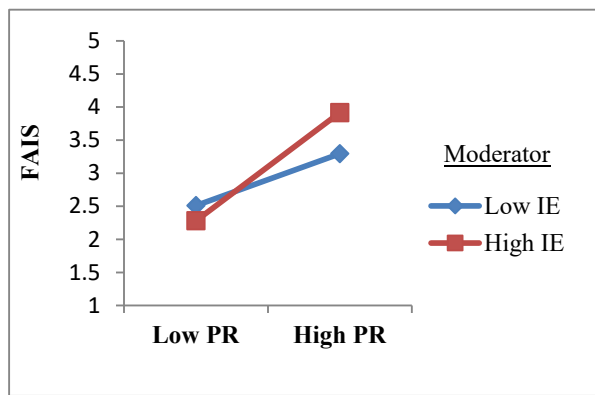


Fig. 3. Dawson's plot (moderating of IE)

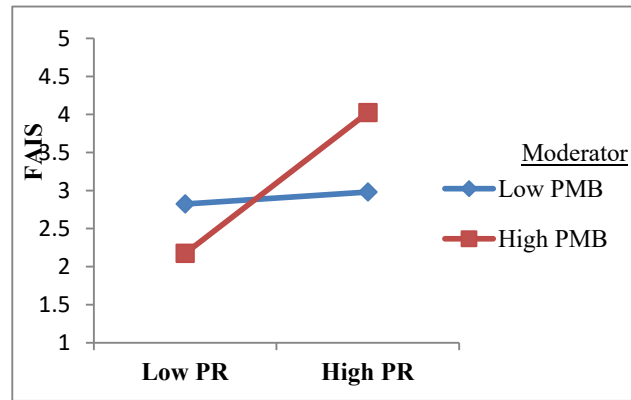


Fig. 4. Dawson's plot (moderating of PMB)

4.3.2 Importance-Performance Matrix Analysis (IPMA)

The results of Importance-Performance Matrix Analysis (IPMA) of financial artificial intelligence services are shown in Fig. 5 and Table 5.

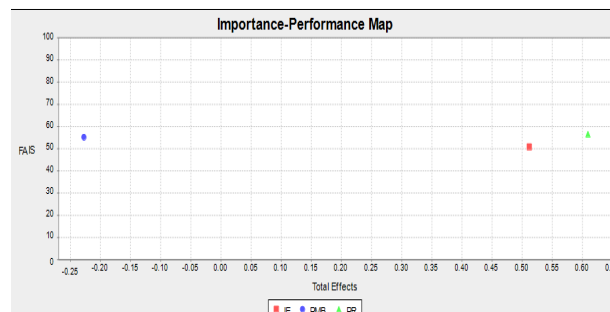


Fig. 5. The importance-performance map

There are three variables: perceived risk, influencer endorsement and perceived monetary benefits. The results show high performance of perceived risk, and this means that this variable is the most important, aside from demonstrating the highest performance among the variables. Based on this outcome, companies should include policies in order that perceived risk can be prevented from disrupting the system of the company. As such, the use of moderators in increasing the intention to use financial artificial intelligence services is justified.

Table 5
Importance and performance matrix (IPMA) result

Construct	Importance (Total Effect)	Performance (Index Values)
Perceived Risk	-0.609	56.550
Influencer Endorsement (IE)	0.512	50.820
Perceived Monetary Benefits	0.289	55.142

6. Discussion and conclusion

The present study mainly attempted to investigate the influence of perceived risk on Financial Artificial Intelligence Services. Also, this study applied influencer endorsement and perceived monetary benefits as moderators to the relationship between perceived risk and Financial Artificial Intelligence Services. To this end, two hypotheses were proposed, and the first hypothesis (H1) conjectured the negative impact of perceived risk on Financial Artificial Intelligence Services, and the obtained results supported the hypothesis. This was in line with Amirtha, Sivakumar and Hwang (2021) who reported that perceived risks will cause people to avert using technological financial services owing to fear of loss or the inability in using it. The moderating effect of influencer endorsement on the relationship between perceived risk and Financial Artificial Intelligence Services was examined and expressed in the second hypothesis (H2), that is, the use of influencers in the promotion of the process of utilizing technological processes and expounding and boosting the process of use will increase the intention of user to use financial technology services, particularly if the influencer is trustworthy, credible, an expert, experienced, and appropriate physically. The results accordingly showed the moderating impact of perceived monetary benefits on the relationship between perceived risk and Financial Artificial Intelligence. H3 was therefore supported. In other words, value creation for financial artificial intelligence services and the demonstration of their perceived benefits from their use will increase the use intention of these services even when there are potential risks.

7. Research Suggestions for Additional Research

In this study, the customers were the unit of analysis, that is, the moderating influence of influencer endorsement was based on the viewpoint of the customers. Hence, in order to enrich the understanding of the moderating influence of the moderating influence of influencer endorsement and perceived monetary benefits on the relationship between perceived risk and Financial Artificial Intelligence Services, this study should be replicated focusing on companies as the unit of analysis. Another consideration is the research approach used, whereby future studies should consider utilizing longitudinal and qualitative approaches or other approaches different from that applied in this study. The use of approaches other than quantitative approaches employed in this study will thus enrich the understanding of the topic at hand, as well as the understanding of potential change in consumer viewpoints. Additionally, this study explored the moderating effects of influencer endorsement and perceived monetary benefits on the relationship between perceived risk and Financial Artificial Intelligence Services. Hence, for future studies, the moderating effects of other factors on the relationship between perceived risk and Financial Artificial Intelligence Services should be explored to expand and enrich the knowledge reservoir.

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