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Antecedents of understanding the investors' acceptance of artificial intelligence: Perceptions from Jordanian context

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A B S T R A C T

This study examined the perception of investors toward the factors of Artificial Intelligence (AI) that impact behavioral intention of AI adoption. TAM was used with the addition of three factors of subjective norms, trust in service and service provider, and training. Jordanian stock market investors with basic investment knowledge were selected as the study participants using a convenience sampling method. The analyzed data were obtained from 610 responses. Results demonstrated the significant impact of trust in service and subjective norms on AI. Attitudes, perceived ease of use and perceived usefulness showed statistical significance toward intention to use AI. Results also showed significant impact of training on perceived ease of use.

1. Introduction

The business world today is highly competitive, and retailers need to maintain customer satisfaction to sustain (Abu Daqar & Smoudy, 2019; Almajali, 2021; Al-Bashayreh et al.,2022). Satisfaction of customers can be achieved through the provision of value-added service in the shopping experience that fulfils or goes beyond what is expected. Happy customers can turn into loyal customers, and through these happy and loyal customers, new customers could be brought in (Moore et al., 2022; Almajali et al., 2023). Therefore, the retail industry could significantly benefit from the understanding of customer satisfaction. Additionally, in the retail industry, the use of Artificial intelligence (AI) allows the discovery of creative solutions and the provision of superior customer experiences, and so, AI affects retail industry significantly (Guha et al., 2021; Hsu & Lin, 2023). Within the context of online shopping, AI has been used in many ways, like in voice and photo search, in creating personalized shopping experiences, in chatbots, in product suggestions, and in virtual assistance (Baabdullah et al., 2022; Hsu & Lin, 2023). Indeed, the technology of AI has been utilized in improving business operation and customer experience, by providing customers with personalized experience based on information obtained from customer profile, particularly information regarding their traits, needs, and behaviors. In their study involving online shoppers, Moura el al. (2021) found that 76% of these shoppers expected constant interactions, 66% expected that businesses know their needs and demands, and 52% expected to be provided with a personalized offer. The authors further concluded the need for businesses to improve customer experience.

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There are various tools of AI and among the popular ones are chatbots and virtual assistants. These tools have been examined in terms of their impact on the online shopping experience of customers. However, as indicated by Aw et al. (2022) and Baabdullah et al. (2022), not much is understood on AI and its effectiveness. Baabdullah et al. (2022) added that some factors need to be considered in AI usage such as gender, age and educational level. In this regard, the goal of this study is to close the gap between theoretical research and real-world data mining applications, as it transforms the understandings constructed from the data into business value (Liu et al., 2022). The present study accordingly attempted to increase the understanding of how the incorporation of tools of artificial intelligence (AI) for instance chatbots, virtual assistants, voice and photo search into online retail websites can increase the general satisfaction of Jordanian investors.

Having the ability to make purchases online has significantly affected customers globally (Lari et al., 2022; AL-Sous et al., 2023). Meanwhile, online retailers have been providing 24/7 support to online shoppers using AI-powered chatbots or other digital assistants, which could improve the customers' shopping experience. Within the domain of online retail, the use of chatbots intensifies the impact of AI through capabilities like natural language processing (NLP). NLP can comprehend and respond to customer voice conversations, gain more in-depth insights to fulfil the demands of customers, improve over time through self-learning skills, and make targeted or personalized offers to customers (Nimbalkar & Berad, 2021). Many studies have examined the impacts of AI on online retail, within the settings of various countries. In Palestine, Abu Daqar and Smoudy (2019) carried out a study to find out how artificial intelligence (AI) could improve customer experiences, and the authors reported a strong link between customer experience and AI-enabled personalized customer support and post-purchase customer assistance. In another study in the USA by Brill et al. (2019), the connection between customer satisfaction and AI-enabled digital assistants was examined, and results proved positive impact of AI applications on customer satisfaction. In India, Ersoy (2022) found that most of the people surveyed, specifically 92.3%, expressed intent to recommend AI-enabled online shopping. The author also reported a significant positive relationship between AI-enabled online shopping and customer experiences. In China, Li et al. (2020) reported that 71.5% of surveyed consumers stated their acceptance or non-rejection (at least) towards the use of AI in customer support. Also in China, Yang et al. (2022) found that AI adoption allows retailers to achieve stronger return policies, maximize resale returns, and reduce the possibility of running out of stock and incurring leftovers. Clearly, extant studies have shown the inclination of online shoppers towards using AI-powered services. However, knowledge on AI is still rudimentary as this subject is still inadequately studied in the Jordanian context.

2. Theoretical Foundation

There have been many theories and models proposed in the literature in understanding acceptance and use of new technology. Among the commonly used theories and models in the literature are Technology Acceptance Model (TAM) proposed by Davis et al. (1989), Theory of Planned Behavior (TPB) (Ajzen, 1991), Innovation Diffusion Theory (IDT) (Rogers, 2003), and Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003). Among these theories and models, TAM is the most popularly referred to in extant studies. This model is grounded upon a psychological theory called theory of reasoned action (TRA) which describes acceptance behavior. The popularity and vast acceptance of TAM have been factored by its ease of use (King et al., 2006). TAM uses two important independent variables to determine behavioral intention to use. They are perceived ease of use and perceived usefulness. These two variables have a close connection with the construct of actual usage in TRA of (Fishbein and Ajzen, 1975). Still, despite the popularity of TAM, this model has restricted explanation power. According to Venkatesh and Davis (1993), TAM only represents 40% of the total variance.

Limitations of TAM have been pointed out by scholars. Firstly, as indicated by Davis (1993), self-reported usage of TAM could lead to bias in the process of technology adoption. In addition, as highlighted by Fishbein and Ajzen (1975) and Davis et al. (1989), TAM is challenging to use in empirical studies. Another issue with TAM is its lack of actual full measures, especially in studies that employ beliefs, attitudes, and user intentions as measures (rather than using actual usage behavior as measure) (Mathieson, 1991). Another issue with TAM according to Davis et al. (1989), is its failure in considering subjective norms as an important element, because of the use of uncertain theories in its development. TAM also has a low explanatory power due to its neglect of the social, individual, and cultural (subjective norms) effects of technology on individuals (Bagozzi, 2007; Benbasat & Barki, 2007) . Lucas et al. (1999) described subjective norms as the effect of opinions of other user(s) on the behavior of a person. These perceptions mostly relate to the social influence of the user toward belonging to a given group (relatives, friends, etc.). Subjective norms can be both in the form of internal and external influences. Training, design system, decision-making properties, enjoyment etc. are among the influencing factors (Agarwal & Karahanna, 2000). Belanche et al. (2019) relevantly examined the factors impacting new technology services adoption among customers in Anglo-Saxon countries and reported subjective norms as a key influencing factor.

Another factor found significantly affecting technology adoption is the factor of trust (Gupta et al., 2019). Trust is essentially a set of beliefs constructed by a person concerning some attribute mainly because of the environment, society, education, and other factors (Wang et al., 2006). In technology adoption, the factor of trust has been regarded as a crucial determinant of the effectiveness of any intended change to take place. Belle (2013) indicated that the effectiveness of change initiatives can be determined through trust level. Ajzen (1991) described trust as a construct established through the perception of customers towards privacy and security and trust also decreases the perceived risk in the adoption of any new technology. In general, trust in new technology encompasses trust in the service and trust in service providers. In describing trust in service, Varshney

(2002) stated that it means that the use of new technology should be free from any data security and privacy issues during the execution of financial transactions. According to Lee et al. (2003) and Kim et al. (2002), a service provider is trusted if they have a good reputation and can carry out operations without causing their clients any financial hardship. Trust has been suggested as a crucial antecedent of ease of use and perceived usefulness in the context of technology adoption (Sun & Han, 2002). Additionally, it has been suggested that perceived ease of use directly affects customer trust by fostering customer loyalty (Kim et al., 2008).

3. Conceptual Model and Hypothesis Development

There is no single model that could explain the acceptance of consumers of new technology because this phenomenon is highly complicated. Hence, constructs with major impact on certain technology should be integrated with well-established models to increase the comprehension of consumer acceptance of new technology. In this study, TAM constructs are combined with the factors of subjective norms and trust. The study hypotheses are highlighted in this section below. Subjective norms encompass a person's perceptions towards a given new technology/service, grounded upon the environment of the person. Among customers, subjective norms reflect the customers' desire to become a member of or do the same things as their other group members. Subjective norms have been shown to have significant impact on innovation adoption, especially during the early stages of adoption (Taylor & Todd, 1995). Over time and with knowledge amassment, subjective norms are playing an increasingly complex role while also imparting contextual influence on knowledge (Venkatesh et al., 2003). In new technology adoption, for instance, in making purchases online, subjective norms have been found to have an impact on the intention of users (Pavlou & Fygenson, 2006). The same has also been reported in the use of mobile financial services (López-Nicolás et al., 2008). Many studies that employed TAM in understanding the adoption factors of several new technologies, that relate to services especially, have also included the factor of subjective norms (Raue, 2020). These past findings suggested a significant effect of subjective norms for building initial trust in the new technology services. Therefore, the present study proposed the hypothesis below:

H_1: *Subjective norms have a positive impact on the trust in AI services.*

Trust can be viewed as an individual's opinion towards some attributes (Lin et al., 2006), and trust has been reported to have significant impacts on the attitude and intent of users in adopting new technology. Within the context of service, trust means that the system offers reliability and security, as opposed to the conventional investment system (Schmidt-Belz, 2003). Additionally, the technology platform or the new service has to consider performance-related issues; it should be real and offer superior financial outcomes to those offered by conventional investments. In AI-based investments services, performance scalability, reliability, service authenticity, and compatibility with the interests of clients are among the concerns (Olsen, 2012). Technology adoption studies have shown that without institutional infrastructure of security and privacy, customers would not trust the system (Cheung et al., 2001). Hence, the secure provision of valuable information in the best interest of the customer will increase the confidence of the customer to make investment. Pavlou (2003) indicated that trust can reduce the feeling of uncertainty within the customer and makes them feel satisfied towards adopting the new technology. Also, trust assures acquirement of future positive investment outcome to the customer (Manrai et al., 2021). Also, a confident customer is more likely to anticipate potential benefits of using the new technology, and so, trust in the system is expected to impact perceived usefulness and behavioral intention in the adoption of a given service. Therefore, two hypotheses were proposed as follows:

H_{2a}: *Trust in service has a positive impact on the perceived usefulness.*
H_{2b}: *Trust in service has a positive impact on the behavioral intention to use AI services.*

The degree to which a customer is confident that a service provider can function dependably under risky or unclear circumstances is referred to as customer trust. (Manrai et al., 2021). Accordingly, ability, integrity, and benevolence have been proposed as the three dimensions of trust (Benamati et al., 2010). The dimension of ability means the need for service providers to possess sufficient knowledge, skills, and experience in executing their designated tasks, while the dimension of integrity highlights the need for service providers to honestly fulfill their promises to provide security and returns to users. As the third dimension, benevolence requires service providers to also be aware of the interests of their clients (Shin et al., 2016). In contrast to conventional investment methods, these three features show the need for technology businesses that could provide low-risk business portfolios at low expenses and with better transparency (Reher et al., 2016).

Several issues relating to technology have been brought forth by regulatory bodies, especially with respect to conflict of interest and poor risk assessment tolerance of the investor. In addition, regulatory authorities have expressed concern towards the lack of personal interest and unsatisfied fiduciary duties toward investors. Therefore, while offering AI technology for investment to the customers, service providers should inculcate a sense of trust among the customers toward the service provider itself. The following hypothesis was proposed:

H_{2c}: *Trust in service providers has a positive impact on the Behavioral intention to use AI services.*

TAM has been expansively used among researchers in understanding and predicting the intent of customers to use new technology (Alsajjan & Dennis, 2010; Moon & Kim, 2001). Davis (1989) in his groundbreaking study involving TAM suggested that the behavioral intention of a customer to adopt new technology can be justified by three factors namely perceived ease of use, perceived usefulness, and attitude. Additionally, Belanche et al. (2019) described the factor of behavioral intention of a customer as the strength of a customer in carrying out a given task. In TAM, Ajzen (1991) indicated that behavioral intentions of an individual are primarily determined by attitude which can be perceived as the level to which a given individual evaluates a given technology as favorable or unfavorable, while the factor of perceived usefulness is described as the level to which an individual is sure that the utilization of certain system increases his or her performance. As for the factor of perceived ease of use, it can be understood as the level to which an individual is confident that the use of technology would be easy (Davis, 1989).

Attitude of a person toward technology will strongly determine the person's acceptance or rejection towards a given technology. Accordingly, perceived ease of use and perceived usefulness determine the attitude of the customer. Through perceived usefulness, perceived ease of use affects consumer attitude toward new technology adoption both directly and indirectly (Park et al., 2016), as also reported in studies involving mobile games applications by Ha et al. (2007), virtual communities by Hsu and Lu (2007), and electronic banking by Aldás et al. (2011) and Liébana-Cabanillas et al. (2018). Additionally, perceived ease of use has been found affecting adoption attitudes positively in different contexts, like in mobile social network games (Park et al. 2016) and in mobile games (Ha, 2007). Hence, considering the discovery of positive effect of perceived ease of use on adoption intentions, two hypotheses below were proposed:

H_{3a}: *Perceived ease of use has a positive effect on their perceived usefulness.*
H_{3b}: *Perceived ease of use has a positive effect on attitudes toward AI services.*

Countless studies have used perceived usefulness in measuring the performance of new technology within the context of work, study and life (Liu, 2011). Additionally, perceived usefulness has also been regarded by Rogers (2003) as a perceived relative advantage of diffusion of innovation (DOI theory); it demonstrates how the new technology is superior to the past or current technology. In examining new investment technology acceptance, perceived usefulness is regarded as important and relevant because customers with interest towards investing their wealth through new technology are likely interested in knowing the advantages, they would gain from using the new investment technology – among the potential advantages include low investment cost, round-the-clock customer service, and so forth. Furthermore, perceived usefulness is a vital adoption intention factor in other new technologies, for instance, in mobile gaming and in mobile banking (Aboelmaged et al., 2013). As such, this study proposed the following hypothesis:

H_{3c}: *Perceived usefulness has a positive effect on attitudes toward AI services.*

TAM and TRA proposed attitude toward technology as a vital antecedent towards a person's behavioral intention in new technology adoption. Attitude comprises three vital aspects namely cognitive aspect, behavioral aspect and emotional aspect. As described by (Fishbein and Ajzen, 1975) , within the context of the customer, the cognitive aspect covers the experience, belief and opinion of the customer, the behavioral aspect covers the intention to purchase, while the emotional aspect relates to the feelings of the customer. Interestingly, it has been reported that people appear to react more towards the aspect of emotions, not so much on the other two aspects, and so, as indicated by Alcántara-Pilar & Del Barrio (2015), measuring the attitude of a person towards a new technology is not an easy task. Somehow, in technology adoption, attitude is an important determinant. For the customer, attitude could ease transactions and eradicate barriers of technology adoption, to a large extent. In the present study, having a positive attitude toward new technology or AI-based investment would facilitate new technology adoption. This study hence proposed the following:

H_4: *Attitude toward financial services has a positive effect on the Behavioral intention to use AI services.*

The dimension of training has been found to be an antecedent to the construct of perceived ease of use. Online tutorials, refresher courses, group sessions, advanced training, and one-to-one training are among the forms of training. The dimension of training also includes the timing of training and the information that is available to ease the use of the system. During the early stage of technology adoption at the level of organization, training is generally perceived within the context of technology and the training is perceived to be a factor of success (Toktaş-Palut et al., 2014). Furthermore, training affects the perceived effort in technology usage among members of an organization (Reunis et al., 2004). As such, it is expected that training will impact acceptance through perceived ease of use (PEOU), considering that through training, employee's ability will increase, in working with the technology particularly. At the same time, the provision of training reduces employee's perception of the technology's complexity. The following hypothesis was thus presented:

H_5: *Training support has a positive impact on perceived ease of use (PEOU) of individuals towards AI.*

The research model proposed in this study can be regarded as unique. It can be viewed in the following Fig.1.

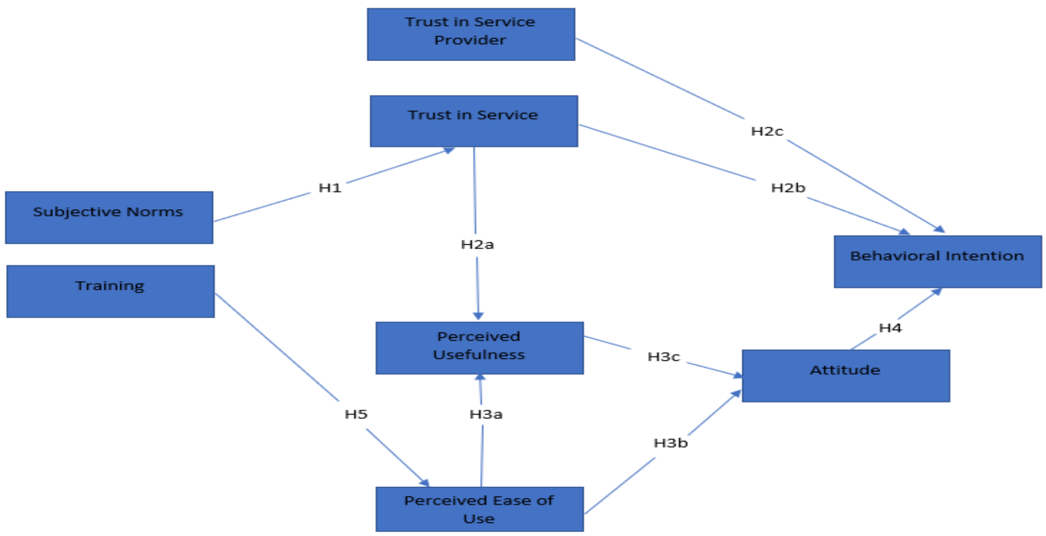

Fig. 1. Research model.

4. Methodology

4.1 Data Collection

The impacts of TAM variables on the intent to use AI was examined in this study. Data were obtained using self-administered questionnaires distributed to the respondents in Jordan. There were 800 investors chosen as the study respondents, and their selection, which was through convenience sampling technique, was based on their AI use experience during the early stage. Amman city residents were chosen as respondents owing to their accurate representativeness to the population of Jordan; Amman is Jordan's capital city while many of Amman residents are active investors. Reliable list of stock market investors in Jordan (Jordan Stock Market (ASE General) - 2023 Data - 1999-2022 Historical - 2024 Forecast (tradingeconomics.com) was referred to in selecting the respondents (convenient sampling method). Questionnaires were distributed to the respondents, and they were asked to return them after completing them. In total, 610 returned questionnaires were usable for analysis (76% response rate). The remaining 190 were omitted owing to incompletion. Table 1 shows personal characteristics of the participants who took part in this survey. As shown, most respondents were male (68%), younger than 20 years old (74%), and were holders of bachelor's degrees (90%). In addition, roughly 36% of the study respondents had been making purchases online for at least ten years.

Table 1
Participants' demographic information

Demographic variables	Number	Percent	Demographic	Number	Percent
Gender					
Male	414	0.68%			
Female	196	0.32%			
Purchasing experience			Age		
Less than 4 years	200	0.33%	Less than20	451	0.74%
5-10 years	190	0.31%	21-29	110	0.18%
Others	220	0.36%	0ther	49	0.08%
Education level					
Bachelor's Degree	550	0.90%			
Master's degree	40	0.07%			
Ph.D. Degree	20	0.03%			

4.2 Measures

As mentioned, this study employed questionnaires to gather the study data. There were two parts to the questionnaire namely Part 1 and Part 2. Part 1 of the questionnaire included nominal scale items on demographic information of the respondents, such as items on the respondent's age, gender, education level and experience in making purchases. Part 2 included items of the study constructs in the proposed model, specifically the intention to use AI, usefulness, attitude, ease of use, subjective norms, training, trust in service provider and trust in service. Each item in Part 2 was validated and was supplemented with a Seven-point Likert scale (from the scale of 1 to represent the reaction of "Strongly Disagree" to the scale of 7 to represent the reaction of "Strongly Agree"). Items in Part 2 can be viewed in Table 2.

Table 2
Questionnaire items

Factor	Code	Measurement Dimensions of Factors
Perceived Usefulness (Davis, 1989)	PU1	I can quickly complete my tasks when I use AI technology.
	PU2	I can complete my tasks easier when I use AI technology.
	PU3	I think AI technology is useful.
	PU4	AI technology use is beneficial in general.
	PU5	AI technology use would make my job simpler.
	PU6	AI technology use seems to support my job.
Perceived Ease of Use (Davis, 1989)	PEOU1	AI technology would not be easy for me to learn.
	PEOU2	My interaction with AI does not need me to think too much.
	PEOU3	AI technology use in my AI tasks completion is easy.
	PEOU4	Interaction using AI technology seems flexible.
	PEOU5	I think I can master AI technology use.
	PEOU6	I believe using AI technology would be simple.
Attitude (Davis, 1989)	ATT1	The use of AI technology is a good concept.
	ATT2	I generally feel positive towards AI technology.
	ATT3	It is clever to choose AI technology use over other services.
Intention to Use AI (Davis, 1989)	IUAI1	I have intention to use AI technology.
	IUAI2	I think I am going to use AI technology in the future.
	IUAI3	I plan to use AI technology.
Subjective Norms (Walton & Johnston, 2018; Mazambani & Mutambara, 2019) and verified by Abbasi et al. (2021).	SN1	My significant others inspire my use of AI in product purchasing or selling, as an effective trading method.
	SN2	My significant others inspire my AI trial usage.
	SN3	My significant others inspire my demonstration of a positive sentiment in my AI use.
	SN4	My significant others inspire my decision in utilizing AI in my purchases of things.
	SN5	My significant others inspire me in my probable AI usage.
Trust in service provider (Zhou, 2011; Kaushik et al., 2015)	TRP	AI is definitely reliable.
	TRP	AI is definitely secure.
Trust in service (Zhou, 2011; Kaushik et al., 2015)	TS1	AI is definitely trustworthy.
	TS2	I have faith in AI.
Training Brandon-Jones (2017)	TRN1	AI offers support feature that promptly trains me to use the system.
	TRN2	AI offers support feature that accurately trains me to use the system.

4.3 Normality and Multicollinearity

The normality of each variable was assessed based on the skewness-kurtosis method recommended by Byrne (2010) and Kline (2005). The evaluation was performed with AMOS 22.0. Results showed skewness values smaller than the recommended value of 3 while the kurtosis values appeared to be smaller than the recommended value of 8 as in Kline (2005) and West et al. (1995). As such, univariate distribution normalcy can be ascertained. Meanwhile, multicollinearity is a high correlation between independent variables within a regression model as described by Kline (1998) – multicollinearity can affect SEM's reliability. This study examined multicollinearity with SPSS. Here, tolerance and VIF values were computed, and the results showed tolerance values smaller than 0.10, and VIF values higher than 10. Both values were considered tolerable.

4.4 Common Method Bias

Harman's single-factor was used in this study to check for common method bias. This technique was created by Harman (1976) and Podsakoff et al. (2003). Accordingly, there were eight (8) constructs (represented by 29 scale items) included in this analysis namely: SN, ATT, PU, PEOU, TS, TRP, TRN, and IUAI. The findings showed no single identifiable factor. In addition, the first component represented 40.63% of variance, and this is lower than the tolerable value proposed by Podsakoff et al. (2003) namely 50%. It was thus concluded that the dataset of this study did not suffer from common method bias issues.

4.5 Structural Equation Modelling Analysis

Measurement Model

Confirmatory factor analysis involves the evaluation of the fitness of the model (unidimensionality), involving the evaluation of reliability and validity of the study constructs.

Model Fitness

In determining the fitness of the study model, major fit indices were used. They were: CMIN/DF, NFI, AGFI, GFI, NFI, CFI, and RMSEA. Results obtained for these indices were as follows: CMIN/DF = 3.222, GFI = 0.73, NFI = 0.78, AGFI = 0.71, CFI = 0.80, and RMSEA = 141.1. Based on Hair et al. (2010), GFI and AGFI had poor score. Hence, the values were refined and reevaluated to increase the fitness of the model, as proposed by scholars including Anderson and Gerbing (1988), Bagozzi and Yi (1988), and Byrne (2010). The refinement process involves examining the weights of standardized regression weights (factor loading), indices of modification, and other factors. In this regard, loading, modification indices, and a standardized covariance matrix should be used as proposed by Byrne (2010) and Holmes-Smith et al. (2006). Details of the results can be viewed in Table 2. From standardized regression weights (factor loading) evaluation performed in this study, it appears that three items had scores of lower than 0.50 as proposed by Byrne (2010) and Hair et al. (2010). As such, these items were omitted. These items were as follows: SN2 representing the construct of subjective norms, PEOU2 representing the construct of perceived ease of use, and PU4 representing the construct of perceived usefulness.

Re-test was performed on CFA and the model fitness was improved. Here, the chi-square values, as proposed by Anderson and Gerbing (1988) and Hair et al. (2010), were reasonable (see Table 3). In particular: CMIN/DF = 1.82, GFI = 0.83 AGFI = 0.89, NFI = 0.88, CFI = 0.90, and RMSEA= 0.030. Based on Byrne (2010) and Hair et al. (2010), it can be deduced that the adjusted measurement model had good data fit. Hence, re-specification or improvement was unnecessary.

Table 3
Measurement of model fit indices

Model	CMIN	DF	P	CMIN/DF	GFI	AGFI	NFI	CFI	RMSEA
Initial measurement model	1144.123	355	0.000	3.222	0.73	0.71	0.78	0.80	141.1
Modified measurement model	322.621	177	0.000	1.82	0.83	0.89	0.88	0.90	0.030

Minimum recommended value: CMIN/DF ≤3.000, GFI ≥0.90, AGFI ≥0.80, NFI ≥0.90, CFI≥0.90, RMSEA ≤0.08.

Construct Reliability

Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE) were employed in determining the reliability of scales of the latent constructs (see Table 4). For Cronbach's alpha, Nunnally (1978) indicated that it should not be lower than 0.70 to denote reliability. Results showed that the Cronbach’s alpha values obtained for all latent variables were between 0.74 (trust in service provider) and 0.91 (training) and so, reliability was affirmed. For CR, Hair et al. (2010) recommended the cut-off value of 0.70. As displayed in the following Table 4, CR value was between 0.76 scored by training and 0.95 scored by perceived usefulness, while AVE scored were between 0.96 and 0.83, which were greater than the proposed cut-off value of 0.50 by Hair et al. (2010) (refer Table 3).

Table 4
Results of measurement model

Constructs	Item Loading		Std. Error	Square Multiple Correlation	Error Variance	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Perceived Usefulness	PU1	0.77	0.011	0.530	0.221	0.77	0.95	0.96
	PU2	0.82	0.021	0.733	0.105			
	PU3	0.85	0.035	0.659	0.238			
	PU5	0.88	0.072	0.548	0.222			
	PU6	0.72	0.055	0.639	0.301			
Perceived Ease of Use	PEOU1	0.80	0.016	0.531	0.340	0.88	0.93	0.94
	PEOU3	0.82	0.021	0.689	0.111			
	PEOU4	0.86	0.011	0.506	0.270			
	PEOU5	0.90	0.033	0.611	0.309			
	PEOU6	0.79	0.045	0.707	0.444			
Attitude	ATT1	0.81	0.063	0.502	0.338	0.81	0.91	0.93
	ATT2	0.94	0.030	0.533	0.111			
	ATT3	0.76	0.020	0.598	0.205			
Behavioural Intention to Use AI	IUEP1	0.73	0.048	0.544	0.357	0.78	0.89	0.92
	IUEP2	0.92	0.015	0.555	0.290			
	IUEP3	0.87	0.037	0.622	0.110			
Trust in service provider	TRP1	0.72	0.060	0.710	0.337	0.74	0.79	0.85
	TRP2	0.84	0.063	0.516	0.306			
Trust in service	TS1	0.73	0.061	0.810	0.444	0.85	0.83	0.88
	TS2	0.91	0.082	0.624	0.107			
Subjective Norms	SN1	0.86	0.031	0.712	0.330	0.82	0.93	0.94
	SN3	0.79	0.022	0.501	0.434			
	SN4	0.80	0.035	0.606	0.303			
	SN5	0.84	0.028	0.690	0.220			
Training	TR1	0.72	0.017	0.530	0.355	0.91	0.76	0.83
	TR2	0.83	0.070	0.628	0.391			

Construct Validity

Convergent validity and discriminant validity of the measurement items were examined in determining the construct validity of the items. The convergent validity analysis showed that the retained items represented substantial standardized regression weight with their latent variables. Also, these items showed modest factor loading of 0.51 with statistical significance of p value of less than 0.0001. Meanwhile, the tolerable value as proposed by Anderson and Gerbing (1988) and Hair et al. (2010) was 0.50. As for the achieved highest value of inter-correlation estimates among the latent components, it was less than 0.66.

On the other hand, Kline (2005) recommended a cut-off value of 0.85. For the latent constructs, the square root of AVE of all of them was larger compared to their inter-correlation estimations with other constructs. Table 5 can be referred to.

Table 5
Discriminant validity using Fornell and Lacker criterion

Construct	SN	PEOU	TRP	TS	ATT	IUAI	TRN	PU
Subjective Norms	0.883							
Perceived ease of use	0.511	0.941						
Trust in service provider	0.301	0.022	0.807					
Trust in service	0.590	0.410	0.578	0.901				
Attitude	0.514	0.397	0.319	0.333	0.875			
Intention to use AI	0.577	0.522	0.303	0.510	0.401	0.911		
Training	0.397	0.011	0.511	0.222	0.550	0.237	0.890	
Perceived usefulness	0.333	0.478	0.656	0.440	0.610	0.110	0.355	0.816

Structural Model

The structural model fit indices showed that the structural model has sufficient goodness of fit to the observed data and Path coefficient analyses were carried out and the results showed significance of nearly all the proposed causal paths over the conceptual model. Table 6 accordingly presents the path coefficient and t-value of all the proposed paths. The study hypotheses were all supported by the results. As evidence, the construct of subjective norms was shown to affect trust in service significantly, with P = 0.040. As such, H1 was supported. Results demonstrated significant positive impact of the construct of trust in service on perceived usefulness with P = 0.025. As such, H2a was supported by the result. Trust in service was shown to positively affect intention to use AI, and therefore, H2b was supported with P = 0.011. As for the construct of trust in service providers, results showed that it had positive impact on the intention to use AI, and so, H2c was supported with P= 0.038. Results indicated that perceived ease of use positively influences perceived usefulness and attitude. Therefore, both H3a and H3b were supported with P= 0.006, and P= 0.005 respectively. Perceived usefulness was proven by the result to positively affect attitude. As such, H3c was supported with P= 0.041. Positive impact of attitude on intention to use AI was proven by the results, which means that H4 was supported, with P=0.007. Lastly, results showed a positive impact of the construct of training on perceived ease of use, and therefore, H5 was supported with P= 0.013. The following Table 6 displays the results.

Table 6
Results for the theoretical model

Proposed Paths	**Coefficient Value**	**t-value**	**p-value**	**Evidence**
H1: SN → TS	0.113	5.332	0.040	Supported
H2a:TS → PU	0.303	12.016	0.025	Supported
H2b:TS → IUAI	0.034	4.115	0.011	Supported
H2c: TRP → IUAI	0.027	2.111	0.038	Supported
H3a: PEOU→ PU	0.154	8.227	0.006	Supported
H3b: PEOU →ATT	0.222	2.163	0.005	Supported
H3c: PU→ATT	0.178	3.555	0.041	Supported
H4: ATT→ IUAI	0.111	6.369	0.007	Supported
H5: TRN →PEOU	0.070	4.191	0.013	Supported

5. Discussion

The present study examined several factors that impact the behavioral intention to adopt AI services in Jordan, and for the purpose, TAM was used with the addition of the factor of subjective norms represented by interpersonal influence and external influence, and the factor of trust represented by trust in service and trust in service provider. Results showed significant impact of trust on the AI adoption, and the present study found trust in service as the stronger predictor than trust in the service provider. As can be construed from the finding, the investors are likely to adopt the AI if they are confident in it (AI) or in the process of investment. Relevantly, Belanche et al. (2019) concluded in their study that familiarity with AI applications in the financial field will increase the likelihood of the investor to adopt the AI Services. Additionally, when people see that the service provider of new technology has credibility, the system is secure, and privacy risks are alleviated, they are likely to adopt it. It should be noted that electronic financial transactions are sensitive in nature. Additionally, studies on technology adoption in other settings (e.g., mobile payments and website booking) also reported similar findings (Kaushik et al., 2015; Almajali et al.,2022). Furthermore, investors generally would expect that the service would support consumers in the processing of information as some customers may have some cognitive limitations (Nielsen, 1999). For instance, elderly customers may find technology adoption more challenging because at their age, categorizing and processing information can be difficult. Easy and understandable new technology investment is more easily adopted (Jung et al., 2018a, 2018b; Almajali and Dahalin, 2010).

The formation of trust and confidence of an individual towards new technology can be facilitated by the individual's friends and relatives. In fact, results showed that subjective norms had a strong impact on trust in service. Relevantly, past studies showed that adoption behavior of customers is determined by their trust level, and trust is affected by factors including interpersonal relationships, opinions of industry experts, and information obtained from the media (Lin, 2007 Kim et al., 2009).

Results showed that trust in service could increase perceived usefulness, as evidenced by the affirmation of causal path between trust in service and perceived usefulness. Similarly, past studies have shown trust as a vital extension component in TAM, especially among studies on financial transactions (Chemingui et al., 2013). Trusting that the service offers secure investment, maximum portfolio return, and secure investment will increase the perceived value of investors towards the new technology. Past studies (Venkatesh and Davis, 2000; Tarhini et al., 2015) have shown that perceived usefulness and attitude toward new technology are strongly and significantly linked. Results showed that perceived usefulness explicated change in the attitude of investors towards the adoption of new technology in financial investments.

Results showed perceived ease of use as a strong predictor of investment attitude. Moreover, perceived ease of use showed a direct impact on the investor attitude and on the perceived usefulness of the new product/ service, leading to an increase in the attitude of investors toward the adoption of new technology. Similarly, Kaushik et al. (2015) reported similar findings in their use of TAM in examining technology adoption. The result showed that convenient and easy new technology-based investment service is more likely to be adopted by the investor. Also, past IS/IT studies showed a strong impact of an easy and simple system of new technology on the intent of individuals to adopt (Davis et al., 1989). A new technology that is perceived as easy to use will have higher utility and people will have a better attitude towards it. Moreover, results showed strong and positive impact of investor attitude and the behavioral intention of investors to use AI to make investments. Some technology adoption studies like Bagozzi (2007), Duan et al. (2010) and Lee et al. (2014) found attitude a key antecedent of behavioral intention towards technology adoption. Investors inherently would evaluate the new investment method with a certain level of favor or disfavor, and if the investors trust the technology and perceive that the service provided by the technology is useful, then, their likelihood to adopt AI will increase. On the other hand, trust in service providers and the behavioral intention to adopt new technology to invest showed a fairly weaker relationship. Results showed that trust in service providers became the weakest predictor, which shows that customers are more interested in the service than the service provider. Contrariwise, Kaushik et al. (2015) found trust in the service provider a significant predictor of technology adoption.

Finally, Results showed that training factor affected perceived ease of use significantly. This means that H5 was supported. In a study by Kheng and Al-Hawamdeh (2002) and Vaidya et al. (2006), it was indicated that people's acceptance of AI was increased through training and support. On the other hand, Angeles and Nath (2007) and Gunasekaran et al. (2009) proposed that training should be decreased by way of using initial design of correct navigation and system usability, and by assuring well-functioning of the system particularly in terms of its information and subsequent product flow by suppliers. The use of AI cannot succeed with undeveloped technology.

7. Theoretical Contribution

This study examined the factors that impact AI adoption, to become a valued addition to the field of AI-based investment or new technology, with a focus on technology acceptance. This study is arguably the first to have employed a holistic and integrative approach in trying to describe AI-based investment services adoption in Jordan. Comparatively, past relevant studies were mostly descriptive in nature (Phoon & Koh, 2017; Jung, 2019). TAM was used in this study, with the addition of two factors namely trust and subjective norms. Additionally, this study was the early one that tested the relationship between trust and behavioral intent to adopt AI in making investment among investors through two aspects namely trust in service and trust in service provider, and this is a significant contribution to the AI domain.

8. Implications for Practice

The outcomes obtained in this study are of value to AI/New technology-based companies as they could assist these companies in improving the AI adoption in Jordan especially. Specifically, results showed the impact of subjective norms, trust in service, perceived usefulness, perceived ease of use, and attitude toward AI-based investment on the behavioral intention of investors to use the new technology in making investment. This implies the need for service provider companies to focus on increasing the confidence of investors towards their product while also focusing on increasing their utility. Two factors were found to strongly drive the adoption of technology, and these factors were trust in service and perceived usefulness. Hence, the service provider company should provide an easy and simple platform to allow users to easily establish their portfolio. In addition, it is important that the investors are sure that they will not lose their money when investing via the new technology and that their personal information will be safeguarded. Service provider companies should hence provide training programs for both current and potential investors, at no charge. In this regard, the use of a demo investment could increase the confidence of the trainees, especially among those who are afraid of the system or those who lack knowledge of the system.

Subjective norms could make a person feel more confident in new technology adoption. For instance, older people who are not tech savvy, would be motivated to try to use the system with support from their family members. Additionally, advertisements viewed from electronic media and social media could affect adoption behavior. For investors, their behavior intentions could be changed by these interpersonal and external motivations, and so businesses may use investor contact and target-based media publicity to attract new customers while maintaining existing ones. The investors' attitude toward the new technology-based investment appears to be highly crucial for their new technology adoption. Service provider companies should provide investors from all categories with a comfortable, and easy platform, so that those with good skills and poor skills can equally benefit from the platform. A complicated investment platform is likely to prevent investors from using the new technology, and they would continue using the traditional technique of investment instead. In this regard, certain form of assistance or support should be provided to all levels of investors. This factor has a direct impact on the investor, aside from forming a perception of usefulness of the product/service to the investor and then transforms the changes in the attitude of the investor towards the technology.

In this study, trust in service was important in assuring successful dispersion of this new technology to the investors, and so, in order to increase confidence of customer towards the new technology services, managers of service provider companies should come up with some strategies or trust-building mechanisms like efficient customer service, strategic advertising to contribute familiarity, and service support statements. For Asian and other Middle East countries, this study helps in the AI-based/New technology companies in dealing with digital gap between citizens; in countries of these regions, many investors seem to be reluctant in using the new technology for investment, even though the technology is cost-effective and rather lucrative.

9. Limitations and Future Work

The limitations of this study are several in amount. Firstly, this study employed a convenient method in choosing the respondents and the respondents were selected from only one city in Jordan, and for this reason, the results of this study cannot be comfortably generalized to other populations in other cities or countries. Somehow, when this study is carried out in a different city, results may differ. Even when carried out in a different country, the results may differ. Behavioral intentions to adopt new technology services were examined in this study, and as indicated by Venkatesh and Davis, (2000), behavioral intentions are close to the actual usage. Within the context of volitional behavior, the actual usage and behavioral intentions have high association, especially during the beginning stages of adoption. It should be noted that behavioral intentions and actual usage may change in the future. In this study, attitude and behavior intentions toward the new technology services were the focal point, while continuance of usage was not considered, which could be addressed in future studies. In addition, this study could be replicated but longitudinally and across cities and countries to increase accurateness and generalizability of results.

10. Conclusion

AI is an automated investment tool to facilitate investors in making investments. However, investors who are only familiar with the traditional investment methods may find this new technology difficult to use. Indeed, a new technology will only be adopted if the user feels that it is very secure and strictly protects the user's privacy of data. During the process of AI, it is important that the service provider company shows high commitment towards assuring perceived trustworthiness and riskless investment process, and this will increase the likelihood of use of this technology by the user or investor. In this study, a number of factors that could result in positive attitude and adoption of the AI among users were examined. TAM was employed in this study, and the model was expanded with the addition of three factors namely the factors of subjective norms, trust and training. The factor of subjective norms was represented by the aspects of interpersonal influence and external influence, while the factor trust was represented by the aspects of trust in service and trust in service providers. Clearly, the expanded TAM used in this study yielded high explanatory power, and so, the model demonstrated both theoretical and practical significance. Not only that, But the expanded TAM ALSO used in this study is a comprehensive framework which could be employed in future studies on technology adoption, particularly concerning new information technologies. Subjective norms were found to be a significant factor in this study, and so was the factor of trust, in new technology adoption. Both these factors are crucial in understanding the investors' acceptance of AI, as demonstrated by the results. As such, the service provider company of AI needs to come up with appropriate strategies to increase the adoption of this technology.

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