Explaining the effect of artificial intelligence on the technology acceptance model in media: a cloud computing approach

Seyed Shahramadin Tavakoli
Department of Media Management, Semnan Branch, Islamic Azad University, Semnan, Iran

Afsaneh Mozaffari
Department of Communication and Information Sciences, Science and Research Branch, Islamic Azad University, Tehran, Iran, and

Abolfazl Danaei and Ehtesham Rashidi
Department of Media Management, Semnan Branch, Islamic Azad University, Semnan, Iran

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Abstract

Purpose – The purpose of this paper is to explain the effect of the technology acceptance model in the media environment by using the mediating role of artificial intelligence and the cloud computing approach.

Design/methodology/approach – After reviewing the theoretical foundations, a conceptual model framework and research hypotheses were formed. The statistical population of the study included managers, deputies and experts from the National Iranian Oil Company, and a statistical sample of 368 people was selected by simple random sampling.

Findings – The results of structural equation modelling with PLS 2.0 software show a positive and significant effect on the artificial intelligence variable in the technology acceptance model with the cloud approach. Artificial intelligence has opened a new space in the digital world, especially in the media, so that its profound impact is quite evident and has affected people's lives.

Originality/value – The acceleration of various technologies has severely challenged the approach of organizations, especially the media. The media environment with word of the technologies of the Industry 4.0, especially cloud computing technology, has changed the ways of accessing and using products and services.

Keywords Artificial intelligence, Technology adoption, Modelling, Media, Technology acceptance model, Social media, Cloud computing

Paper type Research paper

Introduction

Reviewing the innovative periods in mankind's history surprisingly talks about the desire of humans to move towards technological transformation (Na *et al.*, 2022). Since Industry 1.0, mankind has always witnessed drastic technological changes referred to as the second and third "waves" (Morrar *et al.*, 2017; Xu *et al.*, 2018). We are currently witnessing Industry 4.0. Since the introduction of Industry 4.0 in January 2016, the topic of technological transformation led by artificial intelligence (AI) has been predicted to be very close (Skilton and Hovsepian, 2018).

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AI in the field of technology offers organizations the opportunity to improve their performance (Borges *et al.*, 2021). Research regarding AI has focused on how to reproduce aspects of human intelligence, including the ability to communicate, within the machine (Frankish and Ramsey, 2014; Guzman and Lewis, 2020). Today, this gulf between AI and communication research is narrowing, bridged by AI technologies designed to function as communicators. Recent advances in AI have led to more powerful and consequential AI technologies being integrated across daily life (Campolo *et al.*, 2017). According to the Pew Research Center, individuals routinely chat with Amazon's Alexa, Apple's Siri and other digital assistants (Olmstead, 2017), with people's interactions with smart devices expected to grow along with the emerging Internet of Things (Rainie and Anderson, 2017). Within the industry, media providers, such as the Associated Press, are using AI-enabled technologies in the production and distribution of news (Marconi *et al.*, 2017). There is still limited knowledge regarding the integration of this technology in management practices, especially in cloud ERP systems (Yathiraju, 2022).

Electronic learning is a new system in which different types of technologies and tools are integrated together and play a major role in creating e-learning. E-learning systems often require a lot of hardware and software resources, which, nowadays, cloud computing technology has changed the development and availability of much software. There are many educational institutes that cannot afford such investments and cloud computing seems to be the best outcome for them. Using a cloud computing e-learning system has its own properties and requires a specific approach. Over the years of research by researchers, various terminology has been applied to the concepts of e-learning, media and technology: computer, bandwidth, multimedia, interactive, hyperlinked, collaborative, distance learning, simulated situation, hyperlearning, media-rich, more formal, structured, broadband, intelligent and usable (Kumar Basak *et al.*, 2018; Laouris and Eteokleous, 2005; Sharma and Kitchens, 2004; Soualah-Alila *et al.*, 2013; Traxler, 2007).

Various organizations, both in public and private sectors around the world, have been using cloud computing for some time, and more and more organizations are moving towards infrastructure and cloud technologies (Yaghubi *et al.*, 2016). Cloud computing is recognized as an important area in information technology innovation, and massive investments have been made in it (Armbrust *et al.*, 2010). Cloud computing technology is one of the most important topics in the field of information systems development, so cloud computing is considered a new paradigm for hosting and providing services on the internet (Avram, 2014; Lian *et al.*, 2013). Cloud computing is a set of easy-to-use virtualized resources that can be dynamically modified to meet customer demand (Yektaei and Ranjbar Noshary, 2016). Cloud computing will certainly change the structure and nature of information systems of organizations in general, and, in particular, it will change the development of telecommunications. Nevertheless, before using cloud computing, organizations should seriously evaluate and choose the appropriate technological model for their organization (Kuo, 2011; Osei Yeboah and Kofi Asare, 2014).

Alhanatleh and Akkaya (2020) declared that cloud computing can be a new horizon whereby technological resources for computing (i.e. processing, memory and storage) are stored in a place other than the user's physical location. Cloud computing is a model that enables easy access from anywhere and on-demand to a repository of configurable computing resources, such as networks, servers, repositories, applications and services. They can be provided or delivered quickly without the need for the intervention of a service provider (Avram, 2014). According to the National Institute of Standards and Technology, cloud computing has four key features: on-demand self-service, broad network access, rapid elasticity and measured service. The goal of some researchers is to study the concept of cloud computing by studying only one type of it, as an example of infrastructure as a service (Bhardwaj *et al.*, 2010). Another group of researchers studies cloud computing on a specific system, such as the human resource planning system (Saeed *et al.*, 2011), presented by providers or e-learning programmes.

Another study was conducted by Low *et al.* (2011), which examined the acceptance factors of cloud computing. They postulated the impact of eight factors on the adoption of cloud computing in high-tech industries in Taiwan. They were trying to identify the factors that led to the acceptance or non-acceptance of the cloud by the owners of these industries. Surveys have shown that a comparative advantage hurts cloud acceptance, as well as the support of senior management, organization size, competitive pressure and a business partner have had a significant positive effect on cloud propagation and acceptance. Also, in this study, compatibility and complexity in cloud acceptance had no significant effect (Low *et al.*, 2011). Important variables influencing the use of cloud computing by researchers have also been presented over the years: organizational factors (information intensity, employee knowledge) (AbuKhousa *et al.*, 2012; Karahanna *et al.*, 2002; Premkumar and Roberts, 1999; Tornatzky and Fleischer, 1990; Yusof *et al.*, 2008); human factors (decision-makers' innovation, decision-makers' knowledge, external support and competitive pressure) (AbuKhousa *et al.*, 2012; Lian *et al.*, 2013; Lin *et al.*, 2012; Lin and Yen, 2011; Yusof *et al.*, 2008); environmental factors (external support, environmental infrastructure and competitive pressure) (Chang *et al.*, 2007; Lian *et al.*, 2013; Thong, 1999; Tornatzky and Fleischer, 1990); technological factors (comparative advantage, complexity, testability, compatibility, technological infrastructure, security and privacy) (Chang *et al.*, 2007; Gupta *et al.*, 2013; Kuo, 2011; Lian *et al.*, 2013; Lin and Yen, 2011; Premkumar and Roberts, 1999; Rogers, 2003; Sultan and Sultan, 2012; Tornatzky and Klein, 1982; Yusof *et al.*, 2008). Gupta *et al.* (2013) in their research considered various factors effective, such as cost reduction, ease of use and persuasiveness, reliability, collaboration and sharing, security and privacy, in the use of cloud computing by small and medium enterprises. Bento *et al.* (2015), in their research on the motivation of organizations to use cloud human resource planning, included in their factors: faster access to new capabilities, increased revenue by offering new products, use of better resources and reduced costs; they also identified decentralization and reported barriers to cloud access: security, regulation, reliability, capability and maturity of cloud services, in addition to government regulations. In their research, Wang *et al.* (2015) addressed the opportunities and challenges that IT executives face in moving to cloud computing, such as data privacy, security, IT governance and local regulation when moving to the cloud.

Therefore, the necessity of using a technology acceptance model (TAM) in the organization with a cloud approach seems necessary. Importantly, the adoption of technology in this regard has been the subject of much research. Hence, different theories have presented new approaches to the acceptance and use of information technology in the individual and organizational dimensions. Among the studies conducted in the group of individual acceptance models, Venkatesh *et al.* (2003) introduced the following eight models as the most important TAMs that are the basis of other models: reasoned action theory, TAM and motivational model, theory of planned behaviour (TPB), combined TAM and planned behaviour, personal computer use model, innovation dissemination theory (IDT) and social cognition theory. In another section, the most important models of technology acceptance are presented as follows: theory of reasoned action (TRA) (Fishbein and Ajzen, 1975); IDT (Rogers, 1983); social cognitive theory (SCT) (Bandura, 1986); TAM1, the basic TAM (Davis, 1989); TPB (Ajzen, 1991); technology acceptance model 2 (TAM2)

(Venkatesh and Davis, 2000); and unified theory of acceptance and use of technology (Venkatesh *et al.*, 2003).

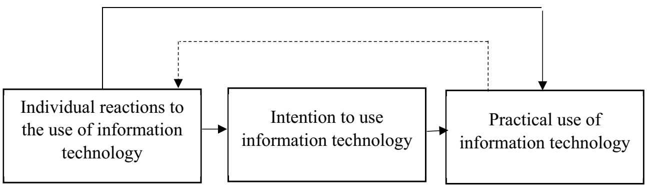
Table 1 compares some important indicators from the perspective of TAMs.

Examining these models, it can be concluded that they all follow the following conceptual structure (Figure 1).

In recent years, social networks have had a significant impact on people's interactions. More and more users are using social media for entertainment, web browsing, news awareness or just to spend time (Sangari *et al.*, 2020). Social media in the workplace, for example, provides employees with new ways to interact with their customers and co-workers and to ask questions and share information (Leftheriotis and Giannakos, 2014). Organizations can reap significant benefits through the use of social media. One of these benefits is the creation of an intelligent knowledge management system in the organization. Interactions between employees and the creation of group discussions cause the exchange of useful information between employees and enable them to improve their performance (Nisar *et al.*, 2019). Organizations can use social media to save money, engage with customers and build trust in customers' minds. Also, media, such as social media, can provide better services day by day with innovations and updates of their features (Khoirina and Sisprasodjo, 2018). The marketing activities of companies in the media affect their

Table 1.
Comparison of indicators from the perspective of technology acceptance models

Item / Model	TRA	TPB	IDT	TAM1	SCT	TAM2
Attitude (feeling)	*	*		*	*	
Mental norm	*	*				*
Perceptual usefulness			*	*	*	*
Ease of perceptual use		*	*	*		*
Anxiety					*	
Computer self-belief					*	
Output quality						*
Facial			*			*
Experience						*
Volunteering						*
Visibility of results						*
Competitive pressure						*
Customer satisfaction						*
Perceptual pleasure						*
Encouragement						*
Technical support						*
Education						*



Source: Venkatesh *et al*. (2003)

Figure 1.
Conceptual structure of individual IT acceptance models

customers' intention to buy by influencing social identity, perceived value and creating customer satisfaction (Chen and Lin, 2019). In such a situation, the company should always analyse the media environment with foresight and obtain accurate information from leading trends and changes so that they can plan to adapt media policies and strategies in the future. When new technology is introduced, the rational presupposition is to use and accept this new technology (Albarran, 2004). Therefore, the issue of AI has arisen since we were faced with a large amount of information, and it has become difficult to decide and process this information; therefore, for information processing, the need for a device similar to the human brain arose (Broussard *et al.*, 2019; Nazari, 2020). In addition to reducing costs, this feature helps to create more cost-effective computing power (de-Lima-Santos and Ceron, 2021). AI is more than 60 years old, and in just the last decade of its development, it has changed all communications in the digital world. Due to its rapid evolution, the scientific dimensions of AI are rarely studied. Also available are AI functions: QC, searching, metadata, compliance, editing, highlights, break structure or advertising, subtitling, close captioning, supervision, presenting the news and more. Therefore, the researcher of this study seeks to explain the role of AI on the application of the cloud TAM in the media. For this purpose, the conceptual model and research hypotheses in Figure 2 are placed in six categories. Therefore, in this research, we are seeking answers to the following questions:

Q1. What is the relationship between usability attributes and the TAM model?

Q2. What is the role of artificial intelligence as a mediator in the model?

Contextual setting

Chemicals and industries in this area have a fundamental role in the life and progress of human society. Chemicals include a large part of the constituent materials in today's world, and in almost every industry and process, traces of the dependence of that industry and process on chemicals can be found in its various parts. Today, the two major challenges of the chemical industry can be seen in the optimization of the industry and businesses in this field and the concerns regarding the degree of damage of industries, processes and chemical substances to the environment and the ecosystem of the planet Earth. In this regard, one of the most sensitive and worrying issues is the emission of greenhouse gases in the atmosphere, which further accelerates global warming. Fortunately, new generation technologies have been able to provide suitable solutions to optimize industries and reduce their harmful effects, along with increasing productivity and reducing costs.

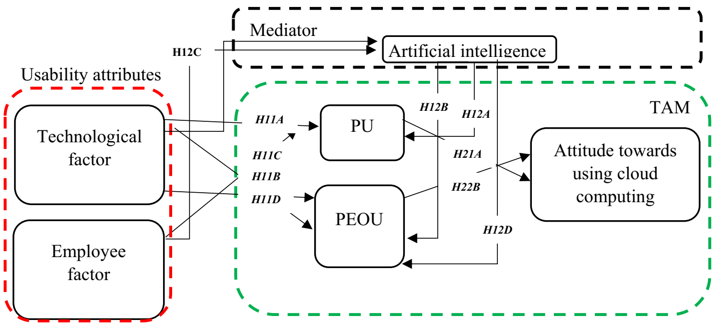


Figure 2.
Conceptual model of research

In the oil industry, one of the latest technologies that has been able to greatly help improve processes, such as control and management in this industry, can be considered AI. AI is a branch of computer science that focuses on building systems and processes that are capable of performing tasks that typically require human cognitive abilities, such as learning and problem-solving. According to the needs of new industries in various areas, such as reducing production costs, energy consumption management and increasing productivity, and also the need for advanced intelligent processing in the steps and processes used in the chemical industry, the use of technologies such as AI by these industries' experts and specialists of this industry are located. The use of solutions and tools based on AI and industry can have significant effects on factors affecting the quality of the environment, including reducing emissions and controlling the disposal of pollutants, increasing energy efficiency and optimal management of natural resources. With the development of the use of intelligent technologies in industrial and service processes, new definitions of industrial systems have been formed, including the Green Industry.

Over the past decade, the chemical industry has used AI to increase operational efficiency, reduce costs and improve customer satisfaction. According to Liao and Yao (2021), a growing number of companies are now using AI technology to reduce greenhouse gas emissions in production processes and improve energy efficiency.

Literature review

Artificial intelligence and media

In the advertising and media sectors, companies seem to be showing similar enthusiasm towards AI. A market survey in Europe found that 80% of media practitioners agreed that AI would have significant impacts on their industry (Shields, 2018). Specifically, while 62% believed AI would improve decision-making, 47% thought it would improve productivity. However, one third of the respondents also felt not quite confident in their understanding of AI and how it might be applied in their work. According to the survey, less human control (47%) and trustworthiness insights (55%) were the two biggest concerns. Overall, few people felt that AI would have a negative impact on their work or job availabilities (Shields, 2018).

Today's audience has elevated expectations in every aspect of their digital lives, thanks largely to tech firms like Amazon that offer responsive services and active engagement. In such a data-driven and direct-to-consumer world, media need to respond faster and better to audience expectations, similar to other tech company counterparts (Raconteur, 2018). As media are now interwoven into consumers' daily lives and technology bundles, media companies must deliver engaging individual experiences to every consumer in context, in the moment, and all the time. Consequently, human resource commitment is significant in this new reality and the solution is logically the adoption of cognitive technologies.

In addition to alleviating the volume of work, AI can make the interaction of media, content, audiences and operations faster and better. To serve audiences as individuals, media companies must understand audience sentiments/preferences towards content and characters, assess resonance and promptly align content with audience preferences. To accomplish this, media companies must acquire insights from large data sets and act on it in real time. The traditional approach of collecting and interpreting audience data is no longer agile enough for such a scenario. For instance, as the appetite for online video on multiple screens increases, AI can help media companies perform mass personalization of video content experiences more efficiently and effectively. Gentzkow (2018) concluded that the key impact of AI will be on the demand rather than the supply side of media, especially in how content is matched to consumers. The application of cognitive technologies offers better means of matching content with demand, optimizing content management and scaling the process of content delivery.

Led by tech companies, such as Facebook, Amazon, Apple, Netflix and Google, with their expansion into the media sector, AI has been applied in various areas of the media industry to make "smarter" products and services. For example, AI enables Spotify's and Netflix's recommendation playlists, more effective content management at media companies and even chatbots to improve customer experience. A survey found that the most common ways in which news media are using AI globally were to improve content recommendations (59%); followed by workflow automation (39%); commercial optimization, such as ad targeting and dynamic pricing (39%); and intelligent agents to help reporters find stories (35%) (eMarketer, 2018). Another survey of media's AI adoption found that cable systems or MSO (44%) had the highest adoption rate, followed by cable networks (30%) and broadcast networks (25%) (Mayeda, 2018).

Strategically, how might AI be applied to improve a media company's competitiveness? Because of the emerging nature and newness of AI, most literature in this area has been industry-based. Some suggested that these cognitive technologies have the potential to benefit media companies by transforming the media audience-content connection process (Berman *et al.*, 2017; Gentzkow, 2018). Specifically, from the perspective of audience insights, AI might be used to understand social conversations and other audience sentiments and preferences (Berman *et al.*, 2017). Natural language processing and other related AI technologies can also be applied to understand and interpret a media company's live and archived content. For example, media content can be tagged, and rich metadata and context would enable faster, easier content management. In addition, AI can be used to integrate audience and content insights, matching audience interest and relevant content in real time to deliver personalized content and a better consumption experience. The value goes beyond developing competitive advantages, as it might help media companies identify new business opportunities as well. For example, consumer conversations about a show, storylines and characters might be integrated with other third-party content sources like events, social media and local news for other potential revenue sources (Berman *et al.*, 2017).

Recently, more studies have begun to examine the topic of human-machine interactions or communication in the context of AI (Kietzmann *et al.*, 2018; Mou and Xu, 2017). From the perspective of business adoption, literature has emphasized the importance of innovative employee roles and working relationships between humans and machines. From the perspective of interactions between consumers and AI-enhanced machines (e.g. chatbots and machine advice), the strategic value of such applications would largely depend on their nature and implementation. There are competing theories regarding how humans might perceive machine-mimicking human behaviour. From the uncanny valley notion that suggests the human tendency to feel uncomfortable towards a human-like machine to the media equation theory, which concluded that humans are likely to see computers, television and new communication technologies similar to real social relationships with humans (Mori *et al.*, 2012; Reeves and Nass, 1996), the effect of AI applications for media firms, like in other sectors, remains uncertain.

The artificial intelligence functions

AI technologies vary in how they function as a communicator, from interpersonal interlocutors to content producers. Voice-based assistants, such as Amazon's Alexa, vocally respond to human questions and requests. Embodied robots interact verbally and non-verbally with people (Peter and Kühne, 2018). Automated programmes called *bots* enter into text-based social media interactions by posing as human conversational partners, influencing the tone and substance of these exchanges (Ferrara *et al.*, 2016). News-writing programmes develop narratives from raw data that appear alongside human-produced stories and cannot be easily distinguished from them (Graefe *et al.*, 2018). What these technologies share is that by functioning as a communicator, they all step into a role that, within the conceptual confines of the communication discipline, historically has been restricted to humans. In doing so, AI more than facilitates communication: it automates communication (Reeves, 2016), as well as the social processes dependent upon it (Gehl and Bakardjieva, 2017).

AI technologies of communication are designed as something with which people exchange messages, a departure from the historical role of media developed as the means through which people communicate with one another (Gunkel, 2012). It is true that talking technologies existed before AI, such as car navigation systems; however, interaction with these devices was restricted to using a narrow range of rote commands. Technology did not adapt to the user, context or message. Interactions with AI-enabled devices and programmes are dynamic rather than static, contingent upon the messages being exchanged within a particular moment and context or upon the data being fed into the program. Some AI technologies also are responsive to individual users, "learning" about their human communication partner and adjusting interactions accordingly. Some scholars go as far as to argue that emerging technologies, such as robots, not only surpass the interactive capabilities of previous devices but may eventually push past the boundaries of human communication in their integration of multiple modalities of communication (Peter and Kühne, 2018). In design and function, AI technologies are positioned as increasingly complex and life-like communication partners.

Furthermore, research in human-computer interaction has demonstrated that when technologies directly exchange messages with people, particularly when designed with human social cues, the devices and programmes are interpreted as distinct "social actors" (Nass *et al.*, 1994). People draw on their knowledge of human interaction to make sense of and guide their exchanges with media (Reeves and Nass, 1996). Although people know that a human programmed the machine, researchers have found that people direct their messages towards the device, not the programmer (Sundar and Nass, 2000). Research into people's behaviour with and conceptualizations of emerging technology has produced similar results, demonstrating that people perceive robots as communicative partners distinct from humans but as social nonetheless (Edwards *et al.*, 2016) and that people interacting with a digital assistant think of themselves as exchanging messages with a technology (Guzman, 2019). Communicative AI technologies are not only designed to function as communicators but are also interpreted by people as such.

Technology acceptance model and technology approach

In particular, TAM was built to explain and predict user acceptance of specific types of technology. Some scholars have adopted TAM in various aspects of modern technology ranging from the use of websites (Chang and Chung, 2001), web retailing (Wang *et al.*, 2006), web browsers (Morris and Dillon, 1997), online purchase intentions (Van der Heijden *et al.*, 2003), email (Karahanna and Straub, 1999), blog usage (Hsu and Lin, 2008), instant messaging (Turel *et al.*, 2007), mobile technology (Hong and Tam, 2006), to ERP (Sternad and Bobek, 2013). However, there is a scarcity of studies explaining the acceptance of cloud ERP using the TAM. In this view, this study used the TAM model in examining the determinant of cloud ERP.

Much research has been done on the technology adoption model and cloud computing, each of which has examined the issue. Lubis *et al.* (2019) conducted a study at Toyota Astra

Motor, and the researchers used the advanced TAM2 to integrate the hybrid TAM and the IS success model with IBM AMOS software. Based on the results, compatibility, perceived ease, perceived usefulness, performance, internal support and intention to use were the determining factors for Toyota's successful ERP implementation. In another study, Alhanatleh and Akkaya (2020) evaluated the factors affecting the acceptance of cloud ERP in Jordanian education. They have used structural equation modelling for analysis, and they identified the technology factor, employee factor, perceived usefulness and perceived ease of use (PEOU) as important variables to influence cloud ERP acceptance. In a review article from 2007 to 2017, Nikam and Prasad (2019) addressed the implementation of the TAM and cloud ERP model. The results of their study increased the correlation between the perception of the TAM model and ERP, which ultimately gives a better understanding of the success of cloud ERP implementation in any organization. Ahn and Ahn (2020), in their research with a comprehensive approach to the factors affecting the intention to accept cloud ERP, showed that the factors of organizational culture, regulatory environment, comparative advantage, testability and vendor locking all had a significant effect on cloud-based ERP acceptance intent, while ICT skills, complexity, visibility, data security and customization had no significant effect on the intention to adopt cloud-based ERP. In their research, Salih *et al.* (2021) prioritized the factors affecting the acceptance of cloud ERP and important issues related to security, usability and vendors. This research will help develop new strategies or review existing strategies and policies aimed at effectively integrating cloud ERP into the cloud computing infrastructure. It also allows cloud ERP providers to set the expectations of organizations and business owners and implement appropriate tactics. Ouaadi and El Haddad (2021), in their research on cloud accounting acceptance using TAMs, showed that some variables, such as the purpose of use, motivation, remote reporting and company size, affect the intention to use cloud accounting, while other variables have no effect, such as professional class and flexibility. Chang and Hsu (2019), in a study using the cost-benefit approach, empirically examined the intention of cloud ERP users. Based on cost-benefit analysis and the TAM, this study presents a research model to examine how benefits (perceived usefulness and PEOU) and costs (perceived problems of risk and privacy) affect organizations' intention to change from planning to developing cloud enterprise resources. This study also calculated perceived trust and control in the field of cloud computing. Perceived usefulness, PEOU and privacy concerns significantly affect intent to change. Trust can increase perceived usefulness and PEOU and reduce perceived risk. Perceived control can also reduce perceived risks and privacy concerns. Gangwar *et al.* (2015), in their research, considered comparative advantage, adaptability, complexity, organizational readiness, senior management commitment and training as important variables to influence cloud computing acceptance using PEOU and perceived utility (PUt) as identified intermediate variables. Also, competitive pressure and business partner support directly affect the goals of cloud computing. In their study, Eldalabeeh *et al.* (2021) identified the factors affecting cloud-based accounting in the Jordanian financial sector using the TAM model. According to their SEM results, senior management support, organizational competency, service quality, system quality, perceived usefulness and PEOU were positively related to the intention to use cloud accounting. The adoption of cloud accounting had a positive effect on the use of cloud accounting.

Hypothesis development

About the characteristics of innovation and their relationship with its application and implementation, Tornatzky and Klein (1982) found that three characteristics of innovation – that is, relative advantage, compatibility and complexity – had the most important fixed relationships with the application of innovation. Every innovation is known as a superior thought to what it replaces. The degree of relative advantage is frequently expressed by economic profitability, social status and other benefits (Rogers, 2003). The complexity of any innovation includes a negative correlation with its application (Yaghubi *et al.*, 2016). It can be stated that if adopting technology is time-consuming or requires other effort to grasp it (e.g. ordinary tasks used to be done in a briefer and more classic time), that work has become complicated. Therefore, complexity will have a negative effect on cloud adoption (Chang *et al.*, 2007; Lian *et al.*, 2013; Premkumar and Roberts, 1999). The technology context, according to Ahn and Ahn (2020), includes the skills related to the use of technology by employees. However, cloud computing provides a challenging environment for employees and offers a fertile ground for technological innovation. They found that technology skills do not hold a significant influence on the intention to use cloud-based ERP. Unlike Kim *et al.* (2017), who adopted three criteria that address the technology context, namely, economic risk, performance risk and security risk – the latter two had a significant influence on the intention to adopt cloud computing and specifically software-as-a-service, as opposed to economic risk which has no impact. Oliveira *et al.* (2014) examined the technological context through the organization's readiness to host cloud computing which exerts a significant impact on cloud computing adoption. Some researchers also argue that security issues related to cloud ERP technology can have negative effects (Arinze and Anandarajan, 2010; Garverick, 2014; Weng and Hung, 2014). So, the following hypotheses are proposed:

H11A. Technological factors will have a significant impact on PU from a cloud computing system.

H11B. Technological factors will have a significant impact on PEOU from a cloud computing system.

One of the most important factors that play a role in the use of technologies is human factors. Factors like perceptions and attitudes of people towards information technology and their demographic characteristics are among the factors that affect people's acceptance and use of these technologies (AbuKhousa *et al.*, 2012; Lin and Yen, 2011; Lin *et al.*, 2012; Yusof *et al.*, 2008). The knowledge of decision-makers and the level of innovation is not only effective in making new decisions of decision-makers but also affects people's ability to do things in different ways (Lian *et al.*, 2013). The importance of the human factor has been emphasized in the studies of researchers, especially ERP systems (Lin, 2010). In addition, there are related indicators in the Davis (1989) study and the later Venkatesh and Davis (1996) study. So, the following hypotheses are proposed:

H11C. Employee factor will have a significant impact on PU from a cloud computing system.

H11D. Employee factor will have a significant impact on PEOU from a cloud computing system.

In general, the literature suggests that AI can enhance the industry value chain by changing relationships, reinventing business platforms and expanding the power of data. AI can also create positive impacts on workflow by improving efficiency (e.g. automated decision-making), expertise/experience/effectiveness (e.g. augmenting human experts) and innovativeness (e.g. identifying alternatives and optimization) (Kelley *et al.*, 2018). Duan *et al.* (2019) stressed that using AI for decision-making, either to support/assist or replace human decision-makers, is one of the most important applications in AI history; and there are research opportunities in understanding and theorizing ways to measure AI use and impact, the role of AI in decision-making, AI system implementations and cultural/ethical/legal implications of AI applications. In addition to addressing the business value of AI, studies have also identified certain risks associated with its business adoption. For example, there are innate risks that might arise from interpretability when machines communicate with humans; verifiability issues due to statistical truth-based decisions (rather than literal or context-based decisions) made by machines; and ethical dilemmas in business automation from the perspectives of different stakeholders, such as the labour force and regulators (Brynjolfsson and McAfee, 2017; Wright and Schultz, 2018). Conceptually, scholars have suggested that the biggest advance of AI is in improving perception (e.g. image/speech recognition) and cognition (e.g. automate insurance claims) in business processes (Brynjolfsson and McAfee, 2017). Agrawal *et al.* (2019) further argued that AI's biggest impact is in the prediction in an uncertain world for better decision-making. Overall, academic investigations of AI business applications have often touched on machine-human bonds/communication/collaboration, innovative business models/ecosystems, labour market disruptions and value creation in specific sectors (Bolton *et al.*, 2018; Garbuio and Lin, 2019; Kelley *et al.*, 2018; Valter *et al.*, 2018).

In the advertising and media sectors, companies seem to be showing similar enthusiasm towards AI. A market survey in Europe found that 80% of media practitioners agreed that AI would have significant impacts on their industry (Shields, 2018). Today's audience has elevated expectations in every aspect of their digital lives. In such a data-driven and direct-to-consumer world, media need to respond faster and better to audience expectations, just like other tech company counterparts (Raconteur, 2018). As media are now interwoven into consumers' daily lives and technology bundles, media companies must deliver engaging individual experiences to every consumer in context, in the moment, and all the time. Consequently, human resource commitment is significant in this new reality, and the solution is logically the adoption of cognitive technologies. So, the following hypotheses are proposed:

H12A. Technological factors will have a significant impact on PU through artificial intelligence from a cloud computing system.

H12B. Technological factors will have a significant impact on PEOU through artificial intelligence from a cloud computing system.

H12C. Employee factor will have a significant impact on PU through artificial intelligence from a cloud computing system.

H12D. Employee factor will have a significant impact on PEOU through artificial intelligence from a cloud computing system.

Bharadwaj and Lal (2012) have admitted that the perceived usefulness (PU) for a cloud-based service can be judged on the basis of increased performance, productivity, work efficiency and service utility. Therefore, organizations which perceive that cloud computing will enable them to benefit from all these advantages will agree to adopt this solution. The firm's operational and strategic advantages that it can reap from cloud computing are known as the system's *perceived usefulness*, which relates to mobility, an efficient decrease of computing costs, ease of installation and maintenance and easy analysis of data online (Arpaci, 2017). Cloud computing is capable of delivering complete service online in such a way that users do not have to be physically present to perform the analysis and operations of data (Eldalabeeh *et al.*, 2021). Through online connectivity, there is enhanced mobility, and because of cloud computing, firms do not need to invest significant resources to develop IS because cloud computing vendors currently install, maintain and upgrade the system, reducing the costs of IT. On the basis of the above discussion, cloud computing is expected to provide a significant advantage as highlighted by Gupta *et al.* (2013) and Lal and Bharadwaj (2016). So, the following hypothesis is proposed:

H21A. Perceived usefulness (PU) will have a significant impact on attitudes towards using cloud computing.

Several research studies have pointed out the evidence on the significant effects of PEOU and the intention to use it directly or indirectly. According to Venkatesh and Davis (2000), PEOU is confirmed by factors related to intrinsic motivations and emotions in relation to system use. Bharadwaj and Lal (2012) have proposed that PEOU can be validated by interaction which is the ease and the understandability of the cloud service, less mental effort in using the solution and the ability to perform tasks, according to the organization's guidelines. In some instances, employees work externally to an actual physical office and can still have easy data access through mobile devices, which is a great advantage (Raut *et al.*, 2017; Zin *et al.*, 2016). Remote access to online transactions, even in remote locations, is required by employees in the face of an increased number of online transactions, and this calls for the need for cloud computing solutions (Chiregi and Navimipour, 2018; Sabi *et al.*, 2016). So, the following hypothesis is proposed:

H22B. Perceived ease of use (PEOU) will have a significant impact on attitudes towards using cloud computing.

Methodology

The present study seeks to explain the role of AI as a mediating variable on the application of the TAM in the media with a cloud computing approach. The purpose of the research is applied studies and from the point of view of data collection is a descriptive survey. The statistical population of the study is the managers, deputies and experts of the National Iranian Oil Company, from which the statistical sample of 368 people, as shown in Table 2, were randomly selected.

Table 3 shows that the highest number were men (with 88%), the highest level of education to participate in this study were people with a master's degree (with 60%), the

Table 2.
Statistical sample

Row	Items		No.	Percentage (%)
1	Gender	Men	324	88
		Women	44	12
2	Education	BA	63	17
		MA	219	60
		PhD	86	23
3	Experience	<10 years	54	14
		11 to 20 years	194	52
		>20 years	128	34
4	Job title	Expert	39	10
		Vice	269	72
		Manager	68	18

highest work experience were people between 11 and 20 years (with 50%), and, finally, the most participants in this study to answer research questions were the company's deputies (with 72%). The researcher also used a questionnaire (see Appendix) as a tool to collect his data based on the following existing questionnaires:

Technological factor (TF): Gangwar *et al.* (2015), in their very influential research, considered two factors of compatibility and complexity. This questionnaire consists of 12 questions. In their study, they stated reliability as 0.821, KMO index as 0.583 and Bartlett test as 0.000, which indicates that their questionnaire was approved.

Employee factor (EF): Lin (2010) stated that employees can increase their productivity in providing complex and technical computer solutions by using a cloud computing system. This questionnaire consists of eight questions. The convergent validity of the structures (minimum 0.5), as well as the combined reliability (above 0.70) for all indicators, were confirmed in this study.

Perceived usefulness (PU): Davis' TAM proposed that "perceived usefulness" and "perceived ease of use" affect "attitude toward usage"; "attitude toward usage" and "perceived usefulness" affect "intention to use"; and finally, "intention to use" affect "usage behaviour". The above-stated relationship has been validated in many research and conference papers (Alhanatleh and Akkaya, 2020). This questionnaire consists of ten questions.

Perceived ease of use (PEOU): According to TAM, potential users' and/or users' PEOU of an ERP system has a positive influence on their intention to use the system and attitude towards the use of the system. The relationship has been tested across different areas related to technology adoption. The above theoretical arguments have been empirically validated by various scholars (Alhanatleh and Akkaya, 2020). This questionnaire consists of 12 questions.

Attitude towards usage (ATU): Santamaría-Sánchez *et al.* (2010) believed that the success or failure of cloud computing has been proven in many projects. This questionnaire consists of five questions. They validated their model using four statistical models.

Artificial intelligence (AI): Since there was no standard questionnaire to measure the variables in the research, a study-based questionnaire was developed by studying the theoretical and experimental foundations and, in coordination with experts, according to the objectives of the research. This questionnaire consists of eight questions, and its validity and reliability have been confirmed.

Also, in this research, PLS 2.0 software has been used for analysis.

Questionnaires	No. of experts	Validity	Reliability
TF	5	KMO: 0.78 Bartlett's test of sphericity: 0.000	0.73
EF		KMO: 0.88 Bartlett's test of sphericity: 0.000	0.88
PU		KMO: 0.73 Bartlett's test of sphericity: 0.000	0.71
PEOU		KMO: 0.79 Bartlett's test of sphericity: 0.000	0.70
ATU		KMO: 0.85 Bartlett's test of sphericity: 0.000	0.82
AI		KMO: 0.89 Bartlett's test of sphericity: 0.000	0.84

Table 3. Validity and reliability of research questionnaires

Analysis and results

Assessment of measurement model

SEM with partial least squares (PLS) was used for evaluation. PLS has been used to validate the causality of structural models (Costa *et al.*, 2020). In this study, the researchers used it to analyse the research hypotheses. The PLS approach is used in small samples with a non-normal distribution that also reduces the residual variance of dependent variables (Hair *et al.*, 2011). Also, although the research structures have been measured in previous research, validity and reliability have been evaluated separately. Table 4 presents the results of the evaluations.

To confirm construct reliability, Coelho and Henseler (2012) believe that 0.800 is appropriate. As shown in Table 5, all structural numbers are above 0.900. Cronbach's alpha for structures is also higher than 0.70 and is therefore approved. The average variance extracted (AVE) index has been used to confirm convergent validity (Fornell and Larcker, 1981). It is clear from the results of Table 5 that all structures have a number higher than 0.600 and are approved. The result of CR > AVE and AVE > 0.5 is also valid for all structures. The quality of the structural model was then evaluated through bootstrapping and the PLS algorithm. Bootstrapping is a resampling technique that draws many subsamples retrieved from the original data set (Costa *et al.*, 2020). For this research, 4,000 resamples were used to determine the path's significance within the structural model. Table 5 shows the correlation of the main research structures.

All indicators load more highly on their own construct than on other constructs, without any exceptions (Hair *et al.*, 2011). Furthermore, another criterion for evaluating discriminant validity is that the square root of the AVE should be larger than the inter-construct correlations (Chin, 1998; Fornell and Larcker, 1981). As shown by comparing the inter-construct correlations and square root of AVE (shaded leading diagonal) in Table 5, all constructs have more variance with their indicators than with other constructs. Hence, the discriminant validity of all the first-order factors and factors are supported.

The results of structural modelling are shown in Figure 3. The technological factor, according to the *H11A* hypothesis, has a positive and significant effect on PU (β = 0.268, $\rho < 0.001$). But the technological factor, according to the *H12A* hypothesis through AI, has a better effect on PU (β = 0.329, $\rho < 0.001$). The technological factor, according to the *H11B*hypothesis, has a positive and significant effect on PEOU (β = 0.274, $\rho < 0.001$). But the technological factor, according to the *H12B* hypothesis through AI, has a better effect on PEOU (β = 0.319, $\rho < 0.001$). Human factor, according to the *H11C* hypothesis, has a positive and significant effect on PU (β = 0.286, $\rho < 0.001$). But the human factor, according to the *H12C* hypothesis through AI, has a better effect on PU (β = 0.343, $\rho < 0.001$). The human factor, according to the *H11D* hypothesis, has a positive and significant effect on PEOU (β = 0.223, $\rho < 0.001$). But the human factor, according to the *H12D* hypothesis through AI, has a better effect on PEOU (β = 0.347, $\rho < 0.001$). According to the *H21A* hypothesis, PU has a positive and significant effect on ATU (β = 0.453, $\rho < 0.001$). Also, according to the *H22B* hypothesis, PEOU has a positive and significant effect on ATU (β = 0.426, $\rho < 0.001$).

The structural model's quality is assessed through squared multiple correlations (R^2) and the model's statistically predictive accuracy (Q2). After the validation of these two measures and assessment of the model's quality, it was concluded that the model is valid. The latent variable's coefficient path was analysed to study the hypotheses and if each one had statistically predictive evidence, and it was considered significant ($\rho < 0.050$) and the relationships between constructs were considered supported. Table 6 summarizes all the hypotheses results.

Construct	Item	Loading	Internal reliability	Composite reliability	Cronbach's alpha	AVE	Discriminant validity
TF	Tf1	0.802	0.772	0.903	0.900	0.591	Yes
	Tf2	0.771	0.719				
	Tf3	0.842	0.807				
	Tf4	0.726	0.699				
	Tf5	0.773	0.728				
	Tf6	0.812	0.743				
	Tf7	0.901	0.828				
	Tf8	0.800	0.783				
	Tf9	0.764	0.732				
	Tf10	0.719	0.667				
	Tf11	0.643	0.598				
	Tf12	0.697	0.601				
	Tf13	0.708	0.619				
EF	Ef1	0.808	0.606	0.937	0.916	0.670	Yes
	Ef2	0.846	0.657				
	Ef3	0.876	0.729				
	Ef4	0.789	0.637				
	Ef5	0.743	0.608				
	Ef6	0.839	0.760				
	Ef7	0.881	0.666				
	Ef8	0.759	0.633				
PU	Pu1	0.776	0.674	0.962	0.893	0.667	Yes
	Pu2	0.881	0.799				
	Pu3	0.909	0.843				
	Pu4	0.832	0.800				
	Pu5	0.826	0.764				
	Pu6	0.819	0.777				
	Pu7	0.765	0.739				
	Pu8	0.777	0.681				
	Pu9	0.770	0.701				
	Pu10	0.803	0.669				
PEOU	Peou1	0.917	0.883	0.961	0.917	0.768	Yes
	Peou2	0.934	0.922				
	Peou3	0.902	0.829				
	Peou4	0.886	0.797				
	Peou5	0.808	0.736				
	Peou6	0.789	0.709				
	Peou7	0.793	0.711				
	Peou8	0.855	0.699				
	Peou9	0.888	0.782				
	Peou10	0.946	0.886				
	Peou11	0.834	0.743				
	Peou12	0.946	0.829				
ATU	Atu1	0.904	0.844	0.960	0.954	0.785	Yes
	Atu2	0.825	0.792				
	Atu3	0.863	0.803				
	Atu4	0.918	0.842				
	Atu5	0.918	0.842				
AI	Ai1	0.858	0.810	0.930	0.892	0.764	Yes
	Ai2	0.827	0.799				
	Ai3	0.843	0.762				
	Ai4	0.878	0.824				
	Ai5	0.973	0.759				
	Ai6	0.806	0.722				
	Ai7	0.884	0.815				
	Ai8	0.913	0.850				

Table 4. Measurement model results

The mediator has been called an intervening or process variable. Complete mediation is the case in which independent variable no longer affects a dependent after the mediator has been controlled, making the path a direct zero. Partial mediation is the case in which the path from independent to dependent is reduced in absolute size but is still different from zero when the mediator is introduced. So, what has happened in this study suggests complete AI mediation in the model. Also, the fit indices of the research model are listed in Table 7.

Therefore, according to the results of Table 7, the model has a good fit.

Discussion

Hypotheses discussion

The current research shows that, at present, electronic learning has a very low acceptance scale at the infrastructure level. Today, the world is facing rapid changes in the field of organizational and educational systems, which require special solutions. In information technology, progress along with new technologies means increasing growth and gaining benefits from the birth of new technologies. An option that has recently been introduced in the world of information technology for the infrastructure of electronic learning systems is cloud computing technology. This technology has made a significant impact in the field of information and communication technology by changing ways of payment and costs and the use of software and hardware. The popularity of cloud computing is due to its two key features:

(1) all processing needs are provided as a service; and

(2) ability to provide computing and processing resources dynamically.

Table 5. Inter-construct correlation coefficients and square root of AVE (in *italic* on diagonal)

Items	TF	EF	PU	PEOU	ATU	AI
TF	*0.819*					
EF	0.552	*0.862*				
PU	0.491	0.443	*0.924*			
PEOU	0.451	0.369	0.563	*0.964*		
ATU	0.623	0.346	0.490	0.556	*0.911*	
AI	0.796	0.884	0.608	0.538	0.629	*0.902*

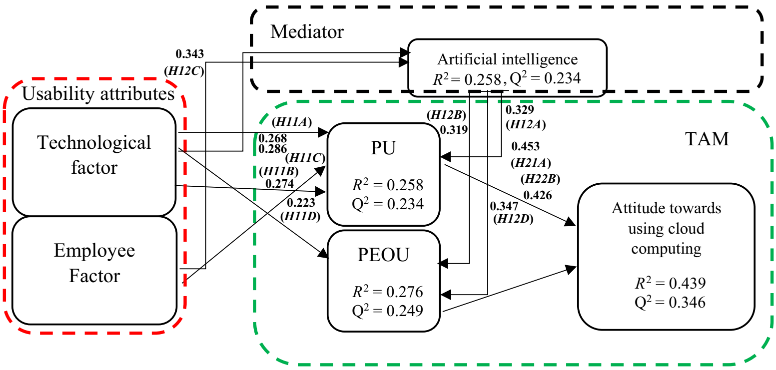


Figure 3. Hypotheses testing results

Hypothesize	IV		DV		Mediator	Findings	Conclusion
H11A	FT	→	PU			0.268 Positively and statistically significant	Supported
H12A	FT	→	PU	→	AI	0.329 Positively and statistically significant	Supported
H11B	ET	→	PU			0.274 Positively and statistically significant	Supported
H12B	ET	→	PU	→	AI	0.319 Positively and statistically significant	Supported
H11C	FT	→	PEOU			0.286 Positively and statistically significant	Supported
H12C	FT	→	PEOU	→	AI	0.343 Positively and statistically significant	Supported
H11D	ET	→	PEOU			0.223 Positively and statistically significant	Supported
H12D	ET	→	PEOU	→	AI	0.347 Positively and statistically significant	Supported
H21A	PU	→	ATU			0.453 Positively and statistically significant	Supported
H22B	PEOU	→	ATU			0.426 Positively and statistically significant	Supported

Table 6.
Hypotheses results

Type	Index	Measurement model	Recommended value
x^2 test	x^2	452.26	
	df	292	
	x^2/df	1.54	≤3.00 (Bagozzi and Yi, 1988)
Absolute fit index	GFI	0.85	≥0.80 (Seyal *et al.*, 2002)
Comparative fit index	NNFI	0.91	≥0.90 (Bentler, 1988)
	CFI	0.90	≥0.90 (Bentler, 1988)
	RMSEA	0.0573	≤0.08 (Hair *et al.*, 2011) *Note:* ≤0.10 is acceptable (Rai *et al.*, 2002)

Table 7.
Fit indices for measurement and structural model

Before analysing the hypotheses, the research results showed that all the factor loadings are higher than 0.4, and therefore, all of them remain for analysis. Also, the validity and reliability analysis of research questionnaires indicates their approval. Also, the output results of the correlation and validity analyses of the constructs showed that all constructs have more variance with their indicators than with other constructs. Hence, the discriminant validity of all the first-order factors and factors are supported.

What was proven in this study, as in other studies, is the effect of usability attributes on the TAM model structures, which has already been obtained in researchers' prior research (*H11A-H11B-H11C-H11D-H21A-H22B*) (Ahn and Ahn, 2020; Davis, 1989; Kim *et al.*, 2017; Oliveira *et al.*, 2014; Lin, 2010; Venkatesh and Davis, 1996). But the main topic of the article is to address the effect of AI on the model. But what was obtained about the research hypotheses (*H12A-H12B-H12C-H12D*) has a positive and significant effect on the mediating effect of AI in the TAM with cloud approach. de-Lima-Santos and Ceron (2021) believed that AI can make it easier to use resources without embedding unique skills. AI can also enhance new forms of participation and new products for media use (Diakopoulos, 2020; Jamil, 2020). In areas such as advertising, companies also seem eager to use AI (Chan-Olmsted, 2019). Shields' (2018) study on the European market showed that 80% of media activists agreed with the use of AI; while 62% believed that AI influences decisions and 47% believed that it increases productivity. The results of this study also showed that few felt that AI could negatively affect performance. In addition to reducing workload, AI can speed up and improve the interaction of media, content, audience and operations (Chan-Olmsted, 2019). Gentzkow (2018) concluded that the key impact of AI is and will be on demand rather than the supply side of media, especially in how content is matched to consumers. The application of cognitive technologies offers better means of matching content with demand, optimizing content management and scaling the process of content delivery. An eMarketer survey found that the most common ways in which news media are using AI globally were to improve content recommendations (59%), followed by workflow automation (39%), commercial optimization (e.g. ad targeting and dynamic pricing) (39%) and intelligent agents to help reporters find stories (35%) (eMarketer, 2018). Another survey of media's AI adoption found that cable systems or MSO (44%) had the highest adoption rate, followed by cable networks (30%) and broadcast networks (25%) (Mayeda, 2018).

Also, the results related to the fit of the structural model showed that the normalized chi-square index was equal to 1.54, the GFI index was equal to 0.85, the NNFI index was equal to 0.91, the CFI index was equal to 0.90 and the RMSEA index was equal to 0.057, and were confirmed. One of the most important limitations of the research was the lack of research related to media, AI and cloud computing.

Theoretical implications

AI has opened up a new space in the digital world, so that its profound impact is quite evident and has affected people's lives. Different industries benefit from AI to varying degrees. The field of media and communications are also in the middle categories of the capacity to use AI. The main area of effectiveness of AI is in data classification and metadata extraction. It can be expressed that with the help of AI, this division can be done in real time. So that we can use this technology in the daily affairs of a television network and even in live programmes, such as news. However, the benefits of AI are not limited to producing information directly from the media. The accuracy, speed and amount of information obtained from AI tools is applied in many other branches of the media industry. Adding information from any content gives the user more searchable parameters in the content. The user's needs are easily adapted to these parameters, and more useful and concise results are obtained. In addition, thanks to the processes performed by machine learning, it is possible to train the system and adapt it to the specific needs of the user. An example of this is by holding the image of an anonymous person; we can find it in all archived content.

Based on content analysis by AI, users can not only access all the content of a media but also specific sections of the content can be retrieved (such as special scenes in a movie, an important person talking about a particular topic or even a scene error in a sports match). Using the available editing tools, users can automatically view video, separate the existing parts and present it in the form of a new clip. The analysis of languages, translations and advances in the field of speech-to-text conversion has been able to help build an automatic translation and subtitling system, also online. AI tools are very useful in the processes of converting speech to text, marking texts and so on. By law and policy, it is sometimes necessary to delete or edit portions of existing content. AI enables us to edit or delete content based on desired parameters (such as recognizing content in images, recognizing emotions or linguistic analysis of beauty).

Conclusion

A practical view of the future

In the future, AI will have a profound impact on almost every software on the market, including enterprise resource planning systems. AI in ERP affects the controlled business nature of the system. While AI technology is still in its infancy, machine learning is making serious waves in the software market, impacting applications, such as business management, and giving them superstructure power. AI has the potential to bring about massive scale change for companies whose customer and operational data is their core business. Also, in general, every industry uses a corner of its advantages. Meanwhile, the impact of AI technology is more prominent in data-intensive and processing-intensive sectors that are most dependent on future predictions based on historical information. AI can help companies organize large amounts of data quickly and overcome limitations, then turn it into an opportunity. AI is sure to revolutionize the future of ERP solutions. New machine learning technology that appears to mimic human actions will impact any company or organization regardless of size or industry. AI can influence daily operations as part of an ERP system. This smart technology will recognize the user's behaviour pattern and automatically perform their normal tasks. AI is reshaping ERP functions, and incorporating AI into ERP systems will make business management tools more powerful. With the advent of cloud computing, more vendors are offering cloud hosting options, making ERP solutions more accessible to SMBs. By using these systems, users no longer have to worry about the heavy costs of maintaining and upgrading systems. In addition, they can choose only the modules they need, which gives them more control over their budget. In the future, ERP users can benefit from more powerful analytics and better reporting capabilities. The future of ERP refers to a global tool that can process both structured and unstructured data. This suggests that another process that ERP managers should focus on is learning how to use big data analytics. ERP solutions will have access to all the data of different departments. Therefore, they have all the information they need to predict future trends. This makes predictive analytics a convenient feature for modern ERP platforms.

When performing any specific task in an ERP system, a specific set of procedures must be followed. AI tools can work in a similar way. For this purpose, an AI system must be programmed with a set of rules governing each action. This technology is smart enough to use these established rules to make accurate decisions and, at the same time, much faster than any human. As a result, AI enables ERP systems to automate routine responsibilities. Freeing the valuable time of employees to focus on tasks that add to business profitability is one of the other benefits of this technology. One of the main functions of AI technology is to provide intelligent outputs based on human inputs. The AI system can read users' previous data and learn from their previous behaviour patterns. This makes ERP applications with AI provide a personalized and extensive user experience, as well as perform faster and more usefully. The latest generation of Focus ERPs has in-memory cloud computing and the ability to provide a large library of modules in finance, such as credit and collections, inventory and warehouse management, production, project costing and many more areas. Focus AIFA is a conversational API system that enables ERP to manage the entire business so that it can answer all requests at the speed of light simply by talking to it.

AI is also changing the way businesses operate. This allows industry players to use augmented reality and virtual reality features in their advertising. They can also offer an impressive list of products to dramatically improve the shoppers' experience even before they buy. Soon, chatbots will improve conversational functionality in the retail industry. They can capture the emotions and moods of customers based on emotional responses. In short, AI enables organizations to provide uniquely personalized responses to customer requests and significantly improve customer loyalty. AI creates tremendous opportunities to enhance human capabilities in industries.

References

AbuKhousa, E., Mohamed, N. and Al-Jaroodi, J. (2012), "E-health cloud: opportunities and challenges", *Future Internet*, Vol. 4 No. 3, pp. 621-645.

Agrawal, A., Gans, J.S. and Goldfarb, A. (2019), "Exploring the impact of artificial intelligence: prediction versus judgment", *Information Economics and Policy*, Vol. 47, pp. 1-6.

Ahn, B. and Ahn, H. (2020), "Factors affecting intention to adopt cloud-based ERP from a comprehensive approach", *Sustainability*, Vol. 12 No. 16, p. 6426.

Ajzen, I. (1991), "The theory of planned behavior", *Organizational Behavior and Human Decision Processes*, Vol. 50 No. 2, pp. 179-211.

Albarran, A.B. (2004), "Media economics is a field of study that has experienced considerable growth and development over the past 40 years", *The SAGE Handbook of Media Studies*, Sage Publications, p. 291.

Alhanatleh, H. and Akkaya, M. (2020), "Factors affecting the cloud ERP: a case study of learning resources department at Jordanian education ministry", *Management and Economics Research Journal*, Vol. 2 No. 4, pp. 101-122.

Arinze, B. and Anandarajan, M. (2010), "Factors that determine the adoption of cloud computing: a global perspective", *International Journal of Enterprise Information Systems*, Vol. 6 No. 4, pp. 55-68.

Armbrust, M., Fox, A., Griffith, R., Joseph, A.D., Katz, R., Konwinski, A., Lee, G., Patterson, D., Rabkin, A., Stoica, A. and Zaharia, M. (2010), "A view of cloud computing", *Communications of the ACM*, Vol. 53 No. 4, pp. 50-58.

Arpaci, I. (2017), "Antecedents and consequences of cloud computing adoption in education to achieve knowledge management", *Computers in Human Behavior*, Vol. 70, pp. 382-390.

Avram, M.-G. (2014), "Advantages and challenges of adopting cloud computing from an enterprise perspective", *AEC Cloud*, available at: http://aws.amazon.com/ec2/pricing/ (accessed 17 May 2013).

Bagozzi, R.P. and Yi, Y. (1988), "On the evaluation of structural equation model", *Journal of the Academy of Marketing Science*, Vol. 16 No. 1, pp. 74-94.

Bandura, A. (1986), *Social Foundations of Thought and Action: A Social Cognitive Theory*, Prentice-Hall, Englewood Cliffs, NJ.

Bentler, P.M. (1988), *Theory and Implementation of EQS: A Structural Equation Program*, Sage, Newbury Park, CA.

Bento, A., Bento, R. and Bento, A. (2015), "How fast are enterprise resource planning (ERP) systems moving to the cloud?", *Journal of Information Technology Management*, Vol. 26 No. 4.

Berman, S.J., Canepa, S., Toole, D. and Van den Dam, R. (2017), "Becoming a 'living' media partner for your consumers: a cognitive future for media and entertainment", *Whitepaper*, IBM Institute for Business Value.

Bharadwaj, S.S. and Lal, P. (2012), "Exploring the impact of cloud computing adoption on organizational flexibility: a client perspective", *International Conference on Cloud Computing Technologies, Applications and Management (ICCCTAM '12)*, IEEE, pp. 121-131.

Bhardwaj, S., Jain, L. and Jain, S. (2010), "Cloud computing: a study of infrastructure-as-a-service", *International Journal of Engineering and Information Technology*, Vol. 2 No. 1, pp. 60-63.

Bolton, C., Machova, V., Kovacova, M. and Valaskova, K. (2018), "The power of human-machine collaboration: artificial intelligence, business automation and the smart economy", *Economics, Management and Financial Markets*, No. 4, p. 51.

Borges, A.F., Laurindo, F.J., Spínola, M.M., Gonçalves, R.F. and Mattos, C.A. (2021), "The strategic use of artificial intelligence in the digital era: systematic literature review and future research directions", *International Journal of Information Management*, Vol. 57, p. 102225.

Broussard, M., Diakopoulos, N., Guzman, A.L., Abebe, R., Dupagne, M. and Chuan, C.H. (2019), "Artificial intelligence and journalism", *Journalism and Mass Communication Quarterly*, Vol. 96 No. 3, pp. 673-695.

Brynjolfsson, E. and McAfee, A. (2017), "The business of artificial intelligence: what it can – and cannot – do for your organization", *Harvard Business Review*, Vol. 98 No. 4, pp. 3-11.

Campolo, A., Sanfilippo, M. and Whittaker, M. (2017), "AI now 2017 report", *AI Now, New York, NY*, available at: https://ainowinstitute.org/reports.html (accessed 3 May 2019).

Chang, M.K. and Chung, W. (2001), "Determinants of the intention to use internet/WWW at work: a confirmatory study", *Information and Management*, Vol. 39 No. 1, pp. 1-14.

Chang, Y.W. and Hsu, P.Y. (2019), "An empirical investigation of organizations' switching intention to cloud enterprise resource planning: a cost-benefit perspective", *Information Development*, Vol. 35 No. 2, pp. 290-302.

Chang, I.C., Hwang, H.G., Hung, M.C., Lin, M.H. and Yen, D.C. (2007), "Factors affecting the adoption of electronic signature: executives' perspective of hospital information department", *Decision Support Systems*, Vol. 44 No. 1, pp. 350-359.

Chan-Olmsted, S.M. (2019), "A review of artificial intelligence adoptions in the media industry", *International Journal on Media Management*, Vol. 21 Nos 3/4, pp. 193-215.

Chen, S.C. and Lin, C.P. (2019), "Understanding the effect of social media marketing activities: the mediation of social identification, perceived value and satisfaction", *Technological Forecasting and Social Change*, Vol. 140, pp. 22-32.

Chin, W.W. (1998), "The partial least squares approach to structural equation modeling", *Modern Methods for Business Research*, Vol. 295 No. 2, pp. 295-336.

Chiregi, M. and Navimipour, N.J. (2018), "Cloud computing and trust evaluation: a systematic literature review of the state-of-the-art mechanisms", *Journal of Electrical Systems and Information Technology*, Vol. 5 No. 3, pp. 608-622.

Coelho, P.S. and Henseler, J. (2012), "Creating customer loyalty through service customization", *European Journal of Marketing*, Vol. 46 Nos 3/4, pp. 331-356.

Costa, C.J., Aparicio, M. and Raposo, J. (2020), "Determinants of the management learning performance in ERP context", *Heliyon*, Vol. 6 No. 4, p. e03689.

Davis, F.D. (1989), "Perceived usefulness, perceived ease of use and user acceptance of information technology", *MIS Quarterly*, Vol. 13 No. 3, pp. 319-340.

de-Lima-Santos, M.F. and Ceron, W. (2021), "Artificial intelligence in news media: current perceptions and future outlook", *Journalism and Media*, Vol. 3 No. 1, pp. 13-26.

Diakopoulos, N. (2020), "Computational news discovery: towards design considerations for editorial orientation algorithms in journalism", *Digital Journalism*, Vol. 8 No. 7, pp. 945-967.

Duan, Y., Edwards, J.S. and Dwivedi, Y.K. (2019), "Artificial intelligence for decision making in the era of big data – evolution, challenges and research agenda", *International Journal of Information Management*, Vol. 48, pp. 63-71.

Edwards, A., Edwards, C. and Spence, P.R. (2016), "Robots in the classroom: differences in students' perceptions of credibility and learning between 'teacher as robot' and 'robot as teacher'", *Computers in Human Behavior*, Vol. 65, pp. 627-634.

Eldalabeeh, A.R., Al-Shbail, M.O., Almuiet, M.Z., Bany Baker, M. and E'leimat, D. (2021), "Cloud-based accounting adoption in Jordanian financial sector", *The Journal of Asian Finance, Economics and Business*, Vol. 8 No. 2, pp. 833-849.

eMarketer (2018), "Most common ways in which news publishers are using artificial intelligence (AI) worldwide as of December 2017", *Statista – The Statistics Portal*, available at: www.statista.com/statistics/824314/news-publishers-ai/

Ferrara, E., Varol, O. and Davis, C. (2016), "The rise of social bots", *Communications of the ACM*, Vol. 59 No. 7, pp. 96-104.

Fishbein, M. and Ajzen, I. (1975), *Belief, Attitude, Intention and Behavior: An Introduction to Theory and Research*, Addison-Wesley, Reading, MA.

Fornell, C. and Larcker, D.F. (1981), "Chin – evaluating structural equation models with unobservable variables and measurement error", *Journal of Marketing Research*, Vol. 18 No. 3.

Frankish, K. and Ramsey, W.M. (Eds) (2014), *The Cambridge Handbook of Artificial Intelligence*, Cambridge University Press, Cambridge, MA.

Gangwar, H., Date, H. and Ramaswamy, R. (2015), "Understanding determinants of cloud computing adoption using an integrated TAM-TOE model", *Journal of Enterprise Information Management*, Vol. 28 No. 1, pp. 107-130.

Garbuio, M. and Lin, N. (2019), "Artificial intelligence as a growth engine for health care startups: emerging business models", *California Management Review*, Vol. 61 No. 2, pp. 59-83.

Garverick, M.L. (2014), "Motives and barriers to cloud ERP selection for SMEs: a survey of value-added resellers (VAR) perspectives", dissertation, Georgia State University.

Gehl, R.W. and Bakardjieva, M. (Eds) (2017), *Social Bots and Their Friends: Digital Media and the Automation of Sociality*, Routledge, New York, NY.

Gentzkow, M. (2018), "Media and artificial intelligence", *whitepaper*, Toulouse Network for Information Technology, Palo Alto, CA.

Graefe, A., Haim, M. and Haarmann, B. (2018), "Readers' perception of computer-generated news: credibility, expertise and readability", *Journalism*, Vol. 19 No. 5, pp. 595-610.

Gunkel, D.J. (2012), "Communication and artificial intelligence: opportunities and challenges for the 21st century", *Communication+1*, Vol. 1 No. 1, pp. 1-26.

Gupta, P., Seetharaman, A. and Rudolph Raj, J. (2013), "The usage and adoption of cloud computing by small and medium business", *International Journal of Information Management*, Vol. 33 No. 5, pp. 861-874.

Guzman, A.L. (2019), "Voices in and of the machine: source orientation toward mobile virtual assistants", *Computers in Human Behavior*, Vol. 90, pp. 343-350.

Guzman, A.L. and Lewis, S.C. (2020), "Artificial intelligence and communication: a human-machine communication research agenda", *New Media and Society*, Vol. 22 No. 1, pp. 70-86.

Hair, J.F., Ringle, C.M. and Sarstedt, M. (2011), "PLS-SEM: indeed a silver bullet", *Journal of Marketing Theory and Practice*, Vol. 19 No. 2, pp. 139-152.

Hong, S.J. and Tam, K.Y. (2006), "Understanding the adoption of multipurpose information appliances: the case of mobile data services", *Information Systems Research*, Vol. 17 No. 2, pp. 162-179.

Hsu, C.L. and Lin, C.C. (2008), "Acceptance of blog usage: the roles of technology acceptance, social influence and knowledge sharing motivation", *Information and Management*, Vol. 45 No. 1, pp. 65-74.

Jamil, S. (2020), "Artificial intelligence and journalistic practice: the crossroads of obstacles and opportunities for the Pakistani journalists", *Journalism Practice*, pp. 1-23.

Karahanna, E., Ahuja, M., Srite, M. and Galvin, J. (2002), "Individual differences and relative advantage: the case of GSS", *Decision Support Systems*, Vol. 32 No. 4, pp. 327-341.

Karahanna, E. and Straub, D.W. (1999), "The psychological origins of perceived usefulness and ease-of-use", *Information and Management*, Vol. 35 No. 4, pp. 237-250.

Kelley, K.H., Fontanetta, L.M., Heintzman, M. and Pereira, N. (2018), "Artificial intelligence: implications for social inflation and insurance", *Risk Management and Insurance Review*, Vol. 21 No. 3, p. 373.

Khoirina, M.M. and Sisprasodjo, N.R. (2018), "Media social-Instagram usage and performance benefit: case study on housewives online seller in Indonesia", *International Journal of Entrepreneurship and Business Development*, Vol. 2 No. 1, pp. 132-144.

Kietzmann, J., Paschen, J. and Treen, E. (2018), "Artificial intelligence in advertising: how marketers can leverage artificial intelligence along the consumer journey", *Journal of Advertising Research*, Vol. 58 No. 3, pp. 263-267.

Kim, S.H., Jang, S.Y. and Yang, K.H. (2017), "Analysis of the determinants of software-as-a-service adoption in small businesses: risks, benefits and organizational and environmental factors", *Journal of Small Business Management*, Vol. 55 No. 2, pp. 303-325.

Kumar Basak, S., Wotto, M. and Belanger, P. (2018), "E-learning, m-learning and d-learning: conceptual definition and comparative analysis", *E-Learning and Digital Media*, Vol. 15 No. 4, pp. 191-216.

Kuo, A.M.H. (2011), "Opportunities and challenges of cloud computing to improve health care services", *Journal of Medical Internet Research*, Vol. 13 No. 3, p. e67.

Lal, P. and Bharadwaj, S.S. (2016), "Understanding the impact of cloud-based services adoption on organizational flexibility", *Journal of Enterprise Information Management*, Vol. 29 No. 4, pp. 566-588.

Laouris, Y.N. and Eteokleous, N. (2005), "We need an educationally relevant definition of mobile learning", *Proceedings of MLearn, Cape Town, South Africa*, pp. 290-294, available at: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.106.9650&rep=rep1&type=pdf

Leftheriotis, I. and Giannakos, M.N. (2014), "Using social media for work: losing your time or improving your work?", *Computers in Human Behavior*, Vol. 31, pp. 134-142.

Lian, J., Yen, D. and Wang, Y. (2013), "An exploratory study to understand the critical factors affecting the decision to adopt cloud computing in Taiwan hospital", *International Journal of Information Management*, Vol. 34 No. 1, pp. 28-36.

Liao, M. and Yao, Y. (2021), "Applications of artificial intelligence-based modeling for bioenergy systems: a review", *GCB Bioenergy*, Vol. 13 No. 5, pp. 774-802.

Lin, H. (2010), "An investigation into the effects of is quality and top management support on ERP system usage", *Total Quality Management and Business Excellence*, Vol. 21 No. 3, pp. 335-349.

Lin, S.C. and Yen, E. (2011), "Asia federation report on international symposium on grids and clouds (ISGC)", *The International Symposium on Grids and Clouds and the Open Grid Forum*, 19-25 March, *Academia Sinica, Taipei, Taiwan*.

Lin, C.H., Lin, I.C., Roan, J. and Yeh, J.S.S. (2012), "Critical factors influencing hospitals' adoption of HL7 version 2 standards: an empirical investigation", *Journal of Medical Systems*, Vol. 36 No. 3, pp. 1183-1192.

Low, C., Chen, Y. and Wu, M. (2011), *Industrial Management and Data Systems*, Vol. 111 No. 7, pp. 1006-1023.

Lubis, M., Witjaksono, W. and Azizah, A.H. (2019), "Implementation of enterprise resource planning (ERP) using integrated model of extended technology acceptance model (TAM) 2: case study of PT. Toyota Astra motor", *7th International Conference on Cyber and IT Service Management (CITSM '19)*, IEEE, Vol. 7, pp. 1-6.

Marconi, F., Siegman, A. and Journalist, M. (2017), "The future of augmented journalism: a guide for newsrooms in the age of smart machines", *Report, Associated Press*, New York, NY, available at: https://insights.ap.org/uploads/images/the-future-of-augmented-journalism_ap-report.pdf (accessed 30 May 2019).

Mayeda, K. (2018), "New survey: media and entertainment companies are already capitalizing on AI", *Quantum*, available at: http://blog.quantum.com/new-survey-mediaand-entertainment-companies-are-already-capitalizing-on-ai/

Mori, M., MacDorman, K.F. and Kageki, N. (2012), "The Uncanny valley", *IEEE Robotics and Automation Magazine*, Vol. 19 No. 2, pp. 98-100.

Morrar, R., Arman, H. and Mousa, S. (2017), "The fourth industrial revolution (industry 4.0): a social innovation perspective", *Technology Innovation Management Review*, Vol. 7 No. 11, pp. 12-20.

Morris, M.G. and Dillon, A. (1997), "How user perceptions influence software use", *IEEE Software*, Vol. 14 No. 4, pp. 58-65.

Mou, Y. and Xu, K. (2017), "The media inequality: comparing the initial human-human and human-AI social interactions", *Computers in Human Behavior*, Vol. 72, pp. 432-440.

Na, S., Heo, S., Han, S., Shin, Y. and Roh, Y. (2022), "Acceptance model of artificial intelligence (AI)-based technologies in construction firms: applying the technology acceptance model (TAM) in combination with the technology-organization-environment (TOE) framework", *Buildings*, Vol. 12 No. 2, p. 90.

Nass, C., Steuer, J. and Tauber, E.R. (1994), "Computers are social actors", *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, Boston, MA*, *ACM, New York, NY*, *24-28 April*, pp. 72-78.

Nazari, M. (2020), "The role played by the artificial intelligence and modern technologies in promotion of media literacy of the blind", *Rasaneh*, Vol. 31 No. 2, pp. 67-82.

Nikam, S. and Prasad, V. (2019), "Technology adoption model (TAM) and enterprise resource planning system (ERP) implementation review paper", *International Journal of Emerging Technologies and Innovative Research*, Vol. 6 No. 3, pp. 310-323.

Nisar, T.M., Prabhakar, G. and Strakova, L. (2019), "Social media information benefits, knowledge management and smart organizations", *Journal of Business Research*, Vol. 94, pp. 264-272.

Oliveira, T., Thomas, M. and Espadanal, M. (2014), "Assessing the determinants of cloud computing adoption: an analysis of the manufacturing and services sectors", *Information and Management*, Vol. 51 No. 5, pp. 497-510.

Olmstead, K. (2017), "Nearly half of Americans use digital voice assistants, mostly on their smartphones", *report, Pew Research Center, Washington DC*, available at: www.pewresearch.org/fact-tank/2017/12/12/nearly-half-of-americans-use-digital-voice-assistants-mostly-on-their-smartphones/ (accessed 30 May 2019).

Osei Yeboah, E.-B. and Kofi Asare, E. (2014), "Factors influencing the adoption of cloud computing by small and medium enterprises in developing economies", *International Journal of Emerging Science and Engineering*, Vol. 2 No. 4, pp. 13-20.

Ouaadi, I. and El Haddad, M. (2021), "Determinants of cloud accounting adoption intention: the TOE, DOI and TAM models", *Journal of Accounting Research, Organization and Economics*, Vol. 4 No. 3, pp. 216-233.

Peter, J. and Kühne, R. (2018), "The new frontier in communication research: why we should study social robots", *Media and Communication*, Vol. 6 No. 3, pp. 73-76.

Premkumar, G. and Roberts, M. (1999), "Adoption of new information technologies in rural small business", *Omega*, Vol. 27 No. 4, pp. 467-484.

Raconteur (2018), "Future of media and entertainment", available at: www.dalet.com/sites/default/files/2018-07/Future%20of%20Media%202018%20Report%20-%20Dalet.pdf

Rai, A., Lang, S.S. and Welker, R.B. (2002), "Assessing the validity of is success models: an empirical test and theoretical analysis", *Information Systems Research*, Vol. 13 No. 1, pp. 50-69.

Rainie, L. and Anderson, J. (2017), "The internet of things connectivity binge: what are the implications?", *Report, Pew Research Center, Washington DC*, available at: www.pewinternet.org/2017/06/06/the-internet-of-things-connectivity-binge-what-are-the-implications/ (accessed 30 May 2019).

Raut, R.D., Gardas, B.B., Jha, M.K. and Priyadarshinee, P. (2017), "Examining the critical success factors of cloud computing adoption in the MSMEs by using ISM model", *The Journal of High Technology Management Research*, Vol. 28 No. 2, pp. 125-141.

Reeves, J. (2016), "Automatic for the people: the automation of communicative labor", *Communication and Critical/Cultural Studies*, Vol. 13 No. 2, pp. 150-165.

Reeves, B. and Nass, C. (1996), "The media equation: how people treat computers", *Television and New Media like Real People and Places*, Cambridge University Press, New York, NY.

Rogers, E.M. (1983), *Diffusion of Innovations*, 4th ed., Free Press, New York, NY.

Rogers, E.M. (2003), *Diffusion of Innovations*, 5th ed., Free Press, New York, NY.

Sabi, H.M., Uzoka, F.-M.E., Langmia, K. and Njeh, F.N. (2016), "Conceptualizing a model for adoption of cloud computing in education", *International Journal of Information Management*, Vol. 36 No. 2, pp. 183-191.

Saeed, I., Juell-Skielse, G. and Uppström, E. (2011), "Cloud enterprise resource planning adoption: motives and barriers", *International Conference on Research and Practical Issues of Enterprise Information Systems*, pp. 99-122.

Salih, S., Hamdan, M., Abdelmaboud, A., Abdelaziz, A., Abdelsalam, S., Althobaiti, M.M., Cheikhrouhou, O., Hamam, H. and Alotaibi, F. (2021), "Prioritising organisational factors impacting cloud ERP adoption and the critical issues related to security, usability and vendors: a systematic literature review", *Sensors (Basel, Switzerland)*, Vol. 21 No. 24, p. 8391.

Sangari, N., Heidaripour, M. and Nouhzadeh Malekshah, N. (2020), "The impact of organizational social networks on social capital", *Journal of Sustainable Human Resource Management*, Vol. 2 No. 3, pp. 195-211.

Santamaría-Sánchez, L., Núnez-Nickel, M. and Gago-Rodríguez, S. (2010), "The role played by interdependences in ERP implementations: an empirical analysis of critical factors that minimize elapsed time", *Information and Management*, Vol. 47 No. 2, pp. 87-95.

Seyal, A.H., Rahman, M.N. and Rahim, M.M. (2002), "Determinants of academic use of the internet: a structural equation model", *Behaviour and Information Technology*, Vol. 21 No. 1, pp. 71-86.

Sharma, S.K. and Kitchens, F.L. (2004), "Web services architecture for m-learning", *International Journal of Mobile Communications*, Vol. 2 No. 1, pp. 203-216.

Shields, R. (2018), "What the media industry really thinks about the impact of AI", *The Drum*, available at: www.thedrum.com/news/2018/07/06/what-the-mediaindustry-really-thinks-about-the-impact-ai

Skilton, M. and Hovsepian, F. (2018), *The 4th Industrial Revolution*, Springer, Berlin/Heidelberg.

Soualah-Alila, F., Nicolle, C. and Mendes, F. (2013), "Towards a methodology for semantic and context-aware mobile learning", *The Encyclopedia of Information Science and Technology*, 3rd ed., IGI Global, p. 10, (hal-00876023).

Sternad, S. and Bobek, S. (2013), "Impacts of TAM-based external factors on ERP acceptance", *Procedia Technology*, Vol. 9, pp. 33-42.

Sultan, N. and Sultan, Z. (2012), "The application of utility ICT in healthcare management and life science research: a new market for a disruptive innovation", *The European Academy of Management Conference (EURAM '12), Rotterdam, The Netherlands*.

Sundar, S.S. and Nass, C. (2000), "Source orientation in human-computer interaction: programmer, networker, or independent social actor?", *Communication Research*, Vol. 27 No. 6, pp. 683-703.

Thong, J.Y. (1999), "An integrated model of information systems adoption in small businesses", *Journal of Management Information Systems*, Vol. 15 No. 4, pp. 187-214.

Tornatzky, L.G. and Fleischer, M. (1990), *The Process of Technological Innovation*, Lexington Books, Lexington, MA.

Tornatzky, L.G. and Klein, K.L. (1982), "Innovation characteristic and innovation adoption implementation: a meta-analysis of findings", *IEEE Transactions on Engineering Management*, Vol. EM-29 No. 1, pp. 28-45.

Traxler, J. (2007), "Defining, discussing and evaluating mobile learning: the moving finger writes and having writ", *The International Review of Research in Open and Distributed Learning*, Vol. 8 No. 2, pp. 1-12.

Turel, O., Serenko, A. and Bontis, N. (2007), "User acceptance of wireless short messaging services: deconstructing perceived value", *Information and Management*, Vol. 44 No. 1, pp. 63-73.

Valter, P., Lindgren, P. and Prasad, R. (2018), "Advanced business model innovation supported by artificial intelligence and deep learning", *Wireless Personal Communications*, Vol. 100 No. 1, p. 97.

Van der Heijden, H., Verhagen, T. and Creemers, M. (2003), "Understanding online purchase intentions: contributions from technology and trust perspectives", *European Journal of Information Systems*, Vol. 12 No. 1, pp. 41-48.

Venkatesh, V. and Davis, F.D. (1996), "A model of the antecedents of perceived ease of use: development and test", *Decision Sciences*, Vol. 27, pp. 451-481, doi: 10.1111/j.1540-5915.1996.tb01822.x.

Venkatesh, V. and Davis, F.D. (2000), "A theoretical extension of the technology acceptance model: for longitudinal field studies", *Management Science*, Vol. 46 No. 2, pp. 186-204.

Venkatesh, V., Morris, M.G., Davis, G.B. and Davis, F.D. (2003), "User acceptance of information technology: toward a unified view", *MIS Quarterly*, Vol. 27 No. 3, pp. 425-478.

Wang, I.S., Lin, H.H. and Luarn, P. (2006), "Predicting consumer intention to use mobile service", *Information Systems Journal*, Vol. 16 No. 2, pp. 157-179.

Wang, C., Wood, L.C., Abdul-Rahman, H. and Lee, T.Y. (2015), "When traditional information technology project managers encounter the cloud: opportunities and dilemmas in the transition to cloud services", *International Journal of Project Management*, Vol. 34 No. 3, pp. 371-388.

Weng, F. and Hung, M.C. (2014), "Competition and challenge on adopting cloud ERP", *International Journal of Innovation, Management and Technology*, Vol. 5 No. 4, p. 309.

Wright, S.A. and Schultz, A.E. (2018), "The rising tide of artificial intelligence and business automation: developing an ethical framework", *Business Horizons*, Vol. 61 No. 6, pp. 823-832.

Xu, M., David, J.M. and Kim, S.H. (2018), "The fourth industrial revolution: opportunities and challenges", *International Journal of Financial Research*, Vol. 9 No. 2, pp. 90-95.

Yaghubi, N.M., Hemmat, Z. and Rashki, M. (2016), "The proposed model of factors influencing to adoption of cloud computing ecosystem in Iran (university, industry and services sectors)", *Iranian Journal of Information Processing and Management*, Vol. 31 No. 2, pp. 555-580.

Yathiraju, N. (2022), "Investigating the use of an artificial intelligence model in an ERP cloud-based system", *International Journal of Electrical, Electronics and Computers*, Vol. 7 No. 2, pp. 1-26.

Yektaei, M. and Ranjbar Noshary, A. (2016), "Model adoption of cloud computing in IT outsourcing", *Future Study Management*, Vol. 27 No. 107, pp. 1-11.

Yusof, M.M., Papazafeiropoulou, A., Paul, R.J. and Stergioulas, L.K. (2008), "Investigating evaluation frameworks for health information systems", *International Journal of Medical Informatics*, Vol. 77 No. 6, pp. 377-385.

Zin, M., Ibrahim, H. and Hassan, Z.L.M. (2016), "The determinants of human resource information system success in Japanese manufacturing companies", *The East Asian Journal of Business Management*, Vol. 6 No. 4, pp. 27-34.

Further reading

Behrand, T., Wiebe, E.N., London, J.E. and Johnson, E.C. (2010), "Cloud computing adoption and usage in community colleges", *Behaviour and Information Technology*, Vol. 30 No. 2, pp. 231-240.

Doelitzscher, F., Sulistio, A., Reich, C., Kuijs, H. and Wolf, D. (2011), "Private cloud for collaboration and e-learning services: from IaaS to SaaS", *Computing*, Vol. 91 No. 1, pp. 23-42.

Song, S. (2017), "Historical development of industrial revolutions and the place of so called the fourth industrial revolution", *Journal of Science and Technology Studies*, Vol. 17 No. 2, pp. 5-40.

Appendix

Dear expert,

The questionnaire that has been provided to you has been developed to conduct field research entitled “Explaining the effect of Artificial Intelligence on the Technology Acceptance Model in Media: Cloud Computing approach”. I request you to answer the relevant questions, according to the response range.

General questions	
Gender	Men
	Women
Education	BA
	MA
	Dr
History	<10 years
	11 to 20 years
	>20 years
Job side	Expert
	Vice
	Manager

Responsiveness range

- I strongly disagree = 1
- I disagree = 2
- No idea = 3
- I agree = 4
- I agree very much = 5

Specialized questions

Technology factor

- Steps to complete a task in the cloud e-learning system follow a logical sequence.
- Performing an operation in the cloud e-learning system led to a predicted result.
- Screens of the cloud e-learning system were clearly organized.
- The cloud e-learning system was characterized by rapid response even at peak times.
- The cloud e-learning resources system provided relevant information for work.
- The cloud e-learning system presented the information in an appropriate format.
- The information from the cloud e-learning system was up-to-date enough for my purposes.
- The reliability of output information from the cloud e-learning resources system was high.
- The cloud e-learning system provided the information when I need in time.
- The cloud e-learning system had a modern-looking interface.
- The cloud e-learning system provided the right solution to my request.
- The cloud e-learning system gave me prompt service.
- The cloud e-learning system had a good interface to meet my needs and labour.

Employee factor

- I have experience in using handheld devices (laptops, tablets, smartphones,. . .).
- I have experience in using the internet.
- The cloud e-learning system is exactly what I need.
- I am sure it was the right thing to adopt the cloud e-learning system.
- Owning the cloud e-learning system has been a good experience.
- I am satisfied with the performance of the cloud e-learning system service.
- I am satisfied with the decision to work over the cloud e-learning system.
- I am pretty satisfied with the cloud e-learning resources system which has been chosen.

Perceived usefulness

- Using the cloud e-learning system improved the quality of the work I do.
- Using the cloud e-learning system gave me greater control over the activities in my work.
- The cloud e-learning system enabled me to accomplish tasks more quickly.
- The cloud e-learning system supported critical aspects.
- The cloud e-learning system increased my productivity.
- The cloud e-learning system improved my job performance.
- The cloud e-learning system allowed me to accomplish more work than would otherwise be possible.
- The cloud e-learning system enhanced my effectiveness on the job.
- The cloud e-learning system made it easier to do my job.
- Overall, the cloud e-learning system was useful in my job.

Perceived ease of use

- Overall, I found the cloud e-learning system interface easy to use.
- My interaction with the cloud e-learning system was clear and understandable.
- The cloud e-learning system required the fewest steps possible to accomplish what I want to do with it.
- Using the cloud e-learning system is effortless.
- I could use the cloud e-learning system without written instructions.
- I did not notice any inconsistencies when I use the cloud e-learning system.
- I could recover from mistakes quickly and easily over the cloud e-learning system.
- I could use the cloud e-learning system successfully every time.
- Learning to use the cloud e-learning system interface was easy for me.
- It was easy for me to become skilful at using the cloud e-learning system interface.
- I found the cloud e-learning system interface to be flexible to interact with.
- I easily remembered how to use the cloud e-learning system.

Attitude towards use

- I had a generally favourable attitude towards using the cloud e-learning system.
- I believed it was a good idea to use the cloud e-learning system for my work.

- I liked the idea of using the cloud e-learning system.
- Using the cloud e-learning system provided me with a lot of enjoyment.
- Overall, I enjoyed using the cloud e-learning system.

Artificial intelligence

- By using smartphones and their educational materials, my communication with my organization has improved.
- It has become easier to do the work of the organization by using smart devices and appliances at home.
- By using smartphones, it has become easier and easier to control the health of myself and the members of my organization.
- With the use of new communication tools, shopping, travelling, banking and going about my life have become easier.
- With the use of smartphones, the time I spend doing things has decreased.
- The use of smartphones and new communication technologies has increased the accuracy and speed of my work.
- By using relevant programmes and software in smartphones, my imagination of my surroundings has increased.
- With the use of new communication technology, the quality of the tasks assigned in my work environment has increased.

Corresponding author
Abolfazl Danaei can be contacted at: a.danaei@semnaniau.ac.ir