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Understanding managers' attitudes and behavioral intentions towards using artificial intelligence for organizational decision-making☆

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ABSTRACT

While using artificial intelligence (AI) could improve organizational decision-making, it also creates challenges associated with the "dark side" of AI. However, there is a lack of research on managers' attitudes and intentions to use AI for decision making. To address this gap, we develop an integrated AI acceptance-avoidance model (IAAAM) to consider both the positive and negative factors that collectively influence managers' attitudes and behavioral intentions towards using AI. The research model is tested through a large-scale questionnaire survey of 269 UK business managers. Our findings suggest that IAAAM provides a more comprehensive model for explaining and predicting managers' attitudes and behavioral intentions towards using AI. Our research contributes conceptually and empirically to the emerging literature on using AI for organizational decision-making. Further, regarding the practical implications of using AI for organizational decision-making, we highlight the importance of developing favorable facilitating conditions, having an effective mechanism to alleviate managers' personal concerns, and having a balanced consideration of both the benefits and the dark side associated with using AI.

1. Introduction

Artificial Intelligence (AI) enables machines and systems to do things that would require intelligence if done by humans. Using AI for organizational decision-making has been and remains one of the most important applications of AI. A recent report by MIT Sloan Management Review and Boston Consulting Group indicated that 57% of the responding companies are piloting AI and 59% of them have an AI strategy (Ransbotham et al., 2020), while a McKinsey survey indicated 50% of responding companies have adopted AI in at least one business function (McKinsey, 2020). With the rise of super computational information processing capacity and big data analytics technologies, AI has the potential to undertake more complex tasks that require cognitive capabilities such as making tacit judgements, sensing emotion and driving processes which previously seemed impossible (e.g. Mahroof, 2019). This opens up new application domains such as transforming the way organizations base their decisions (Aaldering and Song, 2020) while interest in AI applications has surged across all industrial sectors (Dwivedi et al., 2021).

Focusing on general organizational decision-making, AI is believed to be able to reveal hidden insights from data, closer to real time (Jovanovic et al., 2021), "to support decision-making and knowledge management, and to automate customer interfaces" (Brock and von Wangenheim, 2019, p.115), to help organizational employees boost their analytic and decision-making abilities and heighten creativity (Wilson and Daugherty, 2018). AI-based decision-making is seen to be more effective, accurate, and flexible (Agrawal et al., 2017a; Deloitte, 2019; Metcalf et al., 2019). However, the potential benefit of human-AI symbiosis in organizational decision-making can only be fully realized if human decision makers accept the use of AI (Edwards et al., 2000; Mathieson, 1991). Few studies have examined managers' attitudes and behavioral intentions towards using AI; there is very limited empirical

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research focusing on understanding managers' behavioral intentions towards using AI from a human centered perspective (Duan et al., 2019; Dwivedi et al., 2021) and it is still unclear if and when people are willing to cooperate with machines (Haesevoets et al., 2021), although conditions favoring information technology (IT) acceptance have long been seen as a central pillar in research into IT innovations (Verdegem and De Marez, 2011).

Furthermore, using AI has always been contentious (Dreyfus and Hubert, 1992; Duan et al., 2019) and controversial (Breward et al., 2017) on both organizational and personal levels. While the potential of using AI to significantly improve decision-making is increasingly recognized (e.g. Agrawal et al., 2017b; Duan et al., 2019), some leading experts (e.g. Davenport et al., 2020; Patrick et al., 2019; Ransbotham et al., 2018; Weld and Bansal, 2019) also have serious concerns about AI's negative impacts, such as that "AI could get out of control and affect human beings and society in disastrous ways" (Johnson and Verdicchio, 2017, p.2267). At the organizational level, there are concerns raised about the implications and impact of the "dark side" of AI (e.g. Dwivedi et al., 2021; Weld and Bansal, 2019), such as bad decision-making, various types of discrimination, and other hidden biases and challenges (European-Commission, 2020; Shrestha et al., 2019). At the personal level, in addition to hope, AI is also creating fear among managers and workers because of the potential job losses (Ransbotham et al., 2018) or "technological unemployment" a term that was coined as long ago as 1930 (Jarrahi, 2018). Elkins (2013) found that human experts may feel threatened by AI systems that could contradict their own judgements: "When asked about new technologies, experts in deception detection are very enthusiastic and interested in new tools and technology. However, when confronted with the actual technology, they reject its use and ignore it all together." (p.252).

Consequently, managers' attitudes and intentions towards using AI for organizational decision-making are likely to be affected by both the benefits and risks associated with using AI. Understanding managers' perceptions of using AI would, thus, require a "net valence approach that considers both benefits and concerns" (Breward et al., 2017, p.760) thereby being able to examine and explain the attributes of a whole rather than attributes of its parts (Venkatesh et al., 2016; Weber, 2012). However, the IT adoption literature shows a bias towards offering models that can only be used to understand either the acceptance or avoidance of IT separately; it does not seem to provide any models that explain and predict IT adoption by considering both benefits and concerns simultaneously (Breward et al., 2017) as "IT acceptance theories are not intended to explain avoidance behavior" (Liang and Xue, 2009, p.73). Despite the fact that the integration of both positive and negative variables to understand AI adoption for decision-making is critical, such a need is largely ignored by the existing literature (Agogo and Hess, 2018) while a generally accepted comprehensive framework for understanding IT adoption is still lacking (Verdegem and De Marez, 2011). In order to address this knowledge gap, we formulate the following research question:

To what extent are positive and negative factors affecting managers' attitudes and intentions towards using AI for organizational decision-making?

To answer this research question, we have developed and tested the integrated AI acceptance-avoidance model (IAAAM) that includes three types of constructs: technology acceptance (facilitating conditions, peer influence, performance expectancy, effort expectancy, attitude, and intention to use), technology threat avoidance (perceived threat in terms of perceived severity and perceived susceptibility), and concerns of personal development and wellbeing. We tested the research model based on an analysis of 269 responses collected from UK managers. Our research contributes to the emerging literature on using AI for organizational decision-making by developing a holistic view of the factors that influence managers' attitudes and behavioral intention towards using AI in decision-making and by extending the appreciation of individual characteristics being central to behavioral intentions in the context of AI for decision making. The empirical evidence supports IAAAM and its associated relationships that provide valuable practical implications, including developing favorable facilitating conditions for using AI, having an effective mechanism to alleviate managers' personal concerns, and having a balanced consideration of the benefits and the dark side associated with using AI for organizational decision-making.

The rest of the paper is structured in the following way. Section 2 will present a brief review of the concept of and the current debate on AI for decision-making, and theories of IT acceptance and avoidance. Section 3 will develop the research hypotheses. Sections 4 and 5 will explicate our selected research methodology, and research model testing and findings, respectively. Section 6 will discuss our findings, including their limitations and ideas for future research. Finally, we will present our conclusions in Section 7.

2. Literature review

We first give an overview of AI for decision-making, then look at the literature relevant to the current debate, especially managers' attitudes to the use of AI for decision-making.

2.1. A brief overview of AI for decision-making

There are many theories of decision-making: see Dastani et al. (2005) for a comparison of the most commonly cited. One theory often seen in the decision support literature is the phased model of intelligence-design-choice (leading to implementation, added as a phase later) first proposed by Simon (1947). We think it is appropriate to mention Simon's model given his AI connections (e.g. Simon, 1969).

Consistent with Simon's view, decision-making can be thought of as "choosing between various alternatives" (Pomerol, 1997, p.3). It might be argued that this would cover virtually all applications of AI, since even image recognition or natural language understanding could be conceived of as choosing between a very large number of alternative image subjects or sentences. More useful, however, is to restrict our consideration, again following Pomerol (1997), to situations that begin with recognition that a decision needs to be made (Simon's intelligence phase) leading to some form of diagnosis/design, a choice process and eventually action. This would exclude AI applications such as image recognition and natural language understanding *per se*.

In this conception, there have been two main eras of interest in using AI for decision-making. The first began quite slowly in the mid-to late 1970s, peaking at the start of the 1990s. The second, which is still ongoing, has gradually increased over the past decade.

In the first era, expert systems, then regarded as an AI method for capturing knowledge (Liao, 2005), and specifically proposed for decision-making (Gupta, 2000; Youngohc and Guimaraes, 1995) were intended to replicate the performance of a skilled human decision maker. One of the first was MYCIN (Shortliffe, 1976), an expert system which diagnosed microbial infections and recommended appropriate medical treatment. In terms of the Simon model, the intelligence phase was realizing that such an expert system could be built; design was building the alternatives into the system; and choice was MYCIN's main function.

The three types of technology underlying expert systems from the first era carry over to today: rule-based systems, systems relying on similarity measures (such as case-based reasoning), and machine learning systems. We do not have space to explain their technical aspects here. A major advantage of the first two of these types was said to be the systems' ability to explain the reasoning that led to their decisions (D'Agapayeff, 1985; Waterman, 1986). Machine learning systems, by contrast, operated as a "black box", which may behave in unexpected ways (Schuetz and Venkatesh, 2020).

Over time, the term expert system was replaced in some domains, especially business and management, by the almost contemporary term knowledge-based system (Newell, 1982). The reasons for this included

(Duan et al., 2019): the bad reputation of some expert systems, that meant it was not an attractive label; the difficulty of representing all of an expert's knowledge in a system, leading some to feel that the use of the term "expert" was unreasonable; and the tendency for the system to be used to support or assist a human decision maker, rather than acting as an expert telling the human what to do, or replacing the human completely.

More recently, research from two perspectives has suggested that human experts have two different ways of making decisions: quick and intuitive, and slow and reasoned. Dreyfus and Dreyfus (2005) argued that computer systems could not reach the quick and intuitive level, which they regarded as denoting a true expert. Instead, the systems were restricted to slow and reasoned, which they termed "competent". Kahneman (2011) independently arrived at a similar distinction, which he referred to as system 1 and system 2. More recently, Jarrahi (2018) suggested that "AI is more useful for supporting analytical rather than intuitive decision making" (p.579).

AI generally was in the doldrums during the 2000s, or "has been intermittent" (Benbya et al., 2021, p.283), but in the past decade has increased rapidly (Benbya et al., 2021; Dwivedi et al., 2021) and undergone a major revival, spearheaded by research into deep learning systems (Schmidhuber, 2015), which are the descendants of the machine learning systems of the 1980s. Headline examples such as the victory in 2016 of the AlphaGo AI system over the world champion at the game of Go (Lee et al., 2016) and AI based self-driving cars have done much to inspire interest. Unfortunately, much of the recent work on AI for decision-making does not seem to have been informed by the work done in the first era, even where it has identified similar issues (Duan et al., 2019).

The specific issues we pick up in the next section include: the role of the system; the effect on people's jobs; and attitudes towards the adoption of AI systems.

2.2. Current debate on AI for decision-making

From the earliest days, there was always the unresolved question of whether the systems were supposed to augment the decision maker or replace them, or perhaps replace them for part of the job. Bader et al. (1988) identified no fewer than six different roles the system could play: assistant, critic, second opinion, expert consultant, tutor, and automaton. Syam and Courtney (1994) argued that AI should learn from the field of decision support systems, which assumed "a man-machine symbiosis is capable of a higher level of intelligent action than either man or machine operating independently" (p.450). Spyropoulos and Papagounos (1995) strongly advocated that the role of AI systems in medicine should be that of "supporting instruments" rather than "decision-making devices".

Twenty-five years later, the position in medicine has changed little, especially in respect of deep learning systems. Ghosh and Kandasamy (2020) are typical of many with the view that "clinical decision-making cannot be assigned to something we do not understand" (p.1138). However, Pee et al. (2019) argue that the relationship between humans and AI-based medical imaging diagnostic systems in healthcare could be "cooperator, collaborator, competitor, and competitor" (p.366).

One element of this issue is the possibility that humans would lose their jobs because of the introduction of AI systems. Zuboff (2015) saw AI as a leading example of a technology "with explosive social consequences" (p.80). Her particular concern was the lack of public oversight of how corporations use such technologies. The literature contains plenty of exhortations to employees like that of Huang et al. (2019) "Rather than worrying about whether someday AI is going to take over their jobs, it is more constructive for employees to learn how to work with AI in their jobs" (p.59). Of course, these exhortations all come from academics and AI practitioners who presently have little fear of their own jobs being taken over.

This raises the question of managers' attitudes to AI systems. In the first era, there was virtually no research into managers' attitudes towards AI/expert systems in general. Sviokla (1990) observed that the literature fell into three categories: how to build expert systems; theoretical computer science issues; and "system biographies" by practitioners. None of these covered the attitudes of managers or the workforce. The position has not changed much in the second era: for example, Kraus et al. (2020) considered the technical accuracy, potential value and data availability in respect of deep learning systems, but not managers' attitudes towards using them.

In the first era, what little work on attitudes there was concentrated on a specific system in one organization. Sviokla (1990) reported the shifts in roles and responsibilities resulting from the use of Digital's XCON. The views of technical editors at Digital could be summed up in the remark (p.137) "it was more fun before XCON". Berry et al. (1998) described the reactions of managers in the Florida Department of Highway Safety and Motor Vehicles to using a human resource management expert system. Factors significantly affecting usage were found to be: senior management encouragement to use the system; perceived helpfulness of its recommendations; perceived ease of use; perceived adequacy of the training received; and the extent of their involvement in designing the system. Perceived reduction in discretion had no influence on usage.

Turning to recent work, Ransbotham et al. (2018) surveyed business executives, managers and analysts around the world about AI. They found 73% somewhat or strongly agreed with the statement "I hope that AI will do some of the current tasks in my job", but also that 33% somewhat or strongly agreed that "I fear that AI will do some of the current tasks in my job". Experts, and specialists, followed by business analysts, were most fearful that AI would take over some of their own job tasks.

Brock and von Wangenheim (2019) surveyed executives and managers about applications of AI in business, but did not ask about attitudes towards AI at all. The nearest they came was when discussing leadership, with the recommendation that "Managers should lead and actively endorse the firm's AI project(s)" (p.129). This requires a positive attitude towards the projects, but they did not consider if that might be problematic.

Another survey (van Esch and Black, 2019) examined candidates' reactions to applying for jobs using an AI recruitment system. The most relevant finding to this study was the informal claim that "in our many interactions with [human resources] executives and staff, there is little worry that AI recruiting tools will be perceived as a job threat" (p.738).

Gursoy et al. (2019) looked at how consumer willingness to use AI devices was influenced by several constructs in a three-stage model: social influence, hedonic motivation and anthropomorphism were hypothesized to influence performance expectancy and effort expectancy; these two were hypothesized to influence emotion, which was hypothesized to influence willingness to use the devices or objection to their use. All of the factors were found to have a significant influence on the final outcome, although two of the path coefficients in their structural equation model were not significant.

The combination of hope and fear (Ransbotham et al., 2018) is a good summary of the little that is known about managers' attitudes. There is thus a gap in the literature for an empirical study of middle and senior managers' attitudes to using AI systems.

2.3. Theories of IT acceptance and avoidance

Research on individuals' attitudes, acceptance and use of IT has attracted extensive attention in the information systems (IS) research community. Consequently, various theories and models have been developed and improved over time to explain and predict the acceptance and use of the new technologies to reflect and address the dynamic and changing nature of technology advancement. Among them, the most widely adopted are the theory of planned behavior (TPB), technology acceptance model (TAM), innovation diffusion theory (IDT), unified theory of acceptance and use of technology (UTAUT), and extended unified theory of acceptance and use of technology (UTAUT2). Due to their popularity, numerous researchers have undertaken systematic literature reviews and offered comprehensive analysis and evaluation on their applications, effectiveness and limitations (e.g. Venkatesh and Davis, 2000; Venkatesh et al., 2016; Williams et al., 2015). The UTAUT model aims to explain user intentions to use an IT/IS and usage behavior under the voluntary condition (Venkatesh et al., 2003). It includes four key constructs. These are performance expectancy, effort expectancy, social influence, and facilitating conditions. The model suggests that performance expectancy, effort expectancy and social influence directly determine the behavioral intention, and indirectly influence the behavioral use. The facilitating conditions directly influence the behavioral use. These core constructs are in turn moderated by gender, age, experience, and voluntariness of use.

Since the publication of the UTAUT model (Venkatesh et al., 2003), it has been integrated and extended to improve its predictive power in different contexts. There are four main types of UTAUT extensions (Venkatesh et al., 2016): new exogenous mechanisms, new endogenous mechanisms, new moderating mechanisms, and new outcome mechanisms; and the model is also integrated with other theoretical models to study technology acceptance and use and related issues. The UTAUT model has been widely used and is seen to exhibit satisfactory measurement properties and invariance. However, traditional technology adoption models, such as TAM and UTAUT, are not considered suitable for studying the adoption of AI because they mainly focus on the use of functional technologies and cannot fully explain the complex decision-making process involved in the context of AI adoption (Gursoy et al., 2019).

IT can arguably create a negative effect on users due to various concerns, such as trust, risk, fears, and wellbeing (e.g. Agogo and Hess, 2018; Beaudry and Pinsonneault, 2005; Balakrishnan and Dwivedi, 2021a; Vimalkumar et al., 2021; Zhang, 2013). But compared to extensive publications focusing on improving adoption and diffusion, there is limited literature on developing theoretical models for understanding the factors influencing an individual's technology avoidance intention. Among that literature, the most cited model is the technology threat avoidance theory (TTAT) (Liang & Xue, 2009, 2010). The TTAT model aims to explain why and how an individual avoids IT threats in voluntary settings, based on the literature from a range of areas including psychology, healthcare, risk analysis, and information systems. The model defines the process and suggests the factors that influence IT users' threat avoidance behavior (Liang and Xue, 2009). In the TTAT model, the perceived technology threats and the effectiveness, costs and self-efficacy of safeguarding measures are the core constructs that determine the IT users' avoidance motivation directly, which in turn impacts on their avoidance behavior ultimately. TTAT proposes that users' threat perceptions are determined by the perceived probability of the threat's occurrence and the perceived severity of the threat's negative consequences as well as their interaction.

3. Research model and hypotheses

To achieve the research aim, we develop and test a theoretical model to understand the factors and their effects on managers' attitudes and behavioral intentions towards using AI for decision-making.

As explained in sections 1 and 2, it is expected that using AI for decision-making can be perceived to have both positive and negative impacts, yet the literature does not seem to offer any models that explain and predict IT adoption by considering both benefits and concerns (Breward et al., 2017). Although UTAUT has been very widely used to predict the behavioral intention towards technology acceptance, it does not consider the effect of negative perceptions and concerns of users and their impact on the users' behavioral intentions. Therefore, its power to predict users' attitudes and intentions could be limited in the context of AI for organizational decision-making. Recently, researchers also called attention to IT-related technostress, technophobia, anxiety (e.g. Agogo and Hess, 2018; Zhang, 2013), personal wellbeing concerns (e.g. Ho and Ito, 2019; Mensmann and Frese, 2019), and in particular the "dark side" of AI (e.g. Cheatham et al., 2019; Dwivedi et al., 2021).

In order to develop a fuller understanding of the complex issues related to AI acceptance or avoidance owing to the specific human-machine partnership in the context of decision-making, we integrate UTAUT with TTAT, and also the factors capturing the personal concerns that specifically reflect the application context of using AI for decision-making. Based on the literature review and by considering the unique characteristics of using AI for organizational decision-making by managers, we propose a theoretical model, underpinned by the basic premises of UTUAT, TTAT, and other relevant studies (e.g. Agogo and Hess, 2018; Beaudry and Pinsonneault, 2005; Duan et al., 1995; Edwards et al., 2000; Zhang, 2013). Fig. 1 shows the research model and its associated hypotheses.

In summary, our research model is based on the following main considerations:

- Human centered approach – Studying managers' behavioral intentions towards using AI for organizational decision-making must follow the human centered approach because of the unique nature of the human–AI partnership. Humans and AI cannot be treated as separate entities in order to make the partnership work. Therefore, the research model we propose should include human perceptions, concerns and attitudes.
- Inclusion of both technology acceptance and avoidance factors – As using AI for organizational decision-making has the potential to create both positive and negative impacts, that could influence managers' attitudes and behavioral intentions to either accept or avoid using AI.
- Factors related to personal concerns – As using AI for organizational decision-making may raise serious concerns among managers about their personal development and wellbeing, which could significantly influence managers' attitudes and behavioral intentions towards using AI. Thus, personal wellbeing and development concerns are also included in our proposed research model.

The variables used in the model are defined in the context of this study as outlined in Table 1. As shown in Fig. 1, we developed four sets of hypotheses based on UTAUT, its associated empirical studies, and the emerging AI literature. According to Venkatesh et al. (2016), contextual factors, facilitating conditions and social influence, can explain and predict intention to use ITs in organizational contexts, which has been empirically demonstrated by various prior studies (e.g. Brown et al., 2010; Hong et al., 2011; Hossain et al., 2019; Queiroz and Fosso Wamba, 2019; Shibl et al., 2013; Wang et al., 2014; Yueh et al., 2016). Similarly, the UTAUT model can be extended to this research context by arguing that behavioral intentions towards using AI can be explained and predicted by facilitating conditions and peer influence (social influence). While there is a lack of empirical research on using AI for organizational decision-making, conceptual AI studies indicated that facilitating conditions play a key role in using AI. For example, it is suggested that using AI requires the support of sophisticated technological structures (e.g. Dwivedi et al., 2021; Schoemaker and Tetlock, 2017) or enabling infrastructure (Ransbotham et al., 2017), otherwise using AI "may be limited by legacy infrastructures" (Davenport et al., 2020, p.29); and that using AI requires development of employees' technology skills (e.g. McKinsey, 2017; Ransbotham et al., 2018; Schoemaker and Tetlock, 2017) so they and AI can work effectively together (Ransbotham et al., 2017; Schoemaker and Tetlock, 2017). Conceptual research also suggests that using AI can be significantly influenced by peer pressure (part of the social influence) such as "the negative consequences of being left behind" (e.g. van Esch and Black, 2019). Additionally, although not in the context of managers using AI for organizational decision-making, Gursoy et al. (2019) demonstrated empirically that social influence is

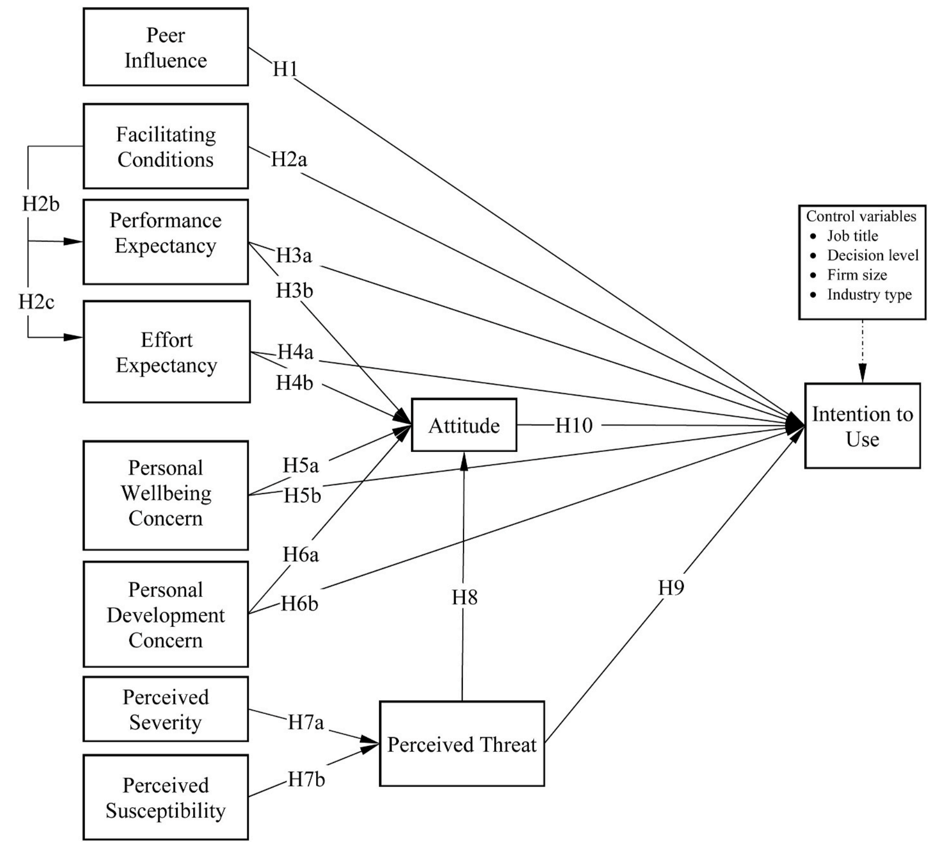

Fig. 1. Proposed integrated AI acceptance-avoidance model (IAAAM).

Table 1
Variable definitions.

Key variables	Working definition	References
Attitude	An individual's positive or negative feelings about using AI for organizational decision-making.	Dwivedi et al. (2017)
Performance expectancy	The degree to which an individual believes that using AI will help him or her to attain gains in job performance.	Venkatesh et al. (2012)
Effort expectancy	The degree of ease associated with the use of AI.	Venkatesh et al. (2012)
Facilitating conditions	The degree to which an individual believes that an organizational and technical infrastructure exists to support the use of AI.	Venkatesh et al. (2012)
Peer influence	The degree to which an individual perceives that important others believe he or she should use AI.	Venkatesh et al. (2012)
Perceived susceptibility	An individual's belief regarding the likelihood that using AI will make bad decisions.	Chen and Zahedi (2016); Liang and Xue (2009)
Perceived severity	An individual's belief regarding the degree of the negative consequences of using AI to make bad decisions.	Chen and Zahedi (2016); Liang and Xue (2009)
Perceived threat	The extent to which an individual believes that using AI to make decisions is dangerous or harmful.	Chen and Zahedi (2016); Liang and Xue (2010)
Personal wellbeing concerns	An individual's concerns regarding the degree of personal anxiety and stress caused by the use of AI.	Agogo and Hess (2018); Brougham and Haar (2018)
Personal development concerns	An individual's concerns regarding the degree of preventing personal learning from own experience by the use of AI.	Duan et al. (1995); Edwards et al. (2000)

a key antecedent to customers' willingness to accept AI device use in service encounters, while Pan et al. (2019) showed that subjective norm has a positive effect on clinicians' behavioral intention towards using AI-driven smart healthcare services. Thus, we propose the following hypotheses:

H1. Peer influence will have a significant positive influence on intention to use AI.

H2a. Facilitating conditions will have a significant positive influence on intention to use AI.

There is evidence in the IT adoption literature to support the positive and significant impact of facilitating conditions on both performance expectancy (e.g. Rana et al., 2017; Rana et al., 2016; Schaper and Pervan, 2007) and effort expectancy (e.g. Dwivedi et al., 2019; 2017; Schaper and Pervan, 2007). For example, Schaper and Pervan (2007) examined IT acceptance and utilization by Australian occupational therapists and found that organizational facilitating conditions had a positive and significant impact on both performance expectancy and effort expectancy. Rana et al. (2016) and Rana et al. (2017) examined electronic government system adoption by citizens from selected cities in India and found that facilitating conditions such as government support in terms of providing training had a positive and significant impact on performance expectancy. In addition, conceptual AI studies suggested the importance of facilitating conditions such as the support of sophisticated technological structures (Dwivedi et al., 2021) and/or establishing strong policies, procedures, and worker training (Cheatham et al., 2019) in shaping managers' perceptions of using AI for organizational decision-making. For example, it is suggested that through providing training, employees and AI can work effectively together (Ransbotham et al., 2017; Schoemaker and Tetlock, 2017) to identify business opportunities afforded by AI (Ransbotham et al., 2018). Therefore, we propose the following two hypotheses:

H2b. Facilitating conditions will have a significant positive effect on performance expectancy.

H2c. Facilitating conditions will have a significant positive influence on effort expectancy.

Along with peer influence and facilitating conditions, intention to use ITs in organizational contexts could be explained and predicted by technology attributes: performance expectancy and effort expectancy (Venkatesh et al., 2016), which have been verified empirically by many prior studies (e.g. Brown et al., 2010; Hong et al., 2011; Wang et al., 2014). In the same way, it seems plausible to extend the UTAUT model to the context of using AI for organizational decision-making by arguing that behavioral intentions towards using AI can be similarly explained and predicted by performance expectancy and effort expectancy. While there is little empirical research on using AI for organizational decision-making, conceptual AI studies indicated that using AI may lead to improved business decision-making (e.g. Brock and von Wangenheim, 2019; Dwivedi et al., 2021; McKinsey, 2017; Metcalf et al., 2019; Ransbotham et al., 2018) and performance (e.g. Duan et al., 2021; Ransbotham et al., 2018; Ransbotham et al., 2017), which relate broadly to performance expectancy. Besides, empirical support for the relationship between technology attributes and intention to use AI can be found in the context of consumer acceptance of AI. Gursoy et al. (2019) and Lin et al. (2020) demonstrated empirically that performance expectancy and effort expectancy are key antecedents to customers' willingness to accept AI device use, while Lin et al. (2020) further showed that compared with limited-service hotel customers, full-service hotel customers' emotions toward the use of AI devices are less likely to be influenced by effort expectancy. Thus, we propose the following hypotheses:

H3a. Performance expectancy will have a significant positive influence on intention to use AI.

H4a. Effort expectancy will have a significant positive influence on intention to use AI.

The individual's attitude, which is influenced by technology attributes, performance expectancy and effort expectancy, is another key construct which has been included in several IT adoption models and has been verified empirically in various contexts by many studies (e.g. Balakrishnan and Dwivedi, 2021b; Dwivedi et al., 2019; 2017; Rana et al., 2017; Rana et al., 2016; Venkatesh et al., 2011). While there is virtually no empirical research examining managers' attitudes towards using AI for organizational decision-making, empirical evidence to support the relationship between the individual's attitude and technology attributes can be found in other studies. Schweitzer et al. (2019) demonstrated that consumers intend to use voice-controlled smart assistants if they have mastered their interaction with the intelligent object. However, while Niehueser and Boak (2020) assumed individuals' attitudes towards the introduction of AI based recruitment systems in the context of human resource management are affected by their general "tech-savviness" that is related to effort expectancy, they found no statistically significant relationship between these two factors. Nevertheless, we propose the following hypotheses:

H3b. Performance expectancy will have a significant positive effect on attitude towards using AI.

H4b. Effort expectancy will have a significant positive influence on attitude towards using AI.

Due to the rapid technology development and its profound impact on society and individuals, there have been increasing concerns about the affective dimension of human interaction with ITs (e.g. Agogo and Hess, 2018; Beaudry and Pinsonneault, 2005; Zhang, 2013), especially the negative responses to the use of AI (e.g. Duan et al., 1995; Edwards et al., 2000; Ransbotham et al., 2018; Weld and Bansal, 2019). Apart from Brougham and Haar (2018), who indicated that the use of AI may lessen employees' future prospects so that their wellbeing consequently suffers, leading to depression and cynicism, there is little empirical research on personal wellbeing concern caused by using AI. Nevertheless, there is evidence from other studies. For example, Mensmann and Frese (2019) in the context of entrepreneurship training found that an entrepreneur's constant retention of personal initiative might not necessarily foster the individual's wellbeing even if they enjoyed the challenge. As a result, it can be expected that personal wellbeing concern caused by using AI may negatively affect managers' perceptions of using AI for organizational decision-making. Thus, we propose the following two hypotheses:

H5a. Personal wellbeing concern will have a significant negative influence on attitude towards using AI.

H5b. Personal wellbeing concern will have a significant negative influence on intention to use AI.

As well as concerns about personal wellbeing, previous relevant studies (e.g. Duan et al., 1995; Edwards et al., 2000) reveal the AI users had concerns regarding how AI may prevent them learning from their own experience in making better decisions. This is echoed to a degree by emphasizing "opportunity for advancement" (Youngohc and Guimaraes, 1995). These findings suggest that concerns about personal development would have negative effects, thus we also propose the following hypotheses:

H6a. Personal development concern will negatively influence on attitude towards using AI.

H6b. Personal development concern will negatively influence on intention to use AI.

According to TTAT (Liang and Xue, 2009), individuals' perceived IT threat is determined by their perceived susceptibility to, and the subsequent severity of negative consequences from the IT. While IT threat related research is still scarce, TTAT has been applied to explaining the determinants of individuals' intentions to avoid IT threats in several different contexts (e.g. Alomar et al., 2019; Breward et al., 2017; Carpenter et al., 2019; Liang and Xue, 2009; Zahedi et al., 2015). Most such empirical studies adopted only pieces of TTAT and have found mixed results regarding the relationship between perceived severity, susceptibility, and threat (Carpenter et al., 2019). For example, Zahedi et al. (2015) investigated how performance and cost-related elements of detection tools influenced users' perceptions of the tools and threats, efficacy in dealing with threats, and reliance on such tools using a controlled lab experiment in two distinct domains. They found that threat severity and threat susceptibility were not statistically related to the reported reliance on the detector in the context of online pharmacies; but threat severity was statistically significant in the banking domain. As there are serious concerns about the possibility that using AI will make bad organizational decisions with grave negative consequences (e.g. Dwivedi et al., 2021; European-Commission, 2020; Shrestha et al., 2019; Weld and Bansal, 2019), TTAT could be applied to understanding AI related threat. Thus, we propose the following two hypotheses:

H7a. Perceived severity will have a significant positive effect on perceived threat.

H7b. Perceived susceptibility will have a significant positive effect on perceived threat.

Furthermore, TTAT suggests that individuals' perceived IT threats influence their behavior to avoid the threats or the IT itself (Liang and Xue, 2009), which has been verified to varying extents by prior studies in different contexts (e.g. Breward et al., 2017; Carpenter et al., 2019; Liang and Xue, 2009; Zahedi et al., 2015). For example, Breward et al. (2017) examined consumer acceptance of biometric identity authentication for banking transactions through automated teller machines in the United States and found that privacy concerns and security concerns each had a significant and negative impact on attitude towards using biometric identity authentication. The most relevant of these findings to our study is the idea that an individual's perception of IT threat influences the person's IT adoption behavior. This seems to be consistent with the view suggested by several conceptual AI studies (e.g. Brock and von Wangenheim, 2019; Duan et al., 2019; Dwivedi et al., 2021; Ransbotham et al., 2018) that an individual's perception of using AI is a key factor influencing implementing AI based decision systems within organizations.

Besides, the notion that an individual's perception of IT threat influences the person's IT adoption behavior can be supported by findings from other studies. Pan et al. (2019) showed that perceived risk of using AI-driven smart healthcare services has a negative impact on non--clinicians' attitude. Sharma et al. (2020) suggested that perceived risk negatively influences internet banking adoption usage intention, although Bhuasiri et al. (2016), examining the determinants of citizens' intention to adopt an e-tax filing and payment system in Thailand, found that perceived risk did not influence users' intentions. Thus, we propose the following hypotheses:

H8. Perceived threat will have a significant negative influence on attitude towards using AI.

H9. Perceived threat will have a significant negative influence on intention to use AI.

The individual's attitude was not initially included in the UTAUT as it was seen not to affect intention to use directly (Venkatesh et al., 2003, 2016). Recent IT adoption studies (e.g. Dwivedi et al., 2021; Rana et al., 2017; Rana et al., 2016), on the other hand, argued that the individual's attitude should be included in UTAUT as it is central to understanding behavioral intention. The key argument is that "all else being equal, people form intentions to perform behaviors toward which they have positive attitude" (Dwivedi et al., 2019, p.721). Likewise, the individual's attitude is seen to be most relevant to the current study to understand managers' perceptions of using AI for organizational decision-making, as several conceptual studies indicate that the individual's perception is a key factor influencing implementing AI based decision systems within organizations (e.g. Duan et al., 2019; Dwivedi et al., 2021; Ransbotham et al., 2018). Although empirical research on using AI for organizational decision-making is almost non-existent, there is evidence from other studies. Feng et al. (2019) showed empirically that, in the context of airlines fully replacing service employees, customers are likely to perceive the forced adoption of self-service intelligent technologies as a threat to their freedom, causing them to have negative emotions and perceptions towards the adoption; thus, their adoption intention decreases. Pan et al. (2019), in the context of using AI-driven smart healthcare services in the medical market, suggested that both clinicians' and non-clinicians' attitudes influence their adoption intentions. Thus, we propose:

H10. Attitude will have a significant positive effect on intention to use AI.

4. Research methodology

We tested the hypotheses empirically using partial least squares structural equation modeling (PLS-SEM), which is implemented in the SmartPLS3 software and is recommended as well-suited for research situations where theory is less developed (Gefen et al., 2011; Hair et al., 2013; Wetzels et al., 2009), and/or the research model is large and complex (Akter et al., 2017; Chin et al., 2008). While UTAUT is well developed and empirically examined; TTAT is arguably insufficiently examined (Carpenter et al., 2019); and the IAAAM is proposed for the first time by the present study. Additionally, IAAAM consists of complex interrelationships among 11 constructs and 49 indicators. Thus, PLS-SEM is seen to be highly appropriate for empirically testing the research model.

4.1. Measures of constructs

Table 2 summarizes the constructs and their indicators adopted from prior studies.

Attitude was measured using four indicators from Dwivedi et al. (2017) in terms of the extent to which managers feel that they like the idea of using AI; using AI is a good idea, a foolish idea, and/or pleasant. Four indicators from Venkatesh et al. (2012) were used to measure effort expectancy. They measured the extent to which managers feel that AI is easy to use; interaction with AI is clear and understandable; learning how to use AI is easy; and it is easy for them to become skillful at using AI. Facilitating conditions were measured using four items from Venkatesh et al. (2012) in terms of the resources and the knowledge necessary to use AI, AI's compatibility with other technologies used by managers, and the help from others when there are difficulties using AI. Five items from Venkatesh et al. (2012) were used to evaluate performance expectancy in terms of the extent to which AI is useful in decision-making; using AI increases the chances of making important decisions; helps make decisions more quickly; increases managers' productivity in general and in decision-making. Peer influence was rated using five indicators (Venkatesh et al., 2012). These indicators measured the extent to which a manager feels s/he should use AI with reference to peers/superiors/partners who are important to the manager and/or influence the manager's behavior.

Three indicators (Chen and Zahedi, 2016; Liang and Xue, 2009) were used to measure the perceived susceptibility in terms of the possibility of AI making bad decisions at some point or in the future. Perceived severity was measured using seven indicators (Chen and Zahedi, 2016; Liang and Xue, 2009), in terms of the extent to which a manager perceives that AI may perpetuate cultural stereotypes; amplify discrimination; reproduce institutional biases; intensify systemic bias; have the wrong objective; and perform poorly due to insufficient training. Four indicators (Chen and Zahedi, 2016; Liang and Xue, 2009) were used to measure perceived threat in terms of the extent of a manager's fear of, worry and/or anxiety about, AI's risks.

Personal development concern was measured using four self-developed indicators based on prior studies (e.g. Duan et al., 1995; Edwards et al., 2000) in respect of the impact of AI supported decision-making on a manager's learning ability, career development, losing control of personal development, and losing the opportunity to learn from her/his own experience. Personal wellbeing concern was measured using six self-developed indicators based on prior studies (Agogo and Hess, 2018; Brougham and Haar, 2018) regarding the extent to which AI makes a manager feels relaxed, anxious, redundant, useless and/or inferior; and AI increases the manager's job satisfaction.

Three items from Venkatesh et al. (2012) were used to measure intention to use with reference to the extent to which a manager will use AI in the future, in the manager's workplace, and/or frequently.

4.2. Sample and data collection

To test the hypotheses in Fig. 1, we distributed a questionnaire survey through Qualtrics via e-mail to collect data from both medium (50–249 employees) and large (250 or more employees) UK firms. Medium and large firms were selected because only firms with "substantial resources" have the "capabilities" to employ analytical systems (Gillon et al., 2014). The target population was middle and senior managers in the firm and their email addresses were identified from the FAME (Financial Analysis Made Easy) database.

Considering FAME does not have all managers' e-mail addresses, a quota sampling approach was seen to be appropriate to identify a representative sample. The minimum sample size requirement can be determined based on the expected minimum R^2 values of constructs (Hair et al., 2014). Given that the maximum number of arrows pointing at a construct in the structural model is eight, 238 responses are required in order to detect a minimum R^2 value of 0.10 in any of the constructs at

Table 2
Constructs and indicators of the study.

Construct	Indicator (from 1- strongly disagree to 7-strongly agree)	Reference
Attitude	ATT1-Using AI is a good idea ATT2-Using AI is a foolish idea[a] ATT3-I like the idea of using AI ATT4-Using AI would be pleasant	Dwivedi et al. (2017)
Effort Expectancy	EE1-Learning how to use AI is easy for me EE2-My interaction with AI is clear and understandable EE3-I find AI easy to use EE4-It is easy for me to become skillful at using AI	Venkatesh et al. (2012)
Facilitating Conditions	FC1–I have the resources necessary to use AI FC2–I have the knowledge necessary to understand AI FC3-AI is compatible with other technologies I use FC4–I can get help from others when I have difficulties using AI	Venkatesh et al. (2012)
Performance Expectancy	PE1-I find AI useful in my decision-making PE2-Using AI increases my chances of making important decisions PE3-Using AI helps me make decisions more quickly PE4-Using AI increases my productivity PE5-Using AI increases my productivity in decision-making	Venkatesh et al. (2012)
Peer Influence	PI1-Peers who are important to me would think that I should use AI PI2-Peers who influence my behavior would think that I should use AI PI3-My superiors who influence my behavior would think that I should use AI PI4-My superiors to whom I report would think that I should use AI PI5-My business partners would think that I should use AI	Venkatesh et al. (2012)
Perceived Susceptibility	PSUS1-AI is likely to make bad decisions in the future PSUS2-The chances of AI making bad decisions are great PSUS3-AI may make bad decisions at some point	Chen and Zahedi (2016); Liang and Xue (2009)
Perceived Severity	PSEV1-AI may perpetuate cultural stereotypes in available data PSEV2-AI may amplify discrimination in available data PSEV3-AI may be prone to reproducing institutional biases in available data PSEV4-AI may have a propensity for intensifying systemic bias in available data PSEV5-AI may have the wrong objective due to the difficulty of specifying the objective explicitly PSEV6-AI may use inadequate structures such as problematic models PSEV7-AI may perform poorly due to insufficient training	Chen and Zahedi (2016); Liang and Xue (2009)
Perceived Threat	PT1-My fear of exposure to AI's risks is high PT2-The extent of my worry about AI's risks is low®[a] PT3-The extent of my anxiety about potential loss due to AI's risks is high PT4-The extent of my worry about AI's risks due to misuse is high	Chen and Zahedi (2016); Liang and Xue (2009)
Personal Development Concern	PDC1-AI supported decision-making has a positive impact on my learning ability®[a] PDC2-AI supported decision-making has a positive impact on my career development ®[a] PDC3-I hesitate to use AI for fear of losing control of my personal development PDC4-It scares me to think that I could lose the opportunity to learn from my own experience using AI supported decision-making	Duan et al. (1995); Edwards et al. (2000)
Personal Wellbeing Concern	PWC1-AI makes me feel relaxed ® PWC2-AI makes me feel anxious[a] PWC3-AI makes me feel redundant[a] PWC4-AI makes me feel useless[a] PWC5-AI makes me feel inferior[a] PWC6-AI increases my job satisfaction®	Agogo and Hess (2018); Brougham and Haar (2018)
Intention to Use	IU1–I intend to use AI in the future IU2–I will always try to use AI in my workplace IU3–I plan to use AI frequently	Venkatesh et al. (2012)

[a] Dropped after the measurement evaluation. ®-reverse worded.

a significance level of 1% (Hair et al., 2014). Thus, the target sample size was decided to be 250, with firm size and industry sectors being controlled as quota variables in the sample.

As the sample size of 250 was too small to cover all industry sectors, we selected a few different industry sectors to represent how industries are using AI for decision-making. As suggested by several reports (Deloitte, 2019; Forrester, 2018; McKinsey, 2017), different industries are at different stages of using AI for decision-making: some are leading while others are lagging behind. Thus, four different industries were selected to form the basis of quota sampling: construction (lagging behind), wholesale/retail (about in the middle), manufacturing (leading), and finance and insurance (leading). Based on the percentages of medium and large firms, and the four industry sectors included in the FAME database, the quotas were decided as summarized in Table 3.

The questionnaire survey used a seven-point Likert scale (ranging from 1-strongly disagree to 7-strongly agree). Table 2 shows the questions used in the survey to measure the research constructs. The survey was scrutinized by subject experts and went through eight revisions. We then piloted the survey with five academic experts and two middle managers to ensure that the respondents understood the questions and there were no problems with the wording or measurements. This resulted in a few formatting and presentation modifications. The survey questionnaire was then distributed to managers through Qualtrics, an

Table 3
Firm size and industry quotas.

Industry	FAME percentage		Rounded quotas		Total
	Medium	Large	Medium	Large	
Construction	12.19%	2.54%	31	6	37
Wholesale/retail	22.77%	6.57%	57	16	73
Manufacturing	30.98%	8.23%	77	21	98
Finance and insurance	11.00%	5.72%	28	14	42
Total	100%		193	57	**250**

online survey tool.

From 28th January to 3rd March 2020, after four follow-ups, 275 responses were received of which 269 were useable, which met the minimum sample size requirement of 250 as discussed above.

4.3. Respondents

Table 4 summarizes the respondents' demographics characteristics. The reported positions of the respondents showed that 26.1% of the respondents were C-level and above senior managers, 55% were department directors or heads, and 18.9% were other managers. Regarding their decision-making responsibilities, 20.8% of the respondents answered strategic, 45.9% tactical, and 33.3% operational. With respect to their working experience in the industry, 11.2% of the respondents had less than five years; 26.8% five to ten years; 27.5% 10–15 years, 14.5% 15–20 years, and 20% over 20 years. Thus, each manager as a respondent was considered to be a key informant (Bagozzi et al., 1991), having the relevant knowledge and experience to be able to address the survey questions about AI for decision-making.

4.4. Common method and non-response bias

We addressed common method bias using both procedural and statistical remedies. The first was a procedural remedy. Respondents' complete anonymity was assured in the survey cover letter, thereby reducing respondents' tendency to make socially desirable responses (Podsakoff et al., 2003). Item ambiguity was reduced by defining scale items clearly and keeping the questions simple and specific (Podsakoff et al., 2003). Scale items were separated by not labelling variables in view of the reported constructs and not grouping items by variables, thus reducing the possibility of respondents guessing and consciously matching the link between variables (Parkhe, 1993). Positively and negatively worded measures were also used to control for acquiescence and disacquiescence biases (Podsakoff et al., 2012).

The second was a statistical approach, using the partial correlation procedure (Lindell and Whitney, 2001) to further examine the potential common method bias in this study. The partial correlation procedure uses a marker variable, which is theoretically unrelated to at least one of the key constructs in the research model, to investigate if the zero-order and partial correlations are statistically consistent. In this study, tenure of the respondents (demographic) was used as a marker variable since it is not theoretically related to UTAUT constructs, as evidenced by prior seminal UTAUT studies (e.g. Venkatesh et al., 2003; Venkatesh et al., 2012, 2016). Following the suggestion made in Simmering et al. (2015), the correlation matrix summarized in Table 6 confirmed that tenure was not statistically related to the dependent variable, intention-to-use, or to three of the other constructs. The result of the partial correlation procedure indicated that there were no significant changes in any of the study correlations, suggesting that common method bias was not a serious problem in this study (Lindell and Whitney, 2001).

We conducted a *t*-test to assess the presence of non-response bias. Early (n = 150) and late (n = 119) respondents were compared on all measures. The *t*-test results did not find significant differences between the two respondent groups, suggesting an absence of non-response bias (Armstrong and Overton, 1977).

Table 4
Respondent profiles (n = 269).

Respondent Positions	No (%)	Decision Level	No (%)	Years of experience (x) in the industry	No (%)
CEO/MD/Partner	9 (3.4)	Strategic	56 (20.8)	$x \leq 5$	30 (11.2)
Vice President	24 (8.9)	Tactical	121 (45.9)	$5 < x \leq 10$	72 (26.8)
Other C-level Executive	37 (13.8)	Operational	92 (33.3)	$10 < x \leq 15$	74 (27.5)
Director/Head of Dept.	148 (55.0)			$15 < x \leq 20$	39 (14.5)
Other Managers	51 (18.9)			$20 < x$	54 (20.0)

5. Model testing and findings

5.1. Evaluation of the measurement model and the structural model

First, the measurement model was evaluated. To avoid measurement model misspecification, following Gudergan et al. (2008) and Hair et al. (2013), we conducted a confirmatory tetrad analysis (CTA-PLS), which confirmed that the measurement model was a reflective model. Following Hair et al. (2014), we evaluated the reflective measurement model by considering the internal consistency (composite reliability), indicator reliability, convergent validity and discriminant validity. Discriminant validity was also further established as the scores of the heterotrait-monotrait (HTMT) ratio of correlations were below the suggested threshold of 0.85 (Benitez et al., 2020). The evaluation results were satisfactory as summarized in Tables 5 and 6.

It should be noted that while the Cronbach's alpha score for personal wellbeing concern was below 0.7, its composite reliability was a satisfactory 0.84. According to Hair et al. (2017), composite reliability is more appropriate because it considers the indicators' differential weights while Cronbach's alpha weights the indicators equally.

Second, we assessed the structural model in terms of collinearity and the significance and relevance of the structural model relationships, following Hair et al. (2014). The result of a bootstrapping procedure (5, 000 samples) (Hair et al., 2014) indicated that no collinearity issue was present. The model's predictive power was assessed by the amount of variance attributed to the latent variables (i.e., R^2). The R^2 values indicated that the full model explained 62% of the variance in intention to use, 64% in attitude, 59% in effort expectancy, 55% in perceived threat, and 53% in performance expectancy (Fig. 2). According to Wetzels et al. (2009), the effect size in IT-related research is large if it is over 0.36 when PLS is used. Thus, the R^2 values were seen to be large.

5.2. Hypothesis testing

Fig. 2 shows the path coefficients and significance levels, which are now used to test the hypotheses. H1 proposes that peer influence has a positive effect on intention to use, which is rejected as the effect is statistically insignificant. H2a posits that facilitating conditions have a positive influence on intention to use, which is also rejected since this effect is not statistically significant. H2b and H2c postulate that facilitating conditions have a positive effect on performance expectancy and effort expectancy, respectively. H2b and H2c are both supported, with path coefficients of 0.725 ($p < 0.001$) and 0.770 ($p < 0.001$). H3 suggests that performance expectancy has a positive influence on intention to use (H3a) and attitude (H3b). H3a is supported, with a path coefficient of 0.41 ($p < 0.001$), but H3b is rejected as the effect on intention to use is not statistically significant. H4 suggests that effort expectancy has a positive influence on intention to use (H4a) and on attitude (H4b). H4a is rejected as not statistically significant, whereas H4b is supported as the path coefficient is 0.194 ($p < 0.01$).

H5 suggests that personal wellbeing concern has a negative influence on attitude (H5a) and intention to use (H5b). Both are supported, the path coefficients being −0.229 ($p < 0.001$) and −0.129 ($p < 0.05$) respectively. H6 proposes that personal development concern influences attitude (H6a) and intention to use (H6b) negatively. H6a is rejected as the effect on attitude is not statistically significant. However, H6b is supported with a path coefficient of −0.220 ($p < 0.01$).

H7a and H7b suggest that perceived severity and perceived susceptibility each positively affect perceived threat. Both H7a and H7b are supported, the path coefficients being 0.329 ($p < 0.001$) and 0.458 ($p < 0.001$) respectively. H8 suggests that perceived threat has a negative

Table 5
Convergent validity and internal consistency reliability.

Construct	Indicators	Loading	Indicator Reliability	Cronbach's α	Composite Reliability	AVE
Attitude (ATT)	ATT1	0.88	0.77	0.86	0.92	0.78
	ATT3	0.91	0.83			
	ATT4	0.86	0.74			
Effort Expectancy (EE)	EE1	0.84	0.71	0.90	0.93	0.78
	EE2	0.89	0.79			
	EE3	0.92	0.85			
	EE4	0.89	0.79			
Facilitating Conditions (FC)	FC1	0.88	0.77	0.88	0.92	0.74
	FC2	0.84	0.71			
	FC4	0.83	0.69			
	FC5	0.83	0.69			
Performance Expectancy (PE)	PE1	0.88	0.77	0.94	0.96	0.81
	PE2	0.92	0.85			
	PE3	0.91	0.83			
	PE4	0.89	0.79			
	PE5	0.90	0.81			
Peer Influence (PI)	PI1	0.92	0.85	0.95	0.96	0.83
	PI2	0.88	0.77			
	PI3	0.91	0.83			
	PI4	0.92	0.85			
	PI5	0.92	0.85			
Perceived Susceptibility (PSUS)	PSUS1	0.91	0.83	0.85	0.91	0.77
	PSUS2	0.90	0.81			
	PSUS3	0.83	0.69			
Perceived Severity (PSEV)	PSEV1	0.84	0.71	0.94	0.95	0.73
	PSEV2	0.74	0.55			
	PSEV3	0.87	0.76			
	PSEV4	0.85	0.72			
	PSEV5	0.89	0.79			
	PSEV6	0.91	0.83			
	PSEV7	0.86	0.74			
Perceived Threat (PT)	PT1	0.87	0.76	0.88	0.92	0.80
	PT3	0.90	0.81			
	PT4	0.92	0.85			
Personal Development Concern (PDC)	PDC3	0.95	0.90	0.88	0.95	0.90
	PDC4	0.94	0.88			
Personal Wellbeing Concern (PWC)	PWC1	0.80	0.64	0.62	0.84	0.72
	PWC6	0.90	0.81			
Intention to Use (IU)	IU1	0.91	0.83	0.93	9.96	0.88
	IU2	0.95	0.90			
	IU3	0.95	0.90			

Table 6
Inter-construct correlations and summary statistics.

	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12
1. ATT	5.31	1.14	**0.88**											
2. EE	4.92	1.21	0.67**	**0.88**										
3. FC	4.65	1.41	0.63**	0.78**	**0.86**									
4. PE	5.03	1.29	0.74**	0.75**	0.73**	**0.90**								
5. PI	4.71	1.42	0.65**	0.69**	0.79**	0.78**	**0.91**							
6. PSUS	3.70	1.34	−0.27**	−0.18**	−0.19**	−0.24**	−0.21**	**0.88**						
7. PSEV	4.09	1.31	−0.19**	−0.13*	−0.18**	−0.17**	−0.18**	0.77**	**0.85**					
8. PT	3.51	1.37	−0.27**	−0.16**	−0.12	−0.15*	−0.13*	0.71**	0.68**	**0.90**				
9. PDC	3.28	1.22	−0.58**	−0.48**	−0.45**	0.64**	−0.54**	0.04	−0.06	0.02	**0.95**			
10. PWC	3.38	1.05	−0.61**	−0.54**	−0.51**	−0.58**	−0.50**	0.10	0.11	0.07	0.70**	**0.85**		
11. IU	5.14	1.29	0.70**	−0.63**	0.56**	0.68**	0.62**	−0.18**	−0.16**	−0.21**	−0.63**	−0.61**	**0.94**	
12. Tenureˆ			−0.15*	−0.15*	−0.16*	−0.20**	−0.13*	0.04	0.03	0.06	0.18**	0.16**	−0.11	1

The diagonal elements (in bold) represent the square root of AVE; **$p < 0.01$ (two tailed), *$p < 0.05$ (two tailed). ˆ- Marker variable.

influence on attitude, which is supported by the path coefficient of −0.122 ($p < 0.01$). H9 posits that perceived threat has a negative influence on intention to use, which is rejected as there is no statistically significant effect. Finally, H10 postulates that attitude has a positive effect on intention to use, which is supported by the path coefficient of 0.274 ($p < 0.001$). The results are summarized in Table 7.

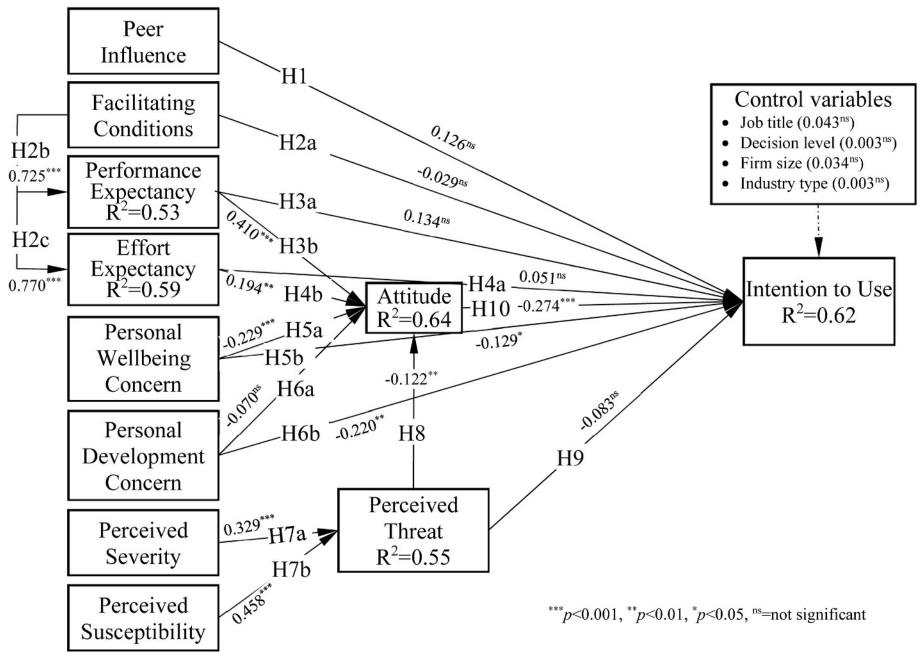

Fig. 2. Hypothesis test results.

Table 7
Summary results of hypotheses testing.

Hypothesis	Hypothesized Path	Path coefficient	Empirical evidence
H1	Peer influence - > Intention to use	0.126^{ns}	Rejected
H2a	Facilitating conditions - > Intention to use	-0.029^{ns}	Rejected
H2b	Facilitating conditions - > Performance expectancy	0.725***	Supported
H2c	Facilitating conditions - > Effort expectancy	0.770***	Supported
H3a	Performance expectancy - > Intention to use	0.134^{ns}	Rejected
H3b	Performance expectancy - > Attitude	0.410***	Supported
H4a	Effort expectancy - > Intention to use	0.051^{ns}	Rejected
H4b	Effort expectancy - > Attitude	0.194***	Supported
H5a	Personal wellbeing concern - > Attitude	−0.229***	Supported
H5b	Personal wellbeing concern - > Intention to use	−0.129***	Supported
H6a	Personal development concern - > Attitude	-0.070^{ns}	Rejected
H6b	Personal development concern - > Intention to use	−0.220**	Supported
H7a	Perceived severity - > Perceived threat	0.329***	Supported
H7b	Perceived susceptibility - > Perceived threat	0.458***	Supported
H8	Perceived threat - > Attitude	−0.122**	Supported
H9	Perceived threat - > Intention to use	-0.083^{ns}	Rejected
H10	Attitude - > Intention to use	0.274***	Supported

6. Discussion

6.1. Discussion of results

We drew on UTAUT, TTAT and personal concerns to develop the IAAAM model to understand the factors that influence managers' attitudes and behavioral intentions towards using AI for organizational decision-making. We examined a total of 17 hypotheses that can be divided into three groups: factors associated with UTAUT, personal concerns, and TTAT.

With respect to four of the UTAUT associated hypotheses that intention to use will be positively affected by peer influence (H1), facilitating conditions (H2a), performance expectancy (H3a), and effort expectancy (H4a), contrary to expectations, our results suggest that all these four hypotheses are rejected. While H2a is in line with the finding from Venkatesh et al. (2003) that facilitating conditions have an insignificant influence on behavioral intention, the other findings may seem to be inconsistent with many prior studies conducted in the context of IT adoption within business organizations (e.g. Brown et al., 2010; Hong et al., 2011; Wang et al., 2014). This seeming inconsistency needs to be interpreted in accordance with the differences between technological, task, and user classes (Venkatesh et al., 2016). Our research's technological class is AI, one type of controversial IT (Breward et al., 2017); its task class is decision-making; and its user class is managers. As a result of the combination of these three classes, our study's context is in stark contrast with the contexts of the three above-mentioned studies (Brown et al., 2010; Hong et al., 2011; Wang et al., 2014), where the technological class is ITs for supporting operational tasks; the task class is operational; and the user class is mainly operational personnel.

The remaining four of the UTAUT related hypotheses are supported, namely the expectations that facilitating conditions have a positive effect on performance expectancy (H2b) and effort expectancy (H2c); and attitude is positively influenced by performance expectancy (H3b) and effort expectancy (H4b). Those findings from the present study in the AI context are largely in agreement with the findings of prior studies conducted in different IT contexts (e.g. Brown et al., 2010; Hong et al., 2011; Wang et al., 2014). Those findings have also validated the existing UTAUT constructs in the context of using AI for organizational decision-making. Nevertheless, the UTAUT related hypotheses are only partially confirmed, which is inconsistent with prior UTAUT studies. While this inconsistency may be to some extent explained by the different technological, task, and user classes considered by different studies, it also suggests that the UTAUT model and its associated factors may not necessarily fully represent the context of using AI for organizational decision-making. This inconsistency seems to be an important issue that deserves further study.

In support of the notion that personal concerns might have negative effects on managers' attitudes and behavioral intentions towards using AI, our findings indicate that attitude is negatively influenced by personal wellbeing concern (H5a) but not by personal development concern (H6a); and that intention to use is affected negatively by both personal wellbeing concern (H5b) and personal development concern (H6b). To a large extent, these findings support prior studies that emphasized the importance of understanding the affective dimension of human interaction with ITs (e.g. Agogo and Hess, 2018; Beaudry and Pinsonneault, 2005; Zhang, 2013), and our study's proposition that personal wellbeing concern and personal development concern could play a significant role in negatively affecting managers' attitudes and behavioral intentions (e.g. Duan et al., 1995; Edwards et al., 2000). An important implication is that firms should take personal concerns into account when implementing AI based decision-making systems. More importantly at the conceptual level, these findings indicate that personal concerns, in addition to the UTAUT factors, are likely to be a key factor influencing managers' perceptions of using AI, and thus should be further examined conceptually and empirically.

With regard to the TTAT related hypotheses, our findings suggest that perceived threat is positively influenced by both perceived severity (H7a) and perceived susceptibility (H7b); perceived threat has a significant negative effect on attitude (H8), but is not statistically related to intention to use (H9). These results not only provide additional empirical evidence in support of the insufficiently examined TTAT (Liang & Xue, 2009, 2010), but also extend the research scope of TTAT into the domain of using AI for organizational decision-making. One important implication is that the TTAT factors should not be excluded from decisions about using AI for organizational decision-making as perceived severity, susceptibility, and threat could negatively influence managers' attitudes.

Finally, regarding the link between attitude and intention to use (H10), we show that attitude has a significant effect on intention to use, thereby providing additional empirical evidence to support for example the revised UTAUT (Dwivedi et al., 2019). Importantly, we confirm that managers' behavioral intentions towards using AI can be explained and predicted by their attitudes. Given that IAAAM explains as much as 62% of the variance in intention to use, we believe our model could be a useful tool for explaining and predicting managers' intentions.

6.2. *Theoretical contributions*

Our study offers several contributions that improve the theoretical understanding of managers' attitudes and behavioral intentions towards using AI for organizational decision-making.

First, we contribute to the emerging literature on using AI for organizational decision-making. Although a number of conceptual studies have highlighted AI's potential benefits (e.g. Agrawal et al., 2017a; Duan et al., 2019; Dwivedi et al., 2021) and concerns about the "dark side" of AI (e.g. Shrestha et al., 2019; Weld and Bansal, 2019), there seems to still be a need for a theoretical model to facilitate the integration of conceptual development and empirical research around the AI phenomenon. By developing IAAAM, we may encourage a more balanced debate about the benefits and the dark side associated with using AI, thereby informing management decisions for using AI based decision systems. By providing new empirical evidence in the context of using AI, we also add to the neglected empirical research on using AI for organizational decision-making (Duan et al., 2019; Dwivedi et al., 2021), and contribute to developing a more comprehensive framework for understanding IT adoption in general (Verdegem and De Marez, 2011).

Second, to have a holistic view of managers' attitudes and behavioral intention towards using AI, we integrate the unified theory of acceptance and use of technology (UTAUT) and the technology threat avoidance theory (TTAT) to develop a new theoretical model, the Integrated AI Acceptance-Avoidance Model (IAAAM), to enhance our understanding of the factors that influence managers' attitudes and behavioral intentions towards using AI for organizational decision-making. Although extant work has indicated that individuals tend to have positive attitudes and intentions to use a specific IT when they perceive the IT's usefulness and ease of use (Dwivedi et al., 2019; Venkatesh et al., 2003; Venkatesh et al., 2016), or are motivated to avoid the threats associated with using the IT or the IT itself when they perceive a threat (Liang and Xue, 2010), little is known about how to explain and predict individuals' attitudes and behavioral intentions by considering both the benefits and dangers of the IT at issue (Breward et al., 2017). Existing IT adoption models are not intended to explain such behavior (Liang and Xue, 2009), thus the need to integrate both positive and dark side variables is largely ignored by the IT adoption literature (Agogo and Hess, 2018). To address this gap, IAAAM provides a valuable "net valence approach that considers both benefits and concerns … when studying the adoption of controversial technologies where people are predisposed to view such technologies with skepticism" (Breward et al., 2017, p.760). This is also in line with the idea of examining and explaining the attributes of a whole rather than attributes of its parts (Venkatesh et al., 2016; Weber, 2012).

Third, we extend the conception that individual characteristics such as attitude are central to behavioral intentions further, to include perceived personal wellbeing concern and perceived personal development concern as additional key constructs. While there is limited research on the affective dimension of human interaction with ITs (e.g. Agogo and Hess, 2018; Beaudry and Pinsonneault, 2005; Zhang, 2013), our study has introduced and empirically supported that perceived personal wellbeing concern and perceived personal development concern can help explain and predict attitude and intention towards using AI. This addition provides supplementary constructs to the literature of IT adoption, which could further enhance our understanding of an individual's attitude and behavioral intention towards using ITs in general and controversial ITs (Breward et al., 2017) in particular.

6.3. *Practical implications*

Our findings offer valuable managerial implications. Firstly, firms wishing to adopt AI to improve their organizational decision-making should develop favorable facilitating conditions, as the findings show that managers' attitudes towards using AI are indirectly affected by facilitating conditions, performance expectancy and effort expectancy. The implication is that firms need to ensure that the enabling technologies and infrastructures are in place (e.g. Dwivedi et al., 2021; Schoemaker and Tetlock, 2017); and that proper training and support (e.g. McKinsey, 2017) need to be provided so managers have the knowledge and technology skills to work with AI based decision systems effectively (e.g. Ransbotham et al., 2017; Schoemaker and Tetlock, 2017).

Secondly, firms need to develop an effective mechanism through which managers' personal concerns could be alleviated as these could negatively influence managers' attitudes and behavioral intentions (e.g. Duan et al., 2019; Duan et al., 1995; Edwards et al., 2000; Tambe et al., 2019). Our findings suggest that personal concerns have negative effects on managers' perceptions of using AI for organizational decision-making, which could seriously diminish the effectiveness of using AI based decision systems. The implication is that firms wishing to use AI for organizational decision-making may need to provide, for example, training so managers could have a better understanding of AI. Additionally, managers could further upskill through training to improve their knowledge and expertise, thereby becoming more confident in their ability to make better decisions while significantly alleviating their perceived concerns.

Thirdly, firms need to address the perceived dark side, or the dangers associated with using AI. Such concerns are fundamental problems that need to be addressed adequately; otherwise, decisions to use AI based systems may "lead to the adoption of inadequately bounded AI; they can lead to AI systems that are unpredictable and even dangerous" (Johnson and Verdicchio, 2017, p.2270). Consequently, such concerns could negatively affect managers' attitudes and behavioral intentions, as confirmed by the empirical findings from this research model. In order to address managers' concerns about the dark side of using AI, firms should develop organizational-level mechanisms that are able to identify, assess, and control the perceived dark side or the dangers associated with using AI. Developing such mechanisms will be necessary as they could assure managers that "AI does not get out of control" (Johnson and Verdicchio, 2017, p.2270).

Finally, IAAAM encourages firms to be aware that using AI involves a balanced consideration of the benefits and the dark side associated with using AI for organizational decision-making. Acceptance-avoidance decisions about using AI based on either the benefits or the dark side of AI may lead to substandard AI adoption decisions, AI-based decision systems not working as efficiently and effectively, and/or missing the opportunities to significantly improve organizational decision-making. Thus, firms can use IAAAM to evaluate the benefits and risks of using AI, and develop organizational interventions designed to increase the potential benefits while mitigating managers' concerns.

6.4. Limitations and future research

Our study has several limitations, some of which could provide avenues for future research. First, our study focuses on developing IAAAM to understand managers' attitudes and behavioral intentions towards using AI; it does not, and was not intended to, include user behavior as a construct due to the fact that the actual use of AI for organizational decision-making is not yet sufficiently widely practiced. Future work could include user behavior to further test the validity and usefulness of IAAAM. For similar reasons, this study does not test the effects of moderators such as age, gender, etc., which could also be examined by future work.

Second, while we focus on understanding the management of AI-supported organizational decision-making, AI is considered to be more effective if it is supported by big data and analytics (e.g. Duan et al., 2019; Gupta et al., 2018). Further, Pappas et al. (2018) suggested that organizations using big data analytics should be viewed as an integral part of a big data and business analytics ecosystem, echoed by Kamaladin et al. (2021) regarding the ecosystem needed for digitally enabled process innovation. Thus, it is thus necessary to understand how the ecosystem's elements interact and interrelate to create knowledge, innovation, and value. Pappas et al. (2018) also identified that in order for organizations to use digital technologies to create business value, data-driven culture plays a critical role, which resonates with the view of Davenport and Bean (2018). Hence, future research could explore how AI-supported organizational decision-making could be influenced by a data-driven culture and/or by being a part of a big data analytics ecosystem.

Third, our study includes two new personal concerns that are relevant to using AI for organizational decision-making. Our findings confirmed that the addition helps explain and predict managers' attitudes and behavioral intentions. Thus, future work could identify and test other personal factors that are pertinent to the research context and the specific IT at issue.

Fourth, our results are based on and limited to UK managers in the private sector. It would be worthwhile to extend this work to managers in the public sector and/or in other countries. Finally, our research is quantitative and based on survey data to examine managers' attitudes and intentions towards using AI. Future research could use qualitative approaches to develop a richer and deeper understanding of how and why managers' attitudes and intentions are influenced.

Finally, as our research model, IAAAM, demonstrates, AI-supported organizational decision making is affected by a number of factors. While we have intentionally used PLS-SEM to understand the hypothesized relationships based on each single predictor's independent effect on an outcome, we are aware that the variables examined may have complex and asymmetric relationships, or the configuration of multiple conditions (Pappas and Woodside, 2021). Due to its capability to best explain such complex and asymmetric relationships, the configurational approach using fuzzy set qualitative comparative analysis (fsQCA) (Ragin, 2008; Ragin and Davey, 2016) has attracted increased attention, as demonstrated in behavioral research (e.g. Pappas, 2018; Pappas et al., 2020) and research on the use of AI-enabled systems (Papamitsiou et al., 2020). Therefore, we suggest that future research could use fsQCA to examine the configuration of multiple conditions, thereby developing a complementary understanding of the configurational pathways to the adoption of AI in organizational decision-making.

7. Conclusion

Our research contributes to a better understanding of managers' attitudes and behavioral intentions towards using AI for organizational decision-making by developing and testing a new model, IAAAM. Our study emphasizes the need for understanding an individual's attitude and behavioral intention by considering both the potential benefits and negative effects associated with using AI based decision-making systems. By integrating UTAUT, TTAT and other personal concerns, the proposed IAAAM model can facilitate a more balanced debate about the benefits and the dark side associated with using AI for organizational decision-making, thereby helping explain and predict an individual's attitude and intention towards using AI and informing management decisions for using AI based systems as well.

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