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Uncovering risk professionals' intentions to use artificial intelligence: empirical evidence from the Italian setting

Luca Ferri, Marco Maffei and Rosanna Spanò
Department of Economics, Management, Institutions, Università degli Studi di Napoli Federico II, Napoli, Italy, and
Claudia Zagaria
Department of Economics, University of Campania "L. Vanvitelli", Capua, Italy

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Abstract

Purpose – This study aims to ascertain the intentions of risk managers to use artificial intelligence in performing their tasks by examining the factors affecting their motivation.

Design/methodology/approach – The study employs an integrated theoretical framework that merges the third version of the technology acceptance model 3 (TAM3) and the unified theory of acceptance and use of technology (UTAUT) based on the application of the structural equation model with partial least squares structural equation modeling (PLS-SEM) estimation on data gathered through a Likert-based questionnaire disseminated among Italian risk managers. The survey reached 782 people working as risk professionals, but only 208 provided full responses. The final response rate was 26.59%.

Findings – The findings show that social influence, perception of external control and risk perception are the main predictors of risk professionals' intention to use artificial intelligence. Moreover, performance expectancy (PE) and effort expectancy (EE) of risk professionals in relation to technology implementation and use also appear to be reasonably reliable predictors.

Research limitations/implications – Thus, the study offers a precious contribution to the debate on the impact of automation and disruptive technologies in the risk management domain. It complements extant studies by tapping into cultural issues surrounding risk management and focuses on the mostly overlooked dimension of individuals.

Originality/value – Yet, thanks to its quite novel theoretical approach; it also extends the field of studies on artificial intelligence acceptance by offering fresh insights into the perceptions of risk professionals and valuable practical and policymaking implications.

Keywords Risk managers, Artificial intelligence, Intention

Paper type Original article

1. Introduction

At the present time, issues regarding the ability of artificial intelligence (AI) to revolutionize business measurement and reporting practices and the danger that a late or incomplete switch could pave the way for systems that are anachronistic and therefore gradually less useful, are under close scrutiny (Akinsola *et al.*, 2022; Bagnoli *et al.*, 2019; Cobianchi *et al.*, 2022; Cong *et al.*, 2018; Žigienė *et al.*, 2019).

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The introduction of such technology can have many benefits (Biancone *et al.*, 2021; Secinaro *et al.*, 2021), however the way in which AI is developed and used can also exhibit important shortcomings. AI applications have led to greater intrusions in personal privacy and more surveillance and social manipulation. In the last few years, politicians, policymakers, regulators, international organizations, societal organizations, the media and academics in many countries have discussed the need for more oversight over the deployment and use of AI in our societies. Here, the organizational dimension cannot be fully appreciated and comprehended without tapping into the perceptions and reactions of individual actors.

While widespread consensus exists among professional bodies and the broader research community on the potential transformative role of automation and AI in terms of the practice of accounting and auditing professionals (CIMA, 2016; IMA, 2013; Leitner-Hanetseder *et al.*, 2021), research on factors affecting the ability of the profession to embrace these technological advancements has been limited, especially concerning other key actors in the control architecture of firms, that is, risk managers. This is even more relevant considering how the interconnection of organizations, society and technology is shaping a new risk landscape, which in turn impacts internal processes.

In the risk management domain, many studies, from both academics and practitioners, recognize the benefits of AI. Some specific attention regarding the effects of the use of AI on the risk manager profession (Copulsky, 2011), which is likely to assume a more strategic perspective, emphasizes how, due to the increasing use of AI, the risk profession is shifting from being technical in nature to being more about making sense of risk (Taarup-Esbensen, 2019). A recent survey from Deloitte (2019) reveals that risk management departments are moving toward using technology and removing duplications and unnecessary layers of governance. However, despite the expected benefits, the implementation of these technologies is proceeding slowly in many institutions (Deloitte, 2021).

Although AI represents a potential opportunity for risk professionals (Deloitte, 2021; Hodge, 2020; Taarup-Esbensen, 2019), possible obstacles may be related to a lack of systematic focus on AI's relevance and usefulness within companies, which can impinge the willingness of individuals to engage in change. Resistance to change, organizational culture, lack of trust and the high price of technology are the most critical barriers that interfere with adopting AI technology in managerial accounting (Vărzaru, 2022). Thus, empirical research on the intentions and capacity of actors to use AI is required to inform planning and practice at the professional and institutional levels. AI acceptance and intention to use remain largely unexplored areas, especially regarding adoption drivers (Vărzaru, 2022). More in depth, there are no published studies exploring the intentions of risk managers to use AI in their activities, despite the role of actors being crucial to fully exploit the value of AI in the domain under scrutiny.

With the aim of filling this lack of literature, our research model integrates two prominent theoretical frameworks, the technology acceptance model 3 (TAM3) and the unified theory of acceptance and use of technologies (UTAUT). Covering all the areas cited in the two frameworks, we developed and disseminated a Likert-based questionnaire among Italian risk managers. The questionnaire was disseminated among risk professionals who use digital tools, such as email and members of Linkedin groups for risk professionals. The survey reached 782 people working as risk professionals, but only 208 provided full responses. The final response rate was 26.59%. The data were analyzed using partial least squares structural equation modeling (PLS-SEM) to measure the effect of the theoretical constructs on the intentions of individuals to adopt digital technologies.

The results reveal that the main predictors of the intentions of risk managers to use AI are social influence, perception of external control and risk perception. Moreover, the performance expectancy (PE) and effort expectancy (EE) of risk professionals in relation to AI implementation and use appears to be a reasonably reliable predictor, thus unveiling interesting areas for further investigation.

The remainder of this paper is organized as follows. Section 2 discusses the relevance of AI for risk managers via an analysis of previous research and outlines the model used in the study. Section 3 describes the hypothesis development while Section 4 presents the research design. Section 5 reports the findings of the analysis and section 6 discusses the results and provides some concluding remarks.

2. Previous studies and theoretical model

Academics (Cong *et al.*, 2018; Žigienė *et al.*, 2019) and practitioners (Deloitte, 2021) agree on the benefits of AI within the risk management domain as these tools enable better risk decision support and process integration. Wilkinson (2011) suggests that it is almost impossible for risk managers to perform well without the storage and processing abilities of advanced IT and the immediate capacity to communicate data-rich material around the organization. Some authors highlight the need for competence from practitioners in AI areas (Holmes and Douglass, 2022). They argue that skills in data management, data cleansing and correcting inaccurate or incomplete data are particularly valued by industry and public accountants. They further recommend accounting educators, as an imperative, and accounting programs rise to the challenge of equipping students to be life-long learners in accounting and to grow with the changes in the profession. Some scholars argue that new technologies will not only change the future of risk management, but also drive it, stating that soon advanced models of AI will help assess emerging risks, early warning signals and potential responses (Hodge, 2020; Saeidi *et al.*, 2019; Žigienė *et al.*, 2019). This allows risk managers to focus on more strategic issues; as technology takes on more of the analytical and processing tasks, risk professionals will be able to take a longer-term view of risks to businesses, with the opportunity to focus more heavily on horizon-scanning for emerging risks that may impact business in two or three years. Similarly, Copulsky (2011) posits that risk management will become more about managing resilience, ensuring that the business can cope with immediate shocks, such as natural catastrophes, power outages and supply chain failures, as well as more long-term disruptive risks, like those caused by new and nimbler challengers entering the market, new technologies, more stringent regulation and changing consumer sentiment.

Taarup-Esbensen (2019) highlights some relevant points on the role of AI in the risk management profession from a broader perspective. First, the author suggests that the role of risk management is shifting from being technical in nature to being about making sense of risk, where the manager engages with the social and physical environment with the aim of acquiring cues that could indicate how future events will unfold. More specifically, the use of technology and the increased focus on the systematic documentation of risk events has changed the role of the risk manager. This means that risk managers have changed their focus from information seeking and structuring, to information identification and making sense of emerging patterns of risk. This suggests that, regardless of the potential uses of the technology, risk professionals will need to be more sensitive to how the business operates and where the organization can take advantage of commercial opportunities.

Aside from the heated debate on the issues under scrutiny, there are currently no published studies exploring the intentions of risk managers to use digital technologies in their activities (Vărzaru, 2022). With the aim to fill this gap in literature, this study seeks to ascertain the intentions of risk managers to use AI in performing their tasks.

Following existing research (Dwivedi *et al.*, 2019; Faqih and Jaradat, 2015; Ferri *et al.*, 2021), the current study is rooted in a research model that combines two influential theoretical frameworks, TAM3 and UTAUT, to grasp the complexity associated with AI implementation, as well as the inherent intricacies of the risk management profession and the combined challenges that emerge when these two domains intertwine. For clarity, we briefly explain here the characteristics of the two theoretical models employed and explain how they have been operationalized in our research design.

TAM3 extends Davis's (1989) model, which offers a solid theoretical basis for the understanding of technology acceptance dynamics by users, in order to gain full comprehension, at a very early stage, of the implementation processes and thus orient the actions of managers accordingly (Venkatesh *et al.*, 2012). The initial proposal by Davis (1989) included two relevant dimensions for observation. The first dimension of perceived usefulness (PU) is understood as the anticipated degree of change in an individual's work output as a result of the implementation of a new technology. The second dimension, the perceived ease of use (PEOU), unveils the perceived level of difficulty by users for their daily work routine and detects whether any additional effort is required.

TAM3 suggests a step forward in this approach by adding two relevant dimensions to interpret behaviors of users: the attitude toward a given technology and the intention to use it. TAM3 theorizes that PEOU and PU are causally related, as an increase in PEOU favors an increase in PU of the technology. Moreover, these two dimensions directly and positively impact the attitudes toward technology and have an indirect positive effect on behavioral intention. TAM3 reveals a broad range of antecedents of PEOU and PU. Among those, we select ones that are relevant to the characteristics of the study. Therefore, in line with a previous study focusing on the auditing profession (Ferri *et al.*, 2021), we consider output quality, job relevance (JR) and demonstrability of results as predictors of PU and computer self-efficacy (CSE) and perceived external control as antecedents of PEOU. We disregard computer playfulness, image and voluntariness as they are not applicable to the professional context under scrutiny.

UTAUT ties together eight adoption models to comprehensively address and explain up to 70% of the variance in the behavioral intention to accept a new technology (Dwivedi *et al.*, 2019). The model developed by Venkatesh *et al.* reveals the prominent role played by four dimensions.

First, we find PE and EE fundamentally overlap with PU and PEOU in TAM3, respectively (Raut *et al.*, 2018). We find social influence (SI) as the pervasiveness of the opinion of a user's social circle and facilitating conditions (FC), indicating that the perceptions of users concerning the availability of any organizational and technical infrastructure supporting the use of the technology; thus, SI overlaps with the perception of external control used in TAM3. UTAUT considers the influence of external factors, such as social factors (Venkatesh *et al.*, 2003).

Both theoretical models consider the risk dimension quite implicitly, as this is of extreme importance in the domain addressed herein. Indeed, further studies indicate that the risk dimension is a relevant theoretical construct in the ICT decision-making process (Ferri *et al.*, 2020, 2021; Pavlou, 2003). The perception of risks refers to any subject and involves the imagination of phenomena and events that could occur. In the current study, to perceive a risk implies full knowledge of a risky event, even if it has not manifested yet; therefore, it is necessary to isolate this perception from other theoretical constructs and consider risk perception not as implicit but as a specific predictor of intention. Therefore, we added the dimension relating to risk perception, which could arguably play a relevant role in shaping the behavioral intentions of risk professionals. The theoretical construct and hypothesis development are explained in the next section.

3. Hypothesis development

3.1 Perception of external control

As previously mentioned, in TAM3 Venkatesh *et al.* (2003) describe the perception of external control (PEC), which overlaps with the FC mentioned in the UTAUT, as the extent to which a person assumes that organizational and technological resources are available to facilitate the system's use. Thus, this is regarded as a dimension that is likely to influence the PEOU, determining greater user acceptance (Venkatesh *et al.*, 2003). Considering that PEOU and EE can be regarded as interchangeable concepts, the literature clarifies that PEC is a crucial antecedent of EE (Dwivedi *et al.*, 2019; Venkatesh *et al.*, 2012), especially in complex settings where an appropriate set of tools and resources can reduce anxiety and stress related to change.

Another stream of research has argued that PEC is one of the main determinants of adoption intention in a broad range of contexts and settings (Putra and Samopa, 2018; Wu and Chen, 2017). More recently, Ferri *et al.* (2021) offered insights into the auditing profession domain, focusing on the processes of blockchain adoption supporting this view. Focusing on the multifaceted context of risk management, we argue that firms may provide adequate support to their employees to implement technology-based practices, such as instructions, workshops, specialized training and support centers. Therefore, risk professionals could be more prone to use innovative technologies as a result of their firm's help making the perceived degree of inefficiency associated with technological transition substantially reduced. Thus, we hypothesize that:

H1. Perception of external control has a positive effect on risk professionals' EE related to AI.

H2. Perception of external control has a positive effect on risk professionals' intentions to use AI.

3.2 Computer self-efficacy

As for CSE, this theoretical construct determines how confident an actor is in relation to their ability to perform a particular role or job using a device and to accomplish specific tasks (Hayashi *et al.*, 2020; Venkatesh *et al.*, 2012). Issues of computer literacy and computing experience are clearly impactful and constitute a source of knowledge that allows individuals to form an opinion with reference to their own CSE (Venkatesh *et al.*, 2012). Thus, the two main constitutive elements of CSE are the perceptions of individuals regarding their ability to perform a given activity relying on a new technology and their perception of efficacy (He and Freeman, 2019; Venkatesh *et al.*, 2012). This prompted an ongoing debate in literature which revealed that there is a relationship between self-efficacy and the use of computers and a wide variety of user behaviors (Hayashi *et al.*, 2020; He and Freeman, 2019). Similarly, positing that CSE has a significant influence on individuals' expectations of the outcomes of using technology, we argue that this is also relevant for risk professionals. Nowadays, risk professionals must increasingly deal with a wide variety of digital processes, technologies and tools, for which full comprehension and deep confidence are paramount. Therefore, we argue that CSE may affect the intentions of risk professionals to use a technology via EE and hypothesize the following:

H3. CSE has a positive effect on risk professionals' intentions to use AI.

3.3 Job relevance

Venkatesh *et al.* (2012) describe JR as an individual's belief that a given technology is applicable to their job and indicates that it positively affects PE. They focus on how JR impacts attitude and intention, unveiling countervailing results. Bhattacherjee and Sanford (2006) unfold the positive relationship between JR and attitude via PE. Focusing on the audit profession, Kim *et al.* (2009) determined how JR positively impacts intention via PE. Accordingly, we hypothesize the following:

H4. Job relevance has a positive influence on the PE of AI for risk professionals.

3.4 Output quality

Output quality (OQ) represents an individual's perception regarding the ability of a technology to perform a task that is necessary for their job (Venkatesh *et al.*, 2012). The literature shows that OQ positively influences PE (Jaradat and Faqih, 2014). In line with this debate, we hypothesize the following:

H5. OQ has a positive effect on risk professionals' PE related to AI.

3.5 Results demonstrability

Results demonstrability (RES) is the degree to which an individual believes that the results of using a given technology are tangible, observable and communicable. The literature presents countervailing results. On the one hand, studies have shown that RES has a positive and significant effect on PE (Al-Gahtani, 2016; Hanif *et al.*, 2018; Zhang *et al.*, 2008). Conversely, others present RES as a theoretical construct with no significant effects on PE (Al-Gahtani, 2016).

Despite these countervailing results, arguably related to different cultural and contextual conditions, given the intrinsic concerns of transparency and accountability in the risk management profession, we argue that RES may play a crucial role. Thus, we hypothesize the following:

H6. RES has a positive effect on risk professionals' PE related to AI.

3.6 Effort expectancy

As stated above, we refer to the EE theoretical construct derived from the UTAUT, acknowledging that it overlaps with the PEOU construct derived from TAM3, as both indicate the individual's PEOU of a given technology (Venkatesh *et al.*, 2012). The literature often relies on this theoretical construct to tap into the understanding of the necessary learning processes involved in organizational change processes derived from the introduction of new technologies. In this regard, authors have demonstrated that when users perceive that the integration of a new tool in their daily work routine does not require excessive effort, it is likely that the adoption intention will increase (Bierstaker *et al.*, 2014; Hayashi *et al.*, 2020; He and Freeman, 2019; Martins *et al.*, 2014). The breadth and complexity of risk management processes, in conjunction with the resources needed, lead to the following hypothesis:

H7. EE has a positive influence on risk professionals' intentions to use AI.

3.7 Performance expectancy

In this study, the PE construct from the UTAUT is interpreted as a concept overlapping the PU postulated in TAM3. We refer to the degree in which the use of a technology allows actors to execute daily activities more efficiently (Venkatesh *et al.*, 2012). The literature indicates that PE positively impacts the intention to use a given technology in general (Martins *et al.*, 2014; Venkatesh *et al.*, 2012) as well as accounting and control contexts (Curtis and Payne, 2014; Rosli *et al.*, 2012). In such contexts, including risk management, the potential of AI is gaining momentum (Deloitte, 2019; Hodge, 2020; Saeidi *et al.*, 2019; Taarup-Esbensen, 2019). Moreover, the disruptive potential of digital tools is largely considered to be substantially reshaping the face and content of accounting-related professions.

Thus, we further explore whether the possible benefits of these technologies affect PE and risk professionals' intentions to use them, formulating the following hypotheses.

H8. PE has a positive influence on risk professionals' intention to use AI.

3.8 Social influence

The issues relating to social influence (SI), as interpreted by UTAUT, encompass how one's social circle impacts one's choices. The literature on these dynamics is quite broad and has investigated a wide variety of domains and subjects (Martins *et al.*, 2014; Rahi *et al.*, 2018; Rodriguez *et al.*, 2016), highlighting that SI impacts technology adoption behaviors of individuals. In the accounting domain, Curtis and Payne (2014) argue that SI positively impacts auditors' intentions to rely on new technologies when this is an option endorsed by their superiors. Accordingly, the authors generalize their results, highlighting that in highly hierarchical settings, the opinions of those with an evaluative authority are taken into consideration by individuals when dealing with such decision-making issues.

In line with this, we contend that risk management is a setting where such dynamics are likely to occur and thus expect that the greater the degree risk professionals perceive the partner's intention to use AI, the higher their own intention is to use this technology. Accordingly, we hypothesize the following:

H9. SI positively affects the intention to adopt AI.

3.9 Risk perception

Previous literature adds the risk perception (RP) dimension to TAM (Ferri *et al.*, 2020; Pavlou, 2003). Hence, we consider the latter as a relevant antecedent for adoption intentions. RP is a well-acknowledged variable influencing human decision-making processes (Slovic, 2000) and this is intended as an antecedent with negative impacts on technology adoption intention (Forsythe and Shi, 2003; Pavlou, 2003), possibly limiting their implementation.

However, to date the literature has neglected to comprehend how individuals, who used the mastery of risk due to their professional role characteristics, may deal with risk perception in relation to technology acceptance. Thus, we formulate the following open hypothesis:

H10. RP negatively affects the intention to adopt AI.

3.10 Control variables

To understand whether any personal factors of those involved may influence their behaviors, this study encompasses several control variables. First, we consider age, which is cited as a possible factor impacting technology adoption with older people more resistant to change (Kim and Song, 2018). Second, we consider gender, which some studies cite as a relevant dimension, although with countervailing results (He and Freeman, 2019; Kim and Song, 2018). Finally, we adopt experience, arguing that risk professionals with more consolidated experience and routinized processes to manage their tasks could be more resistant to change.

By merging TAM3 and UTAUT and adding the consideration of the risk dimension, we obtained the integrated theoretical model illustrated in Figure 1.

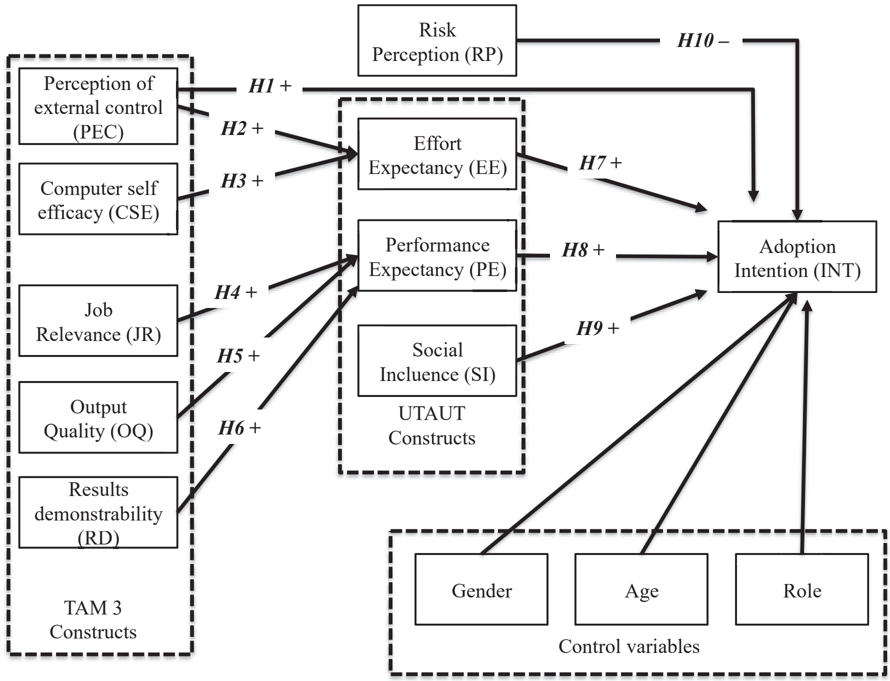


Figure 1.
Proposed model

Source(s): Created by author

4. Research design

4.1 Questionnaire

A Likert-based questionnaire was developed to test our hypotheses. The questionnaire consisted of four sections with 41 questions in total. The first section collected personal information of respondents, while others were aimed at theoretical constructs. All questions were taken from previous studies and modified according to the AI usage and the research context (Ferri *et al.*, 2021). To avoid the risk of central bias, we employed an even-numbered Likert scale for all the questions, ranging from 1 (minimum) to 6 (maximum).

To ensure the reliability of the questionnaire, a pilot test was carried out using volunteers consisting of PhD students, researchers and management students. The test was useful for identifying wording biases such as ambiguous and complex and/or vague questions and other minor problems. We changed relatively infrequent words to the most common words on the condition that such change would not influence the content validity of the construct. Finally, we changed one question, defined as a leading question, using the suggestions collected during the pilot test phase.

4.2 Sample selection and data collection

The questionnaire was disseminated among risk professionals in January and February 2021 using an online method (e-mail and Linked-in), to people working as risk managers or risk management staff in Italy. An invitation letter was sent to each potential participant. We contacted 782 risk professionals, of which only 208 provided full responses. The response rate was 26.59%. Some descriptive statistics of the sample are presented in Table 1.

Variable	Item	n	Percentage
Age	20–30	165	79.33%
	30–40	25	12.02%
	40–50	13	6.25%
	50+	5	2.40%
Role	Assistant/junior risk manager	72	34.62%
	Risk manager	115	55.29%
	Senior manager or higher	21	10.09%
Gender	Male	78	37.50%
	Female	130	62.50%

Source(s): Created by author

Table 1.
Sample description

As Table 1 shows, our sample had a higher prevalence of female respondents (62.50%) than males (37.50%). A total of 34.62% of the sample was employed as assistant or junior risk manager, 55.29% worked as a risk manager, and only 10.09% were employed with role of senior manager or higher. Finally, our sample shows that most respondents were between 18 and 30 years old (79.33%), while respondents aged 30+ represent 20.67% of the sample.

4.3 Reliability and confirmatory factor analysis

Different tests were performed to assess the reliability of the questionnaire. Following previous studies (Ferri *et al.*, 2021), we performed Barlett's test of sphericity and the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy. Both tests provided significant results (0.000 and 0.812, respectively).

Principal component analysis (PCA) and varimax rotation with Kaiser normalization were performed. Variables were grouped into 13 factors, explaining 73.56% of the total variance. No items were dropped after the tests. Finally, we checked for survey reliability using Cronbach's alpha. Descriptive statistics of the questionnaire and Cronbach's Alpha are reported in Table 2.

Each theoretical construct meets the reliability requirement asked for in Cronbach's Alpha because the index value ranges between 0.788 and 0.966. The results are statistically reliable and all items can be used for our model.

4.4 Goodness of fit measure

We performed further tests to assess the model's goodness of fit. The first measure of the overall goodness of fit was performed using the Chi-square test. Our test reveals an overall Chi-square divided by the degree of freedom of 0.730 ($p < 0.001$). Because Chi-square is particularly sensitive to sample size, we carried out the different fit indexes reported in Table 3.

5. Results and discussion

After measuring the model's goodness of fit, we carried out structural equation modeling (SEM) with a confirmatory factor analysis approach to understand the effect of each latent variable on the risk professionals' intention to use AI.

Thanks to SEM, it is possible to simultaneously analyze both the relations of dependence between latent variables and the links between the latent variables and their indicators (Crisci, 2012). However there are different proper methods of estimation that can be used such as: the generalized maximum entropy (GME-SEM), the covariance-based (CB-SEM) and the partial least squares (PLS-SEM).

Table 2.
Descriptive statistics of theoretical constructs, loading factors and Cronbach's alpha

	Question	Loading factors	Min	Max	Mean	Variance	Crombach's alpha
Computer self-efficacy	CSE1	0.723	1	6	3.803	2.236	0.788
	CSE2	0.750	1	6	3.168	1.870	
	CSE3	0.799	1	6	3.135	0.639	
	CSE4	0.728	1	6	3.236	1.060	
Perception of external control	PEC1	0.881	1	6	3.072	0.917	0.857
	PEC2	0.884	1	6	3.462	0.858	
	PEC3	0.855	1	6	3.245	0.920	
	PEC4	0.848	1	6	2.813	1.187	
Job relevance	JR1	0.903	1	6	3.029	0.878	0.835
	JR2	0.867	1	6	2.803	1.048	
	JR3	0.871	1	6	2.615	1.214	
	JR4	0.849	1	6	2.880	1.092	
Output quality	OQ1	0.901	1	6	3.351	1.456	0.858
	OQ2	0.840	1	6	3.303	1.304	
	OQ3	0.847	1	6	3.149	1.161	
	OQ4	0.860	1	6	3.149	1.277	
Results demonstrability	RD1	0.820	1	6	3.178	1.239	0.837
	RD2	0.761	1	6	3.038	1.100	
	RD3	0.833	1	6	2.904	1.015	
	RD4	0.812	1	6	3.063	1.035	
Effort expectancy	EE1	0.856	1	6	3.322	1.012	0.878
	EE2	0.852	1	6	2.971	1.052	
	EE3	0.883	1	6	2.913	0.997	
	EE4	0.877	1	6	3.058	1.001	
Social influence	SI1	0.901	1	6	3.125	1.008	0.897
	SI2	0.916	1	6	3.409	0.958	
	SI3	0.897	1	6	3.255	0.973	
	SI4	0.919	1	6	2.933	1.251	
Performance expectancy	PE1	0.870	1	6	3.558	1.832	0.873
	PE2	0.886	1	6	3.250	1.734	
	PE3	0.891	1	6	3.202	1.205	
	PE4	0.900	1	6	3.240	1.333	
Risk perception	RP1	0.904	1	6	3.481	1.265	0.966
	RP2	0.915	1	6	3.572	1.231	
	RP3	0.911	1	6	3.476	1.236	
	RP4	0.899	1	6	3.486	1.256	
Intention	INT1	0.885	1	6	3.058	1.001	0.906
	INT2	0.912	1	6	3.082	1.206	

Source(s): Created by author

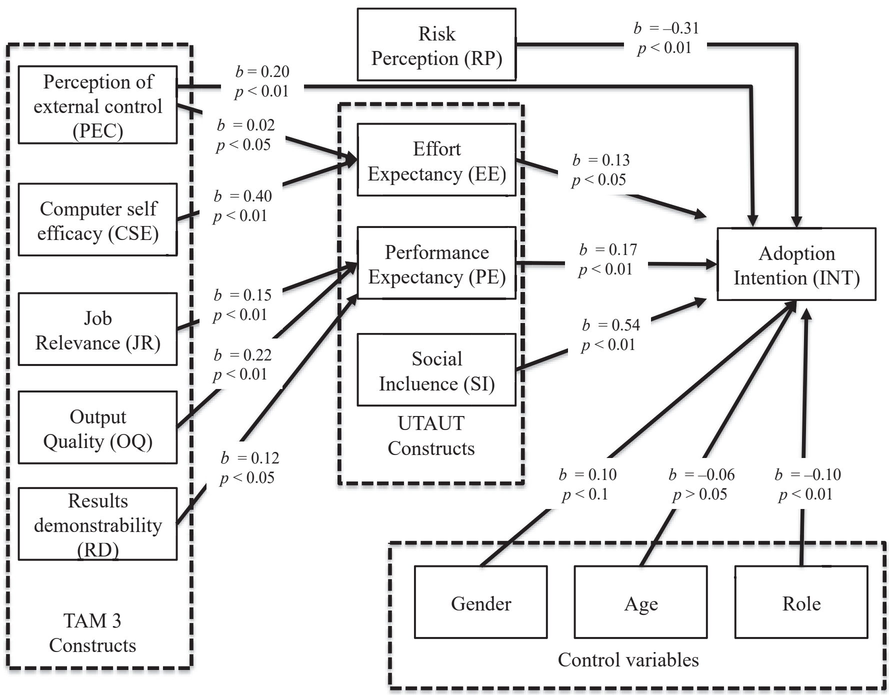
The GME-SEM requires a sample to range between 10 and 40 so it was not applicable for our research (Crisci, 2012). Both of the other two methods can be used thanks to the sample dimension. However, CB-SEM implies the existence of a multivariate normal distribution of items (Crisci, 2012), while PLS-SEM is distribution free so it can be used even if items do not follow a normal distribution and in both reflective and formative way (Crisci, 2012; Hair *et al.*, 2017).

In order to choose between different approaches to structural equation modeling we performed the Shapiro–Wilk test. Our result shows that the data significantly deviates from a normal distribution (result <0.05) so we employ PLS-SEM. The results are presented in Figure 2.

Fit index	Index description	Reference value	Results
Comparative Fit Index (CFI)	Analyzes the model fit by examining the differences between data and the hypothesized model. It can range from 0 to 1	>0.95	0.966
Normed Fit Index (NFI)	Represents the difference between the chi-square of the null model and the chi square of target model, divided by the chi-square of the null model. It can range from 0 to 1	>0.95	0.948
Relative Fit Index (RFI)	Represents a derivate of the NFI. It can vary between 0 (minimum fit) and 1 (maximum fit)	>0.95	0.951
Incremental Fit Index (IFI)	Includes a factor that represents deviations from a null model	>0.95	0.971
Root mean square (RMSEA)	Measures the difference between the observed covariance matrix per degree of freedom and the hypothesized covariance matrix which denotes the model	<0.08	0.030
Simpson's paradox ratio (SPR)	Represents differences in the association between two categorical variables, regardless of how that association is measured	Acceptable => 0.7 Ideally = 1	0.846

Note(s): All indexes are based on their reference values, meaning that the model is reliable
Source(s): Created by author

Table 3. Model reliability analysis



Source(s): Created by author

Figure 2. Model results

According to our results, the intention of risk professionals to use AI is strongly affected by SI, PEC and RP, while EE and PE are the theoretical constructs with a lower effect. The overall model explains 60% of the sample's total variance (R-square = 0.60).

More specifically, with reference to PEC, our results fully confirm H1 and H2. PEC has a low effect on EE (coeff. 0.02, $p < 0.05$) and a higher effect on risk professionals' intention to adopt new technologies (coeff. 0.20, $p < 0.01$). These findings are in line with previous studies that verified the positive effect of PEC on people's EE in new technology usage (Ferri *et al.*, 2021; Putra and Samopa, 2018; Wu and Chen, 2017). Moreover, these findings demonstrate the relevance of PEC as a strong predictor of adoption intention. Our findings show that the intention to use new technologies is directly and indirectly, via EE, influenced by the expected external support that risk professionals expect firms to provide. This result emphasizes the role of firm support in the technological change process, indicating that risk professionals are more likely to adopt new technologies if they feel the support of their organization.

With reference to CSE, our results support H3, showing the existence of a positive effect on EE (coeff. 0.40, $p < 0.01$), confirming the role of CSE in predicting EE. A possible explanation is that risk professionals have to deal with a wide variety of digital processes, technologies and tools, for which full comprehension and deep confidence are paramount; therefore, EE is positively affected by self-confidence. This finding is consistent with other studies (Bierstaker *et al.*, 2014; Hayashi *et al.*, 2020; He and Freeman, 2019; Martins *et al.*, 2014) showing that risk professionals feel comfortable and able to adopt new technologies in their activities. This finding is not in line with other studies that find people who are forced to use new technology will have a bad perception of their technological ability (Ferri *et al.*, 2021).

In line with previous studies (Bhattacherjee and Sanford, 2006; Kim *et al.*, 2009), our results confirm that JR has a positive effect on risk professionals' PE (coeff. 0.15, $p < 0.01$). Risk professionals perceive that new technologies will have a good degree of applicability to their job, at the same time, improving the expectation about performance.

OQ has a positive effect on PE (coeff. 0.22, $p < 0.01$); thus, H5 is supported. Risk professionals feel that new technologies have the potential to improve the effectiveness of their tasks. The positive effect is in line with previous literature and was explained by other authors in different countries and settings. In this case, it is possible to hypothesize that by introducing new technologies in their daily activities, risk professionals can rapidly perform highly standardized tasks, leaving more time for other tasks. OQ can provide a valuable point of reference to develop practical interventions to enhance risk professionals' motivation to adopt new technologies.

For RD, we found a positive effect on PE (coeff. 0.12 with $p < 0.05$). In line with previous studies, our results indicate that risk professionals feel that by introducing artificial intelligence in their tasks, the results can be significantly tangible, observable and communicable (Al-Gahtani, 2016; Hanif *et al.*, 2018; Zhang *et al.*, 2008). Thus, H6 is accepted.

With reference to EE, we found a low positive effect on intention to use (coeff. 0.13, $p < 0.01$); thus, H7 is also supported. This result suggests that risk professionals do not perceive new technologies as particularly difficult to implement and use in their tasks. A possible explanation for this finding is that new technology will reduce the effort of standard activities without completely changing old procedures, processes and activities. This result is in line with Martins *et al.* (2014), who found that when users perceive that the integration of a new tool in their daily work routine does not require excessive effort, the degree of adoption intention is higher. Conversely, this result is not consistent with previous studies that found a negative effect between EE and INT in different counties and settings (Bierstaker *et al.*, 2014; Ferri *et al.*, 2020, 2021).

As for PE, our results reveal the existence of a positive effect on risk professionals' intention to use new technologies (coeff. 0.17 with $p < 0.01$). Thus, H8 is supported. Our result is in line with previous studies that find PE positively impacts the intention to use a technology in accounting and control contexts (Curtis and Payne, 2014; Rosli *et al.*, 2012). This finding suggests that risk professionals expect technologies will have a positive impact on their tasks, thereby improving their performance.

Our findings indicate that SI is the main predictor of INT, with a high positive effect (b = 0.54, p < 0.01). Thus, H9 is fully supported. This result suggests that there is a propensity of risk professionals to use new technologies because of pressure and acceptance from social groups (i.e. colleagues, other risk professionals). This finding is consistent with several other studies that determined SI as the main theoretical construct that affects new technology adoption (Curtis and Payne, 2014; Martins *et al.*, 2014; Rahi *et al.*, 2018), demonstrating the importance of the relational dimension in risk professionals' intention to use AI in their tasks.

Finally, our model supports H10, showing that RP has a negative effect on risk professionals' intention to adopt new technologies (coeff. −0.31, p < 0.01), confirming the negative role of risk perception in new technology implementation (Caldarelli *et al.*, 2017; Forsythe and Shi, 2003). Moreover, the results reveal that risk perception is the theoretical construct that strongly influences risk managers' decision-making processes and can be intended as an antecedent of INT with negative impact (Ferri *et al.*, 2020, 2021; Forsythe and Shi, 2003; Pavlou, 2003).

As for control variables, our model shows that age and the role in the firm both have a low negative effect on risk professionals' intention to use new technologies (coeff. −0.06, p < 0.06 and coeff. −0.10, p < 0.01), while gender has a positive effect (coeff 0.10) with a low significance value (p < 0.1).

A critical cross-reading of all the above described results allows us to go a step further in understanding the intentions of risk professionals to use AI, beyond the mere confirmation or not of previous studies. Leveraging an integrated version of TAM 3 and UTAUT and considering the risk perception, we can better tap into the factors that influence risk professionals' in their willingness to introduce AI in their daily practices. In this regard, the first interesting point to highlight is that the findings show that SI, PE and RP are the main determinants of Italian risk professionals' intention to use AI, with EE also playing a role. More specifically, it is worth noting that such determinants show an opposite influence on the dynamics under scrutiny. That is, while RP exerts a negative effect, the other three theoretical constructs are strong enough to counterbalance RP, thus inducing risk professionals to be willing to implement a technology even if they perceive it as risky. This is reinforced by the indirect effect of other constructs such as CSE, JR and OQ indicating a very interesting phenomenon.

In fact, the whole picture, not only allows us to assert that our research is in line with previous studies that investigated professionals' intention to use new technologies (Hodge, 2020; Taarup-Esbensen, 2019) and with the literature on technology usage and risk perception (Caldarelli *et al.*, 2017; Ferri *et al.*, 2020, 2021; Pavlou, 2003). In addition to this, we demonstrate that, as it happens in other fields (Bierstaker *et al.*, 2014; Ferri *et al.*, 2020, 2021), social pressures are increasingly becoming one of the strongest determinants for risk professionals to decide whether or not to introduce a new technology, even if it is risky. Clearly, PE and EE play a relevant role, but without social pressures we could obtain a different picture. On one hand, a possible explanation could be that risk professionals feel that it is riskier to switch to AI than continue working with consolidated methods, despite the expected advantage in terms of JR, OQ and PE. On the other hand, they are more likely to adopt this technology if they perceive a strong social pressure because they are not really interested in being the first to use a new technology, but they are interested in reducing the "risk of fail" of the new technology implementation.

6. Conclusions

This study builds on the suggestion that AI has the potential to disruptively change the accounting and auditing profession and has been designed to inform the relevant debate based on empirical evidence. The study sought to determine the issues surrounding risk management by examining the factors impacting risk professionals' intention to use AI.

Relying on evidence from 208 risk professionals in Italy, our findings indicate that SI, PEC and RP are the most important determinants for risk professionals to use artificial intelligence, confirming the importance of these variables as predictors that motivate them to use AI (Ferri *et al.*, 2021; Rahi *et al.*, 2018). Moreover, risk professionals' PE and EE, in relation to such technology implementation, appears to be reasonably reliable predictors.

6.1 Theoretical contribution

The theoretical contribution of this study is twofold. The first is related to the fact that this study offers an integrated theoretical model to interpret the dynamics under focus, addressing the lack of previous models that consider only positive factors as determinants of intention to use. By integrating TAM3, UTAUT and risk perception, our model offers a complete viewpoint of risk professionals' intention to use AI, revealing the main predictors of their use. The second theoretical contribution is that it adds to the existing literature on risk professionals' perceptions of AI, offering new insights into the factors influencing the dynamics of acceptance of this technology in the firm. In doing so, this study also contributes to the broader debate on technological innovation in professional fields.

6.2 Practical contribution

From a more practical perspective, our findings offer a solid evidence-based view of the factors affecting risk managers' motivation to use AI. In doing so, the study complements and supplements a heated debate taking place across practitioners worldwide. The research, in fact, may add interesting elements to other results provided in white papers (Deloitte, 2021), meeting the need for empirical research on the intentions and capacity of risk professionals to use AI to inform planning and practice at professional and institutional levels. In addition, for companies who over the last few years have shown a rising tendency to invest heavily in technology, including more spending on security, risk, network, cloud and mobility solutions, this study offers a ground to evaluate and strategically consider the option to leverage AI. In this regard, deeper comprehension of the role of SI, that the paper offers, is paramount as the social dimension of any process of technological change is a crucial factor that impacts the chances of successful acceptance by employees. In the case at hand, this is even more true, as SI is shown to overcome the fear of risks and of risk aware subjects, also suggesting that firms should not only consider whether to adopt AI, but should introduce an additional perspective, the need for an organizational consensus related to the social dimension. Moreover, the study suggests that firms design multiple activities to make risk professionals aware of the methods of applying AI and the possible advantages related to its use, so as to increase their awareness of how well they may improve their performance. Similarly, ongoing organizational support to foster risk professionals' confidence and competence in using such technology is also important as it limits their anxieties related to using AI.

Yet, the findings, in addition to the relevant insights for organizations, provide a solid ground to further reflect on the individuals. The paper shows that risk professionals are moving toward a socio-technical challenge of their profession, jointly considering the technology, the human and the organization equally. Risk professionals are aware of organizational and technical resources that exist to support the use of the system and may act as enabler of technological change.

6.3 Research limitations

The limitations of this study can also be considered as starting points for future research. First, our model examines the intention to use AI at an early stage of technology adoption, while the intention to use a technology may vary over time because of several experiences from different people. Therefore, future studies could broaden our findings by adopting a longitudinal approach to measure employees' perceptions before and after AI introduction in their risk activities.

Second, our sample was limited to people working as risk managers and risk management staff in Italy. Differences in perceptions may arise between risk professionals working in different countries, who are likely to have different motivations to use or avoid AI. Thus, future studies could investigate the existence of differences in technology acceptance within different countries.

Third, this paper investigates the intention to use AI in risk management activities without considering a specific AI or making differences between different tasks. Future studies could investigate how and in which field AI can be used.

Finally, this research did not take into account the change in perception due to the COVID-19 pandemic. Future research could investigate how the pandemic affected the technological decisions and the technology adoption processes.

References

Akinsola, J.E.T., Adeagbo, M.A., Oladapo, K.A., Akinsehinde, S.A. and Onipede, F.O. (2022), "Artificial intelligence emergence in disruptive technology", in Salau, A.O., Jain, S. and Sood, M. (Eds), *Computational Intelligence and Data Sciences*, CRC Press, pp. 63-90.

Al-Gahtani, S. (2016), "Empirical investigation of e-learning acceptance and assimilation: a structural equation model", *Applied Computing and Informatics*, Vol. 12 No. 1, pp. 27-50.

Bagnoli, C., Dal Mas, F. and Massaro, M. (2019), "The 4th industrial revolution: business models and evidence from the field", *International Journal of E-Services and Mobile Applications*, Vol. 11 No. 3, pp. 34-47.

Bhattacherjee, A. and Sanford, C. (2006), "Influence strategies for information technology usage: an elaboration-likelihood model", *MIS Quarterly*, Vol. 30 No. 4, pp. 805-825.

Biancone, P., Secinaro, S., Marseglia, R. and Calandra, D. (2021), "E-health for the future. Managerial perspectives using a multiple case study approach", *Technovation*, Vol. 120, 102406.

Bierstaker, J., Janvrin, D. and Lowe, D.J. (2014), "What factors influence auditors' use of computer assisted audit techniques?", *Advances in Accounting*, Vol. 30 No. 1, pp. 67-74.

Caldarelli, A., Ferri, L. and Maffei, M. (2017), "Expected benefits and perceived risks of cloud computing: an investigation within an Italian setting", *Technology Analysis and Strategic Management*, Vol. 29 No. 2, pp. 167-180.

CIMA (2016), "The world's finance departments do not fear automation or artificial intelligence", available at: https://www.cimaglobal.com/Press/Press-releases/2016/The-worlds-finance-departments-do-not-fear-automation-or-artificial-intelligence/

Cobianchi, L., Verde, J.M., Loftus, T.J., Piccolo, D., Dal Mas, F., Mascagni, P. and Kaafarani, H.M. (2022), "Artificial intelligence and surgery: ethical dilemmas and open issues", *Journal of the American College of Surgeons*, Vol. 235 No. 2, pp. 268-275.

Cong, Y., Du, H. and Vasarhelyi, M.A. (2018), "Technological disruption in accounting and auditing", *Journal of Emerging Technologies in Accounting*, Vol. 15 No. 2, pp. 1-10.

Copulsky, J.R. (2011), "Brand resilience: managing risk and recovery in a high-speed world", *Journal of Product and Brand Management*, Vol. 21 No. 7, pp. 559-560.

Crisci, A. (2012), "Estimation methods for the structural equation models: maximum likelihood, partial least squares e generalized maximum entropy", *Journal of Applied Quantitative Methods*, Vol. 7 No. 2, pp. 1-3.

Curtis, M.B. and Payne, E.A. (2014), "Modeling voluntary CAAT utilization decisions in auditing", *Managerial Auditing Journal*, Vol. 29 No. 4, pp. 304-326.

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.

Deloitte (2019), "Beyond the hype, global digital risk survey 2019", available at: https://www2.deloitte.com/content/dam/Deloitte/uk/Documents/risk/deloitte-uk-digital-risk-survey.pdf

Deloitte (2021), "A moving target: refocusing risk and resiliency amidst continued uncertainty. findings from the global risk management survey", available at: https://www2.deloitte.com/ca/en/pages/financial-services/articles/global-risk-management-survey-financial-services.html

Dwivedi, Y.K., Rana, N.P., Jeyaraj, A., Clement, M. and Williams, M.D. (2019), "Re-examining the unified theory of acceptance and use of technology (UTAUT): towards a revised theoretical model", *Information Systems Frontiers*, Vol. 21 No. 3, pp. 719-734.

Faqih, K.M. and Jaradat, M. (2015), "Assessing the moderating effect of gender differences and individualism-collectivism at individual-level on the adoption of mobile commerce technology: TAM3 perspective", *Journal of Retailing and Consumer Services*, Vol. 22 No. 1, pp. 37-52.

Ferri, L., Spanò, R., Maffei, M. and Fiondella, C. (2020), "How risk perception influences CEOs' technological decisions: extending the technology acceptance model to small and medium-sized enterprises' technology decision makers", *European Journal of Innovation Management*, Vol. 24 No. 3, pp. 777-798.

Ferri, L., Spanò, R., Ginesti, G. and Theodosopoulos, G. (2021), "Ascertaining auditors' intentions to use blockchain technology: evidence from the Big 4 accountancy firms in Italy", *Meditari Accountancy Research*, Vol. 29 No. 5, pp. 1063-1087.

Forsythe, S.M. and Shi, B. (2003), "Consumer patronage and risk perceptions in Internet shopping", *Journal of Business Research*, Vol. 56 No. 11, pp. 867-875.

Hair, J.F.J., Matthews, L.M., Matthews, R.L. and Sarstedt, M. (2017), "PLS-SEM or CB-SEM: updated guidelines on which method to use", *International Journal of Multivariate Data Analysis*, Vol. 1 No. 2, pp. 107-123.

Hanif, A., Jamal, F.Q. and Imran, M. (2018), "Extending the technology acceptance model for use of e-learning systems by digital learners", *IEEE Access*, Vol. 6, pp. 73395-73404.

Hayashi, A., Chen, C., Ryan, T. and Wu, J. (2020), "The role of social presence and moderating role of computer self-efficacy in predicting the continuance usage of e-learning systems", *Journal of Information Systems Education*, Vol. 15 No. 2, pp. 5-17.

He, J. and Freeman, L.A. (2019), "Are men more technology-oriented than women? The role of gender on the development of general computer self-efficacy of college students", *Journal of Information Systems Education*, Vol. 21 No. 2, pp. 1-7.

Hodge, N. (2020), "The evolution of the risk manager", *Risk Management*, Vol. 67 No. 2, pp. 24-29.

Holmes, A.F. and Douglass, A. (2022), "Artificial intelligence: reshaping the accounting profession and the disruption to accounting education", *Journal of Emerging Technologies in Accounting*, Vol. 19 No. 1, pp. 53-68.

IMA (2013), "Digital Darwinism: thriving in the face of technology change", *ACCA Global*, available at: https://www.accaglobal.com/in/en/technical-activities/technical-resources-search/2013/october/digital-darwinism.html

Jaradat, M. and Faqih, K.M. (2014), "Investigating the moderating effects of gender and self-efficacy in the context of mobile payment adoption: a developing country perspective", *International Journal of Business and Management*, Vol. 9 No. 11, pp. 147-165.

Kim, J.P. and Song, E. (2018), "The effects of BlockChain technology benefits on acceptance intentions of BlockChain insurance services: based on the UTAUT model", *Journal of Information Technology Services*, Vol. 17 No. 4, pp. 163-189.

Kim, H.B., Kim, T.T. and Shin, S.W. (2009), "Modeling roles of subjective norms and eTrust in customers' acceptance of airline B2C eCommerce websites", *Tourism Management*, Vol. 30 No. 2, pp. 266-277.

Leitner-Hanetseder, S., Lehner, O.M., Eisl, C. and Forstenlechner, C. (2021), "A profession in transition: actors, tasks and roles in AI-based accounting", *Journal of Applied Accounting Research*, Vol. 22 No. 3, pp. 539-556.

Martins, C., Oliveira, T. and Popovič, A. (2014), "Understanding the Internet banking adoption: a unified theory of acceptance and use of technology and perceived risk application", *International Journal of Information Management*, Vol. 34 No. 1, pp. 1-13.

Pavlou, P.A. (2003), "Consumer acceptance of electronic commerce: integrating trust and risk with the technology acceptance model", *International Journal of Electronic Commerce*, Vol. 7 No. 3, pp. 101-134.

Putra, R.D. and Samopa, F. (2018), "Analysis of factors affecting the acceptance of Surabaya e-government service using Technology Acceptance Model (TAM) 3: a case study of e-lampid", *Advances in Intelligent Systems Research*, Vol. 157, pp. 122-126.

Rahi, S., Ghani, M., Alnaser, F. and Ngah, A. (2018), "Investigating the role of unified theory of acceptance and use of technology (UTAUT) in internet banking adoption context", *Management Science Letters*, Vol. 8 No. 3, pp. 173-186.

Raut, R., Priyadarshinee, P. and Jha, M. (2018), "Understanding the mediation effect of cloud computing adoption in Indian organization: integrating TAM-TOE-Risk model", *International Journal of Service Science Management Engineering and Technology*, Vol. 8 No. 3, pp. 40-59.

Rodriguez, N., Bollen, J. and Ahn, Y.Y. (2016), "Collective dynamics of belief evolution under cognitive coherence and social conformity", *PLoS One*, available at: https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0165910

Rosli, K., Yeow, P.H. and Siew, E.G. (2012), "Factors influencing audit technology acceptance by audit firms: a new I-TOE adoption framework", *Journal of Accounting and Auditing*, Vol. 2012 No. 1, pp. 324-335.

Saeidi, P., Saeidi, S.P., Sofian, S., Saeidi, S.P., Nilashi, M. and Mardani, A. (2019), "The impact of enterprise risk management on competitive advantage by moderating role of information technology", *Computer Standards and Interfaces*, Vol. 63 No. 1, pp. 67-82.

Secinaro, S., Calandra, D., Secinaro, A., Muthurangu, V. and Biancone, P. (2021), "The role of artificial intelligence in healthcare: a structured literature review", *BMC Medical Informatics and Decision Making*, Vol. 21 No. 125, pp. 1-23.

Slovic, P.E. (2000), "The perception of risk", *Science*, Vol. 236 No. 4799, pp. 280-285.

Taarup-Esbensen, J. (2019), "Making sense of risk—a sociological perspective on the management of risk", *Risk Analysis*, Vol. 39 No. 4, pp. 749-760.

Vărzaru, A.A. (2022), "Assessing artificial intelligence technology acceptance in managerial accounting", *Electronics*, Vol. 11 No. 14, 2256.

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.

Venkatesh, V., Thong, J.Y. and Xu, X. (2012), "Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology", *MIS Quarterly*, Vol. 36 No. 1, pp. 157-178.

Wilkinson, M. (2011), "The role of technology in risk management", *Tower Watson*, available at: https://www.towerswatson.com/en-GB/Insights/IC-Types/Ad-hoc-Point-ofView/2011/Insights-The-role-of-technology-in-risk-management

Wu, B. and Chen, X. (2017), "Continuance intention to use MOOCs: integrating the technology acceptance model (TAM) and task technology fit (TTF) model", *Computers in Human Behavior*, Vol. 67 No. 1, pp. 221-232.

Zhang, N., Guo, X. and Chen, G. (2008), "IDT-TAM integrated model for IT adoption", *Tsinghua Science Technology*, Vol. 13 No. 3, pp. 306-311.

Žigienė, G., Rybakovas, E. and Alzbutas, R. (2019), "Artificial intelligence based commercial risk management framework for SMEs", *Sustainability*, Vol. 11 No. 16, pp. 1-23.

Corresponding author
Luca Ferri can be contacted at: luca.ferri@unina.it