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Factors Affecting the Adoption of Artificial Intelligence in Social Media Platforms: Implementation of Technology Acceptance Model in Saudi Arabia

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ABSTRACT

The entire world is experiencing the 4.0 Industrial Revolution, and Artificial Intelligence (AI) is undoubtedly influencing the lives of social media users in developing countries and developed nations. Massive technology trends are impacting the economies of those countries; these transformations are introducing with them many promised benefits and a significant number of challenges to overcome. Therefore, the study examines the impact of technology readiness (i.e., optimism, innovativeness) and technology awareness on technology acceptance model (TAM) variables to measure the intentions in adopting AI-assisted social media platforms. The study collected data from 345 respondents in Saudi Arabia. The study used Smart PLS 4 to test the hypothetical statements. The results showed that technology readiness and awareness significantly influenced perceived usefulness and ease of use. Perceived usefulness and ease of use also significantly and positively influenced the intention to use AI in social media. Additionally, the study found that intention to use significantly and positively influenced the actual use of AI in social media. The study also proposes the practical implications and future directions.

KEYWORDS: Technology readiness, technology awareness, TAM, theory of planned behavior, AI-assisted social media, SEM

INTRODUCTION

In this age of digital technology, the significance of social media cannot be denied. It is now much simpler for individuals to communicate their ideas and for businesses to connect with their target audiences. It operates in precisely the same manner in Saudi Arabia. More than 82% of Saudi Arabian people use social networking sites as part of their daily routines. The National Strategy for Data and AI (NSDAI) of Saudi Arabia was recently made public. The plan's overarching goal is to position the country as a frontrunner in the field of artificial intelligence by the year 2030. The application of AI to social media aims to boost content production and audience interaction by utilizing this technology. This tool can automate the creation of posts, analyze user data and provide advice and suggestions to users. Therefore, the delivery of services on social media is undergoing a sea change due to rapid technological advancements in artificial intelligence (AI) (Belanche et al., 2020; Robinson et al., 2020). According to the predictions made by Huang and Rust (2018), automated technology will gradually replace workers in tasks requiring robotic intelligence, quantitative intelligence, perceptive intelligence, and even emotional intelligence.

According to the research conducted by Wirtz et al. (2018), AI software that operates on its own and acquires new knowledge over time can be differentiated from service robots in terms of their virtual or physical level of personification, and orientation toward their tasks. Because of economies of scale and scope, artificial intelligence (AI) knowledge and information will likely become significant sources of competitive advantage for social media businesses. This will likely result in "winner-take-all" markets (Wirtz et al., 2018). Artificial intelligence's social and economic construction and its influence on humans and society due to its evolution are still being evaluated. Nevertheless, it is evident that there will likely be both losers and winners and that those in charge of making decisions must have a strategic mindset when considering the future. A production process in which intelligent machines are attached within the production process and effectively feature as co-workers for crucial duties or to solve massive issues is likely to see the adoption of AI technologies by

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industrial companies (Haeffner & Panuwatwanich, 2017). Now AI is also used in social media platforms to offer AI-based system in order to support selling and buying (i.e., marketing the products). Because AI is now capable of doing what humans will generally do, there are possibilities for creating content that is both more innovative and relevant.

Even though they now possess a better understanding thanks to the data analysis, advertisers can investigate the possibilities offered by AI to develop content relevant to the customers in response to the growing demand for such content from customers. The content presented here consists of advertisements, views on social media and email marketing (Al-Kurdi et al., 2021; Antonio, 2018). Customers' previous purchases, interests, and perusing behaviours can be used to generate automated marketing campaigns, which can increase the buyers' intention to make additional purchases. AI-led lead-scoring could recognize who is prepared to buy and who within the channel is ready to move from player to consumer (Antonio, 2018). The AI-based social media platform can provide player engagement based on connections and social media interactions. When salespeople use leads identified by AI, they can focus their attention on a significant amount of potentially fruitful sales leads. These leads, once competent, can then be guided thru the buyer's journey toward that buying (Loring, 2018). Territory content and fostering a growing constellation of groups among like individuals in the public space, like on social media sites are two areas in which AI-enabled methods have proven to be extraordinarily effective thanks to the power of these algorithms (Sunstein, 2017). Indeed, it appears that the fear that people have of artificial intelligence (AI) and robots will emerge as a field of growing attention among academics. This new body of knowledge should be added to the already vast body of knowledge about consumers' awareness of the potential dangers of technology (for example, addiction to social media or smartphones (Jiang et al., 2018; Sanz-Blas et al., 2019). An exciting moderating effect has been observed. It was found that insecurity inhibited behavioral intentions to use robo-advisors amongst more consumers who lacked investment experience than it did among customers with investment experience.

Research has shown that AI is having an increasingly significant impact on social media platforms for selling and buying purposes (Dwivedi et al., 2021b; Flavián et al., 2022; Makridakis, 2017; Zeng et al., 2010). As a result, it is essential to investigate the factors contributing to this phenomenon's widespread adoption of AI in social media networking (Dwivedi et al., 2021a; Jarrahi, 2018; Vaishya et al., 2020). The technology acceptance model, also known as TAM, was selected mainly because it is both straightforward and generalizable (Al-Kurdi et al., 2021; Singh & Srivastava, 2019). Insofar as the widespread implementation of AI in social media is concerned, there have been investigators who have defended the viability of TAM's applicability. They have advanced TAM and embedded it with other models developed to include crucial individual and social variables of perceived enjoyment and trust (Rauniar et al., 2014; Shin & Kim, 2008) and technology readiness and awareness (Flavián et al., 2022). Al-Ghaith (2015) presented the idea of perceived social capital (SC) concerning the tacit acknowledgement method. Regarding the utilization of AI in social media marketing, AI plays a significant role (Paschen, 2020). There has only been a modest amount of research conducted on applying TAM to measure AI use of intention, particularly for social media marketing (Singh & Srivastava, 2019). It has not been investigated whether or not social media technology readiness and awareness, in connection with perceived usefulness (PU) and perceived ease of use (PEU), play a role in experiencing AI implementation. Furthermore, concise work has been done to evaluate AI acceptance in social media, particularly in Saudi Arabian culture. Because internet penetration in this country is still a long way behind that in developed nations—it was estimated that 40.1% of people in developing nations had access to the internet in 2016, whereas 81.1% of people in developed nations had access to the internet (Statista: The Statistics Portal, 2017). Moreover, the social and individual metrics of internet usage will be very different. To the best of the researcher's knowledge, they could not locate any studies in which TAM was studied in the sense of implementing AI in social media platforms for various stages of outbound sales and purchases from Saudi Arabia. This study aims to fill the gap that was found.

LITERATURE REVIEW AND THEORETICAL FRAMEWORK

2.1. Theory of planned behaviour and technology acceptance model

Social influences are connected to technology readiness and awareness determined by the theory of planned

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behavior (TPB), aspirational group influences, and implicit reference groups (Gamal Aboelmaged, 2010). These reference groups work to increase the consumers' trust in a product or service, which ultimately results in positive consumer responses. A substantial amount of scientific work is available in the literature investigating the factors influencing the adoption and utilization of information technology among users (Gamal Aboelmaged, 2010; Hsu & Chiu, 2004). TPB and TAM are two of these models that have attracted recognition and confirmation in a wide variety of fields and implementations to recognize end-users intentions to use new technology and systems (Lai, 2017; Venkatesh & Davis, 2000). Such models were developed to recognize end-users intentions to use new technology awareness and readiness (Flavián et al., 2022). Moreover, TPB and TAM were developed as an addition to Ajzen and Fishbein's (1980) theory of reasoned action.

This was done to understand better how individuals make decisions (TRA). The TRA is envisioned as a general framework to explain almost all human behavior. It is founded on the idea that an individual's beliefs are extremely important for accurately predicting that individual's behavior (Ajzen & Fishbein, 1980). Behavioral intention to exhibit a specific behavior is founded, following TRA, based on a user's attitude towards behavior and perceived usefulness and ease of use (Lai, 2017). The individual's opinions that the behavior appears to lead to such outcomes and the individual's assessment of those outcomes, whether favorable or unfavorable, are reflected in the individual's attitude toward the behavior.

The more optimistically one thinks, the more robustly one intends to behave, and ultimately, the greater the likelihood that one will act in a manner that is congruent with that attitude should be. The individual's attitude to the extent toward which his social situation (such as his family, mates, coworkers, the person in authority, or the communications) impacts such a behavior to be expected and attractive is the second factor that plays a role in determining whether or not the behavior will occur. The greater the intensity of this pressure, the higher the intention to engage in the behavior. Therefore, the greater the possibility that the behavior will be carried out in some form or another.

According to Mathieson et al. (2001), the ability of TAM to describe an attitude toward using technology is superior to that of other technology models such as TRA and TPB. TAM continuously explains a significant variation [almost 40%] in usage behavioral intentions. Venkatesh and Davis (2000, p, 186) also mention that TAM compares to possible alternatives such as the TPB and TRA, but TAM is superior to others. In turn, behavior in TAM is impacted by a priori two essential factors that determine technological behavior. These elements are perceived as the technology's ease of use and usefulness (Lai, 2017). Davis (1989, p, 320) described perceived ease of use as the extent to which "an individual believes that utilizing the system would be free of cognitive load" and described perceived usefulness as the extent to which "an individual believes that utilizing the system would then improve his or her performance." A person's behavior in TAM toward using the scheme is also affected by perceived usefulness and perceived ease of use.

In line with TRA, these perceptions toward using the framework ascertain behavior intention, which leads to actual use. TAM and TRA both agree that these behaviors determine actual use. Nevertheless, though TPB and TAM have been used extensively to investigate the use and acceptance of IT, research has shown that neither model consistently provides superior interpretations or estimations of actions (Chen et al., 2007; Venkatesh & Bala, 2008). This is even though TPB and TAM have been broadly applied to investigate the acceptance and use of technology awareness. This may be because of the many factors that play a role in determining how quickly new technologies are adopted, such as the kind of technology, its users, and the environment (Chen et al., 2007). As a result, an increasing body of research has concentrated on incorporating TPB and TAM to investigate technology acceptance due to the complementary and explanation power of using technology readiness and awareness (Chen et al., 2007; Lu et al., 2009). Therefore, the study used the theory of planned behavior in order to measure behavioral intentions using TAM model.

2.2. Technology Readiness, Perceived Usefulness And Perceived Ease Of Use

Technology readiness includes two motivating factors, innovativeness, and optimism (Parasuraman & Colby,

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2015). Previous studies have demonstrated the individuality of the four aspects, as each quantifies the degree to which an individual is open to technological advancement in a distinct manner (Lu et al., 2012), but the study used only two motivations because two other factors were based on demotivating technology. According to Parasuraman and Colby (2015), technological optimism is "a favorable impression of technology and the faith that it provides people actualized, flexibility, and effectiveness in their lives." This meaning can be applied to artificial intelligence (AI), which people may view as either "hell" or "paradise" (Kaplan & Haenlein, 2020). Optimistic people accept circumstances and are greater willing to use technological advances (Lu et al., 2012). Individuals perceive them as workable and trustable, ignoring possible adverse outcomes, then are pessimism internet users (Walczuch et al., 2007). This is because optimists perceive technological advances as usable and trustworthy.

Therefore, customers with a positive outlook are likelier to have a favorable disposition toward emerging technologies (Godoe & Johansen, 2012). "A propensity to be a digital business and thought leader." On the other hand, another factor is technological innovativeness (Parasuraman & Colby, 2015). Martens et al. (2017) and Rodriguez-Ricardo et al. (2018) have found that innovators are open to experimenting with new technologies. According to Oliveira et al. (2016), highly innovative users tend to have an open mind and are willing to use innovations, including innovative sources like the adoption of AI. Moreover, innovativeness is a prerequisite for adoption intentions; innovative users tend to have a positive opinion of the capabilities of technology, even when there is uncertainty concerning the use of technology adoption (Prodanova et al., 2019). Therefore, the study proposes the research hypotheses:

H1: Technology readiness (a) optimism (b) innovativeness significantly and positively influence perceived usefulness.
H2: Technology readiness (a) optimism (b) innovativeness significantly and positively influence perceived ease of use.

2.3. Technology Awareness, Perceived Usefulness And Perceived Ease Of Use

The phrase "being aware of, knowing the stuff of, or being notified about a given perceived behavior" is one definition of the term "awareness" (Christ & Reiner, 2014). Although awareness has not been given a great deal of attention in the research that has been done on the topic of technology acceptance (perceived ease of use and perceived usefulness) up until this point (Flavián et al., 2022), it may be of utmost significance in the investigation of newly introduced technological services such as AI adoption. Users have paid close attention to and are aware of the knowledge provided about a new technology or device. Additionally, "awareness" in branding refers to technology recognition and adoption (Hellofs & Jacobson, 1999). This indicates that the users are aware of the information. The limited body of research on AI awareness primarily focuses on particular fields. According to the findings of the vast majority of studies conducted within the elderly care industry, "awareness" is defined as the users' familiarity with the technology (Andersen et al., 2000). In this context, individuals who have a better knowledge about perceived behaviors are more aware of adopting technology and use them to a more significant extent than those who are hearing about the offerings for the technology adoption (Crist et al., 2007). Therefore, the perceptions that individuals have received, studied, and the experiences that they have had are all related to their awareness of the new technologies (i.e., AI) that are available. Previous studies conducted in the context of organizations have shown that making users aware of the activities their company is involved in as part of its social responsibility initiatives motivates those workers to contribute to the efforts being made by the business (Raub & Blunschi, 2014). When we apply this idea to the field of research that we are examining, we propose that clients who are aware of using AI will have a greater willingness to use those advisors.

H3a: Technology awareness significantly and positively influences perceived usefulness.
H3b: Technology awareness significantly and positively influences perceived ease of use.

2.4. Perceived Usefulness, Perceived Ease of Use And Intention To Use Ai In Social Media

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The intention to behave can be influenced by how helpful something is perceived. The viewpoint justifies this assertion that users' intentions to use the technology will be higher regardless of their behavior toward the adoption of technology if they anticipate a technology to boost their productivity on the job. It has been demonstrated in several previous studies (Gamal Aboelmaged, 2010; Khalifa & Shen, 2008; Lai, 2017; Liao et al., 2007; Lai & Yang, 2009) that the perceived usefulness of an online. On the other hand, the complexity of a single system will become the barrier that prevents the widespread implementation of technology (Paschen, 2020); however, AI increases the use of social media platforms. According to previous research findings, perceived ease of use is a crucial component of e-commerce applications using AI technology (Flavián et al., 2022; Paschen, 2020). Users are likely to be concerned about the amount of effort required to use that implementation and the degree of difficulty involved in the procedure. This favorable and convincing individual's actions should be enabled by the perceived ease of using AI technology in social media. Therefore, the study proposes the research hypotheses:

H4: Perceived usefulness significantly and positively influences intention to use artificial intelligence in social media.
H5: Perceived ease of use significantly and positively influences intention to use artificial intelligence in social media.

2.5. Intention to Use Ai and Actual Use of Ai in Social Media

The discretionary and cognitive depiction of the user's willingness to use social media is known as the intention to use AI-based social networks (Rauniar et al., 2014). Thus, in our model for TAM, AI-based social media by intention to use is considered the safe enabler of social media usage by individuals. The study proposed that the intention to use should be based on the perceived value that the user derives from social platforms (Ritz, Wolf & McQuitty, 2019). The TPB postulates that a user’s intention to engage in a specific behavior is proportional to the degree to which they have a favorable attitude toward that actual behavior (Lai, 2017). The realization of the future goal leads to deeper involvement with the social media website, and it does so in a way that is congruent with the goals derived from the historical data consideration. This connection helps to explain why people use social media sites so frequently. The adoption of digital platforms is not as much of a challenge posed by using technology as it is by knowing which websites to use and how to use them most effectively (Lacka & Chong,2016). Involving personal pages, followed by creating accounts explicitly designed for social media users, is a great way for owners and managers to adopt AI-based social media platforms to get their feet wet with digital marketing. For this discussion, "actual technology use" refers to the behavior of the users who engages in digital marketing on their own. Finally, the study proposes the research hypothesis:

H6: Intention to use significantly and positively influences actual use of AI in social media

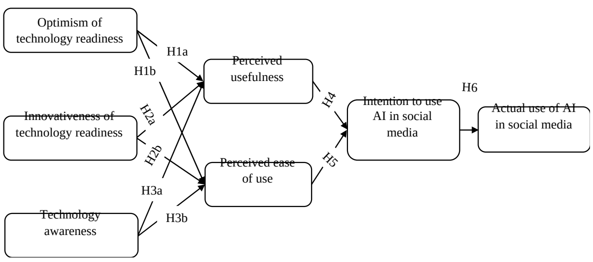

Figure 1 Theoretical Framework

RESEARCH METHODOLOGY

The study used a quantitative research design to test the research hypotheses. A self-administered survey was used to approach the users of social media platforms that intended to adopt artificial intelligence (AI) in social media platforms. This study aimed to investigate the impact of technology readiness and awareness of TAM

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variables on the intention of adopting AI in social media platforms. Instantly after mailing the questionnaire, a letter encouraging having secured the study was emailed out to all of the users that participated in the research. The survey was posted on social media platforms (i.e., Facebook, LinkedIn, Twitter, and emails). The respondents requested that they individually fill out the survey questionnaires and return them to the assigned hubs, which were the ones from which the questionnaires were obtained.

A total of 510 questionnaires were sent out to users of social media that had been chosen randomly belonged to Saudi Arabia. A total of 365 questionnaires were returned after being filled out. This leaves 345 usable survey questionnaires for this research, which results in a response rate of 67.65%. A total of 20 questionnaires were thrown out due to missing data, so the overall response rate is 67.65%. Table 1 presents the demographics of the study's respondents for the study. The majority of the users were using social media for leisure (198, 57.4%) than the users who were using for shopping purposes (147, 42.6%). 304 (88.1%) of the respondents were males and only 41 (11.9%) of the respondents were females. 30 (8.7%) of the respondents were less than 18 years old, 131 (38%) of the respondents were 18-33 years old, 105 (30.4%) of the respondents were 34-40 years old and 79 (22.9%) of the respondents were more than 40 years old. 14 (4.1%) of the respondents were taken from Facebook, 64 (18.6%) of the respondents were taken from LinkedIn, 120 (34.8%) of the respondents were taken from Twitter, and 147 (42.6%) of the respondents were taken by sending emails. 5 (1.4%) of the respondents had 12 years of education, 66 (19.1%) of the respondents had 14 years of education, 231 (67%) of the respondents had 16 years of education, and 43 (12.5%) of the respondents had above 18 years of education.

Table 1 Demographic information

Demographic information		Frequency	Percent	Valid Percent	Cumulative Percent
Purpose	For Shopping	147	42.6	42.6	42.6
	For leisure	198	57.4	57.4	100.0
	Total	345	100.0	100.0	
Gender	Male	304	88.1	88.1	88.1
	Female	41	11.9	11.9	100.0
	Total	345	100.0	100.0	
Age	Less than 18 Year	30	8.7	8.7	8.7
	18 - 33 Years	131	38.0	38.0	46.7
	34 - 40 Years	105	30.4	30.4	77.1
	More than 40 Years	79	22.9	22.9	100.0
	Total	345	100.0	100.0	
Social Media Platform	Facebook	14	4.1	4.1	4.1
	LinkedIn	64	18.6	18.6	22.6
	Twitter	120	34.8	34.8	57.4
	Emails	147	42.6	42.6	100.0
	Total	345	100.0	100.0	
Qualification	12 Years	5	1.4	1.4	1.4
	14 Years	66	19.1	19.1	20.6
	16 Years	231	67.0	67.0	87.5

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18 Years and above	43	12.5	12.5	100.0
Total	345	100.0	100.0	

3.1. Measurement Scales

The majority of the questions on the survey were taken from relevant earlier research, with some necessary validation and phrasing changes made to accommodate the adoption of AI in social media and the professional context that was being studied. The study adapted 8 items of technology readiness (i.e., 4=Optimism, 4=Innovativeness), and 4 items of technology awareness from the study of (Flavián et al., 2022). 4 items of perceived usefulness, 4 items of perceived ease of use (Flavián et al., 2022) and 4 items of intention to use were adapted from the study of Gamal Aboelmaged, 2010). 3 items of actual use were adapted from the study of Rauniar et al. (2014). All variables were measured on 5 points Likert scales ranging from 1=strongly disagree to 5=strongly agree.

3.2. Data Analysis

Analyzing the research model and putting the hypotheses to the test were accomplished with the assistance of SmartPLS 4.0 software using partial least squares structural equation modelling (PLS-SEM). Because prediction accuracy is the primary focus of this investigation (Flavián et al., 2022), PLS was chosen as the appropriate estimation technique (i.e., to predict intention to use IA in social media). PLS is adequate because, compared to the covariance-based SEM, it offers superior predictive power as a variance-based structural equation model (see, for example, Fornell and Bookstein, 1982; Ringle et al., 2015). Additionally, PLS modeling is especially helpful for testing exploratory models formed by a large number of variables under either normality or non-normality in the data distribution (Hair & Alamer, 2022).

RESULTS

4.1 Assessment of Measure Model

In order to determine whether or not the measurement model is reliable, the study first verified the convergent validity of the measurement constructs (Davari & Rezazadeh, 2013). Convergent validity includes factor loadings > 0.7 and average variance extracted (AVE) > 0.5 (do Nascimento et al., 2016). The study runs a series of PLS algorithms to finalize the convergent validity. The study deleted 1 item of optimism (OPT1=0.568) and 1 item of innovativeness (INN3=0.699), which had a loading that was lower than the suggested value of 0.7 (Henseler et al., 2009), was taken out of the model because its loading was higher than the suggested value. On the other hand, the study found the reliability of the measurement constructs, including Cronbach alpha > 0.70 and composite reliability > 0.70 (Davari & Rezazadeh, 2013; Sharif et al., 2012; 2022). According to what is displayed in Table 2, both Cronbach's and the composite reliability were able to surpass the 0.7 thresholds (Ramayah et al., 2018; Ringle et al., 2015) as well as the factor loading values. In addition, each latent factor has a higher AVE value than 0.50 (Hair et al., 2013).

Table 2 Convergent validity and reliability

Constructs	Items	Factor loadings	AVE	Cronbach alpha	Composite reliability
Actual use of AI in social media			0.716	0.803	0.817
	AU1	0.812			
	AU2	0.880			
	AU3	0.845			
Innovativeness (Technology readiness)			0.655	0.737	0.741
	INN1	0.796			
	INN2	0.825			
	INN4	0.806			
Intention to use of AI in social media			0.634	0.809	0.820
	ITU1	0.741			
	ITU2	0.789			
	ITU3	0.829			

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	ITU4	0.823			
Optimism (Technology readiness)			0.629	0.705	0.710
	OPT2	0.813			
	OPT3	0.751			
	OPT4	0.813			
Perceived ease of use			0.729	0.875	0.879
	PEU1	0.782			
	PEU2	0.889			
	PEU3	0.868			
	PEU4	0.874			
Perceived usefulness			0.673	0.836	0.845
	PU1	0.721			
	PU2	0.848			
	PU3	0.858			
	PU4	0.846			
Technology awareness			0.695	0.781	0.785
	TA1	0.839			
	TA2	0.829			
	TA3	0.834			

The study also checked to ensure that the square root of AVE values for each latent construct was higher than the inter-latent correlations so that we could test for discriminant validity (do Nascimento et al., 2016; Sharif et al., 2022) in Table 3 and 4. For this purpose, the study found cross-loadings> than the loadings of another latent construct and the heterotrait-monotrait ratio (HTMT), which assess the average of the HTMT correlations. Finally, the study found that the values of HTMT for each latent construct were below the 0.90 threshold in every instance (Henseler et al., 2015). Finally, the study meets the validity and reliability criteria.

Table 3 Cross-loading

	Actual use of Artificial Intelligence in Social Media	Innovativeness	Intention to use of Artificial Intelligence in Social Media	Optimism	Perceived Usefulness	Perceived ease of use	Technology Awareness
AU1	0.812	0.468	0.392	0.403	0.415	0.444	0.359
AU2	0.880	0.551	0.522	0.471	0.560	0.500	0.514
AU3	0.845	0.430	0.491	0.398	0.449	0.482	0.379
INN1	0.489	0.796	0.384	0.469	0.398	0.397	0.367
INN2	0.457	0.825	0.388	0.516	0.494	0.428	0.446
INN4	0.448	0.806	0.498	0.566	0.526	0.408	0.489
ITU1	0.342	0.363	0.741	0.379	0.288	0.374	0.304
ITU2	0.477	0.412	0.789	0.437	0.392	0.484	0.351
ITU3	0.431	0.418	0.829	0.435	0.430	0.450	0.366
ITU4	0.506	0.470	0.823	0.464	0.523	0.449	0.452
OPT2	0.416	0.545	0.432	0.813	0.491	0.411	0.547
OPT3	0.369	0.436	0.402	0.751	0.434	0.342	0.457
OPT4	0.409	0.539	0.452	0.813	0.488	0.425	0.492
PEU1	0.394	0.423	0.402	0.469	0.388	0.782	0.458
PEU2	0.491	0.420	0.466	0.413	0.474	0.889	0.482
PEU3	0.525	0.405	0.487	0.384	0.466	0.868	0.444
PEU4	0.508	0.484	0.532	0.436	0.464	0.874	0.486
PU1	0.428	0.411	0.367	0.392	0.721	0.380	0.494
PU2	0.431	0.518	0.453	0.488	0.848	0.436	0.556
PU3	0.498	0.477	0.421	0.539	0.858	0.441	0.636
PU4	0.499	0.517	0.470	0.521	0.846	0.464	0.628

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TA1	0.379	0.460	0.404	0.562	0.555	0.429	0.839
TA2	0.409	0.411	0.378	0.520	0.562	0.441	0.829
TA3	0.455	0.478	0.390	0.499	0.648	0.494	0.834

Table 4 HTMT ratio

	1	**2**	**3**	**4**	**5**	**6**	**7**
Actual use of Artificial Intelligence in Social Media							
Innovativeness	0.744						
Intention to use of Artificial Intelligence in Social Media	0.676	0.672					
Optimism	0.665	0.881	0.712				
Perceived Usefulness	0.685	0.741	0.622	0.770			
Perceived ease of use	0.668	0.631	0.653	0.632	0.613		
Technology Awareness	0.619	0.704	0.582	0.849	0.869	0.659	

4.1.1 Model Fitness

PLS-SEM was then used to check whether or not model fit measures were available. For this purpose, the normed fit index (NFI) was calculated to be 0.773, which is extremely close to the threshold value of 0.90 (Hu and Bentler, 1998). The research model had a standardized root-mean-square residual (SRMR) of 0.061, which is less than 0.08 and indicates a good fit between the estimated and saturated model (Hu & Bentler, 1998).

4.2 Structural Equation Modeling

The study tested the research hypotheses using the structural equation modelling (SEM) approach (Figure 2). The study ran a bootstrapping technique with 5,000 different subsamples, which was utilized in order to test the SEM model (Hair & Almari, 2022; Sharif et al., 2022). Table 5 summarizes the findings of the study. Concerning the hypotheses relating to the readiness of technology, the findings indicated that users' optimism significantly and positively influenced perceived usefulness ($\beta = 0.129$, p-value=0.025) and perceived ease of use ($\beta = 0.131$, p-value=0.050); therefore, hypotheses H1a and H1b are accepted. Innovativeness of technology readiness significantly and positively influenced perceived usefulness ($\beta = 0.235$, p-value=0.000) and perceived ease of use ($\beta = 0.244$, p-value=0.000); therefore, the hypotheses H2a and H2b are accepted. Meanwhile, technology awareness significantly and positively influenced perceived usefulness ($\beta = 0.501$, p-value=0.000) and perceived ease of use ($\beta = 0.333$, p-value=0.000); therefore, the hypotheses H3a and H3b are also accepted. Additionally, perceived usefulness ($\beta = 0.321$, p-value=0.000) and perceived ease of use ($\beta = 0.386$, p-value=0.000) significantly and positively influenced intention to use of artificial intelligence in social media. Therefore, the hypotheses H4 and H5 are accepted that showed the intentions of users to adopt AI in social media platforms. Finally, intention to use significantly and positively influenced actual use of AI in social media ($\beta = 0.559$, p-value=0.000); therefore, the hypothesis H6 is accepted.

Table 5 Hypotheses testing

Hypotheses testing	**β**	**t-statistics**	**p-values**
H1a: Optimism -> Perceived Usefulness	0.129	2.243	0.025
H1b: Optimism -> Perceived ease of use	0.131	1.964	0.050
H2a: Innovativeness -> Perceived Usefulness	0.235	3.689	0.000
H2b: Innovativeness -> Perceived ease of use	0.244	3.909	0.000
H3a: Technology Awareness -> Perceived Usefulness	0.501	8.436	0.000
H3b: Technology Awareness -> Perceived ease of use	0.333	5.146	0.000
H4: Perceived Usefulness -> Intention to use of Artificial Intelligence in Social Media	0.321	5.639	0.000
H5: Perceived ease of use -> Intention to use of Artificial Intelligence in Social Media	0.386	7.337	0.000
H6: Intention to use of Artificial Intelligence in Social Media -> Actual use of Artificial Intelligence in Social Media	0.559	14.025	0.000

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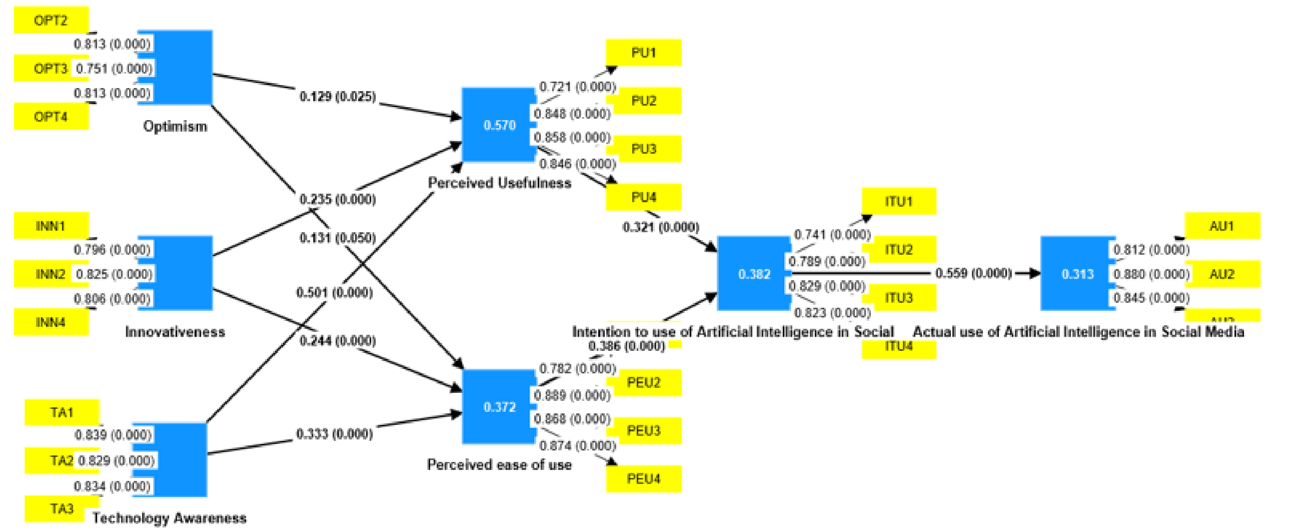

Fig 2 Structural equation modeling (SEM)

DISCUSSION

The study used a quantitative research design using a survey questionnaire. This research measured Saudi Arabian users' perceptions of social media platforms. This study mainly raises technology awareness and readiness to adopt artificial intelligence (AI) in social media platforms. This way, they will enjoy a secure and safe environment where they can create privacy. The survey questionnaire was sent to 510 respondents on different social media platforms (i.e., Facebook, LinkedIn, Twitter, and emails). The study received a total of 345 complete responses from the respondents. The study employed the technology acceptance model (TAM) by using the theory of planned behavior (TPB) because the theory helps the researcher to measure the planned behavior of adopting AI in social media. The study's results showed that optimism about technology readiness significantly and positively influenced perceived ease of use and usefulness. However, optimism has a stronger impact on perceived ease of use, meaning the users of social media perceive ease of control and use of AI in social media platforms. The users are more optimistic about perceiving the easiness of adopting AI technology in social media. On the other hand, innovativeness significantly and positively influenced perceived ease of use and perceived usefulness; however, innovativeness has a stronger impact on perceived ease of use than perceived usefulness. It means that users are always willing to make easy use of AI on social media platforms. The results are consistent with the notions of Flavián et al. (2022) that it is possible that optimism will become highly significant in the era that follows technology readiness when individuals believe that technologies are based on AI (González-Jiménez, 2020). To be more specific, the users should direct their attention toward using AI, which has a higher degree of technological optimism if those users are likely to use the services offered by AI advisors. AI advisors may bring in users who are more open to new ideas because they increase the active role that the users play in the investment process through technology.

Technology awareness also significantly and positively influences perceived ease of use and usefulness. However, it has a stronger impact on perceived usefulness because when the users are aware of the AI technology, they will directly use it in social media. The results are also consistent with the notions of Flavián et al. (2022). On the other hand, perceived ease of use and perceived usefulness significantly and positively influenced the intention to use AI in social media; however, perceived ease of use has a stronger impact on intention to use because the users perceive easiness, so they have higher intention toward adopting new technology. The results are consistent with the findings of the previous studies (Gamal Aboelmaged, 2010; Rauniar et al., 2014). Finally, the intention to use significantly and positively influenced the actual use of AI in social media, and this is the highest relationship. It means that when the users have a higher intention to use AI, they will use AI technology in social media platforms. Therefore, the results are robust to implement the users' perceptions in Saudi Arabia.

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5.1 Practical Implementations

According to the findings of this study, AI in social media constitutes an essential pillar that influences the sustainability, expansion, and processes of the vast majority of new technology adoption in Saudi Arabia. Among the most important takeaways from the research is that AI is on an upward trajectory. Consequently, there has been both a direct and indirect rise in the privacy and security of social media platforms. These findings are in agreement with the majority of the previous research that has been done on the topic of threat and privacy issues related to AI-based technology. According to most of the responses, other positive effects associated with adopting AI in social media include improvements in innovative thinking, enhancements in perceived behaviors, and increased behavioral intentions. Because the aforementioned advantageous characteristics are predictors of increased user behaviors to adopt AI, the resultant implication of this study is that AI, which demonstrates an increasing trend among users in Saudi Arabia, is responsible for an overall increase in the use of AI technology. In the years to come, there will be a demand for academic research that focuses on determining whether or not the proposed solutions are effective in their ability to use AI in social media. This study is significant for Saudi Arabian users, as it can help them improve their buying and selling by expanding their marketing efforts using AI-based social media. It will help reduce the many problems associated with marketing and contribute to an overall improvement in the performance of these businesses. This was one of the first studies that discussed the use of AI-based social media in Saudi businesses, and it was a pioneering study. Thus, practitioners can get assistance from this study to improve performance by reducing various marketing issues.

5.2 Limitations and Future Directions

The study has some limitations, which can be filled by directing future research. The study used a quantitative research design, so there is a need for a mixed-method design to observe real-time users on social media platforms who perceive the use of AI in social media. The study is also a cross-sectional study; however, the future study may be based on a longitudinal study to measure the perceptions of Saudi users sequentially. In the future, research should also include a variety of other factors that impact the marketing practices utilized by social media platforms using AI. In addition, because the research uses only primary sources of information, it is possible that the results could be subject to certain restrictions. For example, the use of questionnaires suggests that there may be misconceptions and misrepresentations on the part of the respondents; consequently, the validity of the findings may be called into question. It is anticipated that the limitation can be overcome by posing questions in the questionnaires in an understandable manner and free of subjective language.

Conflicts of interest

The authors have no relevant financial or non-financial interests to disclose.

The authors have no conflicts of interest to declare that are relevant to the content of this article.

All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

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