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Factors Influencing Senior Executives' Intention To Use Dashboards In The UAE

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Abstract. Decision-making in organisations has shifted from relying on intuition and experience to leveraging data analytics in today's dynamic business environment. Business intelligence (BI) dashboards offer numerous advantages, including efficient decision-making, real-time analytics, and processing large volumes of data. However, the adoption of BI dashboards in the UAE is relatively low compared to other technologies. This study examines the factors influencing employees' intention to use and adopt BI dashboards in the UAE. A quantitative research methodology is employed, using a correlational design and an online survey questionnaire based on the Technology Acceptance Model (TAM). Data from 350 respondents in executive positions in government organisations in Dubai and Abu Dhabi were analysed using the SmartPLS technique. The findings reveal that perceived usefulness and perceived ease of use significantly and positively impact behavioural attitudes and intention to use dashboards. Perceived functional risks and perceived time loss risk negatively affect attitudes toward dashboards. Perceived usefulness has the highest impact on behavioural intention, while perceived time loss risk has the least impact. Surprisingly, perceived information risk has a positive impact on behavioural attitudes, contrary to prior research. This study provides empirical evidence for UAE government organisations and dashboard developers to guide the design and implementation of dashboards, addressing the slow adoption of this critical technology in the complex business environment.

Keywords: Dashboards, behavioural attitude, TAM, perceived risks, intention to use, PU, PEOU

1. Introduction

Timely, quality and accurate decision-making have become a crucial component in today's management environment and a key determinant of an organisation's growth and success. The contemporary business environment is not only turbulent and hypercompetitive but also characterised by increased globalisation and the adoption of rapidly changing technology. Unlike in the past, where decision-makers mostly relied on intuitions, experience, and guesswork to make critical decisions, decision-makers in today's organisations are required to collect and analyse large volumes of data in an ever-changing business environment, making the traditional human-based approaches ineffective and unreliable (Martins et al., 2020). As a result, organisations are increasingly embracing modern decision support systems (DSS) and analytics tools such as dashboards (Lathabhavan & Akshar, 2021). A dashboard is a data visualisation software or tool that provides a real-time graphical representation of business performance (Lathabhavan & Akshar, 2021). Dashboards are designed with consideration of the individual business executive's needs and are capable of pulling real-time data from various sources, including email systems, customer resource management (CRM), website analytics programs, web-based software, and accounting software, among other programs.

While dashboards have become crucial tools for today's time-constrained C-level executives and managers (such as the chief operating officer (COO), chief executive officer (CEO), and chief information officer (CIO)) who use them to track the organisation's key performance indicators (KPIs) and make data-driven decisions after analysing huge amounts of data in organisations (Apter, 2019; Smartsheet, 2019; Martins et al., 2020), the growth in their popularity is not at par with their adoption at the individual level. Bastedo et al. (2017) observed that while many organisations have implemented dashboards, employees' interests and usage of these decision-making tools are quite low. Inside information from various government organisations in the UAE shows that some employees still stick to the traditional decision-making approaches despite implementing dashboards. Similar observations were made in the organisation I currently work for, where many employees are reluctant to use dashboards in their decision-making process. The low interests and usage of dashboards among employees in government organisations in the UAE warrant a study that examines factors that influence employees' acceptance and the intention to use dashboards at an individual level.

Understanding factors influencing the use and intention to adopt dashboards in UAE government organisations from the existing body of knowledge might be challenging since no study has been conducted. Most of the information on this issue is from non-scholarly sources such as websites and blogs with questionable credibility and reliability. While there are a few studies conducted to investigate users' intention to adopt information technologies, such as business intelligence (BI)systems, these studies have produced mixed/ inconsistent findings. Some, for example, Almaiah et al. (2016) and Hou (2013), have shown that intention to use BI systems is primarily determined by quality dimensions, perceived usefulness, and ease of use, while others (for example, Puklavec et al. 2018; Kohnke et al., 2011; Ikart &Ditsa, 2004) have cited facilitating conditions, superior influence, and self-efficacy as critical influencers of user's intention to adopt or use BI systems. While these findings can be extrapolated in the context of dashboards, it is worth noting that the features and functionalities of the involved technologies significantly differ from dashboards, implying that relying on them could lead to erroneous assumptions and conclusions (Wahdain & Ahmad, 2014). Another issue is that the existing literature is based on different social contexts, not UAE, hence demonstrating the need to conduct a new empirical study that examines the user's intention to use dashboards in the context of UAE. Such a study should focus on the senior-level executives who are the targeted users of decision support systems such as dashboards.

Therefore, this study aimed to bridge the literature gap identified above and establish factors or reasons for the low usage of dashboards among employees in UAE government organisations. The study aimed to specifically address the following research objectives:

- To identify the factors that influence behavioural attitudes towards the intention to use business intelligence dashboards in the UAE.

- To investigate the influence of risk dimensions on behavioural attitudes towards users' intention to use business intelligence dashboards in the UAE.

The study aimed to achieve the above objectives by extending the technology acceptance model (TAM) to include perceived risk as a multidimensional construct. As such, the present study enriches the available literature on technology acceptance by introducing new factors that influence the intention to use dashboards among UAE employees. Besides understanding factors behind the intention to adopt BI dashboards, this study equips dashboard developers and managers of organisations in the UAE intending to implement them with practical knowledge of what influences an individual's adoption and utilisation of such systems. This knowledge will significantly influence the design of dashboard systems and organisations' approach to the implementation of such systems, including the policies and regulations.

2. Literature Review

The essence of adopting and implementing new technologies such as dashboards is to enhance the performance of organisations in crucial areas of operations, among other benefits such as improved efficiency, collaboration, employees productivity, and competitiveness (Perkowitz, 2020; Harris et al., 2021). Despite such benefits, research shows that introducing people and organisations to new technologies is not straightforward since the targeted users can resist them for various reasons (Perkowitz, 2020). The complexity surrounding the adoption and implementation of new technologies has attracted the attention of many scholars who have examined how people respond to and interact with new technologies at individual and organisational levels and the reasons or factors influencing such responses.

While there is a growing body of knowledge in this area, studies show that factors influencing the intention to use and adopt emerging technologies vary from one individual, organisation, or technology to another (Ahmad et al., 2020; Perkowitz, 2020). In this regard, studies have devised different classifications of technology adoption determinants. For instance, a systematic review by Ahmad et al. (2020) that focused on BI systems acceptance studies conducted from 2011 to 2020 categorised technology acceptance determinants into individual and organisational factors. The individual determinants pertain to people's cognitive understanding and interpretations of the technology; they include perceived usefulness, perceived ease of use, personal innovativeness, enjoyment of the new technology, personality traits, beliefs (normative, control, or behavioural), personal capabilities, perceived tangible benefits, awareness, intrinsic motivation, performance perceptions, requisite skills and knowledge, prior experience, risk aversion, gender, voluntariness of use, among others (Badi et al., 2021; Ahmad et al., 2020). Organisational factors, on the other hand, include aspects such as structure, size, culture, autonomy, capacity, type of organisation, policies, approaches, actions, and facilitating conditions (for example, incentives and training) provided by the organisation (Ahmad et al., 2020).

Besides individual and organisational factors, technology acceptance is influenced by social, technological, and environmental determinants (Vahdat et al., 2021; Al-Emran et al., 2018; Ahmad et al., 2020; Badi et al., 2021). The social factors pertain to the degree to which an individual's social group can influence their technology acceptance behaviour (social influence). Vahdat et al. (2021) observed that social influence can influence a person's decision to adopt or use new technology. Similar findings were reported by Al-Emran et al. (2018), who observed that people can adopt technology not due to performance-related benefits but rather due to the perceived social pressure from peers and people in their social networks who have used or perceived such technology as important. Other social factors that can influence an individual's decision to adopt new technologies include potential adopter's social status and quality of relationship with their peers, education level, experience, age, and gender (Vahdat et al., 2021).

Technological determinants pertain to how technology characteristics match the task requirements of the potential adopter (Ahmad et al., 2020). In this regard, technology that fails to match and support user's task requirements is perceived as a threat, while the one that matches task characteristics is perceived as an opportunity. Other technological factors that influence user's intention to adopt emerging technology include performance expectancy, perceived benefits, familiarity with the technology, costs, relative advantage, complexity, and compatibility (Ahmad et al., 2020). As described by Badi et al. (2021), environmental factors pertain to issues such as competition, regulations, industry, market trends, external motivation, and vendor support. They also include government/external support, consumer pressures, and stakeholder support (Badi et al., 2021; Ahmad et al., 2020).

From the above findings on technology acceptance determinants, different theories and models have been developed to predict factors influencing individuals and organisations to accept new technology. Some of the commonly used theories include DeLone and McLean's Information Systems Success Model (ISSM), the unified theory of acceptance and use of technology (UTAUT), the Protection Motivation Theory (PMT), the Theory of Reasoned Action (TRA), Technology Acceptance Model (TAM), and diffusion of innovation (DOI) theory. Table 1 below compares the above models based on various technology use and acceptance determinants.

Table 1**.** Comparison of the six models of technology acceptance

Unified Model's Determinants	**Constructs**	**TAM**	**TAM2**	**TAM3**	**UTAUT**	**UTAUT 2**	**PMT**	**D&M IS Success Model**
Effort expectancy	Perceived ease of use (PEU)	✓	✓	✓	✓	✓		
Performance expectancy	Response efficacy or perceived usefulness (PU)	✓	✓	✓	✓	✓	✓	
Facilitating conditions	Response cost				✓	✓	✓	
	Self-efficacy				✓	✓	✓	
	Service quality							✓
Social influence	Subjective norm		✓	✓	✓	✓		
Threat appraisals	Perceived severity						✓	
	Perceived vulnerability						✓	
Perceived reliability	System output quality or perceived quality (system, information, and service)		✓	✓				✓
Price value						✓		

As demonstrated in Table 1, the different models have similarities and differences in scope and approach. For instance, perceived usefulness (PU) and perceived ease of use (PEU) in TAM (and its variants) are similar to UTAUT's performance expectancy and UTAUT2's effort expectancy (EE)

(Elareshi et al., 2022; Le et al., 2022; Ma et al., 2022). Similarly, UTAUT's PE is similar to PMT's response expectancy (RE), even though they are applied in different contexts. PE refers to the likelihood of an innovation to improve an individual's performance, while RE is about the effectiveness of an innovation in mitigating a perceived threat (Rahi et al., 2021). The two constructs are similar in that they both assess how a given technology (such as a dashboard) can help individuals effectively address a problem or accomplish a task. They, however, differ in that PE focuses on improving job performance while RE deals with threat mitigation. However, since dashboards are visualisation tools rather than security systems, it seems more plausible to use PE in UTAUT or PU in TAM instead of PMT's RE. PMT's constructs focus more on evaluating human cognitive processes while evaluating threats and coping mechanisms; hence they are more appropriate for security-related systems or technologies. The risk components (perceived threats and vulnerability) in PMT are not available in other models (UTAUT, UTAUT2, TAM, TAM2, TAM3, and ISSM).

As seen in Table 1 above, none of the available models exhaustively covers all technology acceptance determinants. Some models (for example, TAM and ISSM) have taken a narrow perspective and are overly simplistic. This implies that they may not sufficiently predict determinants of dashboard adoption in the UAE. The ISSM focuses on the quality dimension (service, system, and information quality), making it less comprehensive, reducing its predictive power in explaining technology acceptance determinants. Though UTAUT (and its subsequent developments) is more comprehensive (as it includes more variables than the rest), some of its variables may not be applicable in predicting the factors influencing users' intention to adopt dashboards. PMT, on the other hand, has limited applicability in predicting determinants of technology acceptance and use as it focuses more on adopting protective behaviours or security systems (Grano et al., 2022; Afridi et al., 2021). Therefore, after a critical and comprehensive literature review on the ofove models, TAM emerged as the most suitable for the present study.

TAM was first proposed by Fred Davis (1986) as a modification of the theory of reasoned action (TRA) proposed by Fishbein and Azien (1975). TAM was developed to predict the adoption and acceptance of information systems or technology in various populations (Wallace & Sheetz, 2014; Lim, 2018). TAM expanded TRA's attitude construct to include perceived usefulness (PU) and perceived ease of use (PEU), which significantly influenced users' intention to use email systems and editing technologies. In this study, Davis (1986) defined perceived usefulness as the extent to which the user of a new technology believes that adopting such technology will improve their job performance and their lives and PEU as the degree to which the user believes that using the new technology will be seamless or effortless. The two factors are influenced by other determinants (external variables) (see Figure 1 below).

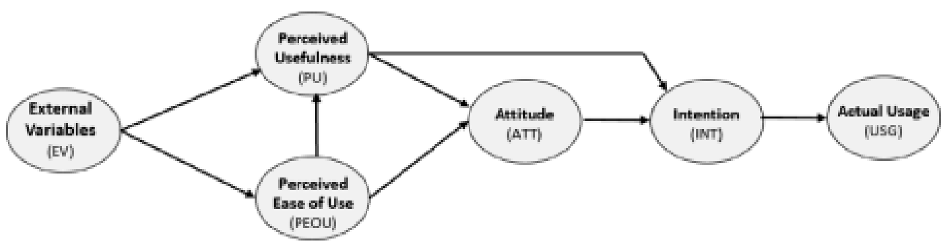


Fig. 1: Original TAM by Davis (1989).

TAM is one of the widely used theoretical models in studies explaining the intention to adopt and use information technology and systems. The model has been used to explain users' behavioural intention to use or adopt Internet and electronic banking systems (Kassim & Ramayah, 2015; Hossain et al., 2020; Albort-Morant et al., 2022), electronic government services (Mensah, 2019), electronic and mobile health records technology (Shemesh & Barnoy, 2020), and digital/e-commerce (Mansur et al., 2019). TAM has also been used in electronic and mobile payment system studies (Türker et al., 2022; Dastan & Gurler, 2016; Kelana & Hilamawan, 2017). According to Ahmad (2018), TAM has an accuracy rate of 40% in predicting users' intention to adopt or accept new technology.

2.1. Conceptual framework

As mentioned earlier, this study adopted the TAM framework after a comprehensive review of the current technology acceptance models, theories, empirical literature on the topic, and consideration of the research problem. The framework has been widely utilised in various studies empirically examining factors influencing users' intention to accept or adopt information technology and systems, making it a suitable theoretical framework for this study. However, it was also observed from the existing literature that perceived risks also significantly influence the intention to use new technologies (Al-Rawad et al., 2015; Choe et al., 2021; Hwang et al., 2021). Therefore, the TAM was extended by including perceived risk as a multidimensional construct comprising three dimensions: functional risk, time loss risk, and information (see Figure 2). Though some previous TAM-based studies have included risk as a variable (for example, Mutahar et al., 2018; Kamal et al., 2020; Wang et al., 2020), none included it as a multidimensional construct comprising of perceived functional risk, perceived time loss risk, and perceived informational risk, which crucially predicted Emiratis' decision to use or accept dashboards. Adding perceived risk to this model enhanced its predictive power in explaining factors influencing the adoption of dashboards in the UAE.

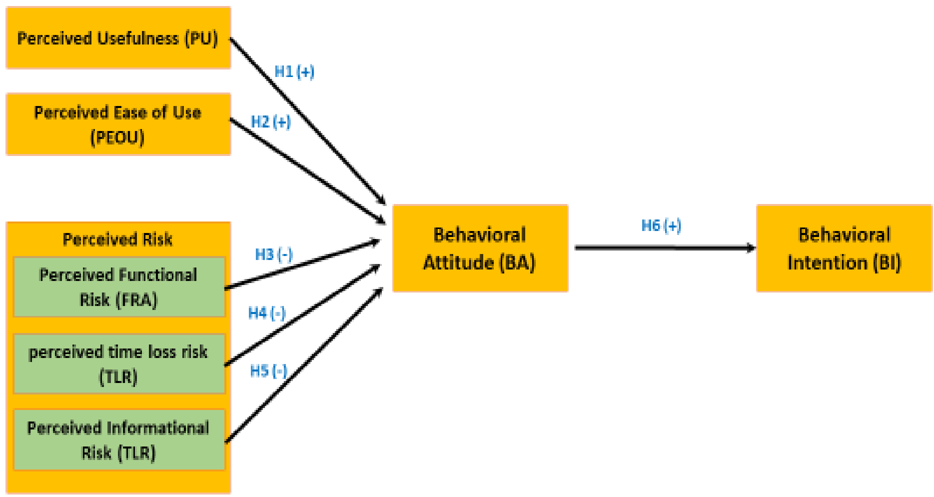


Fig.2: Research Framework.

Based on the research framework developed above, the present study sought to test six hypotheses that show relationships between 7 variables. The independent variables include perceived usefulness (PU), Perceived Ease of Use (PEOU), perceived functional risk (FRA), perceived time loss risk (PTLR), and perceived informational risk (PIR), which are mediated by the Behavioural Attitude (BA), which ultimately determine the behavioural intentions to use and adopt dashboards. The following section critically reviews the association among these variables based on the existing literature.

2.2. Hypothesis development

Perceived usefulness (PU)

PU, a construct derived from Davis's TAM model, refers to a user's subjective assessment of an emerging technology's ability to enhance their lives and job performance (Davis, 1989). PU pertains to the productivity and effectiveness of the new system in carrying out tasks. In this regard, the user evaluates the new system's approach to the task with the previous or existing ones to establish which provides more advantages (Davis, 1989; Kassim & Ramayah, 2015). For example, if a banking institution is planning to introduce an Internet banking system to replace the conventional face-to-face transactions where customers are forced to queue in the banking hall. In that case, the customers compare the advantages of both banking systems and select the one with more advantages. In such a context, the customer's likelihood to accept and use the Internet banking system is higher because they perceive them to offer more advantages than the traditional approach in terms of convenience and easing their job (Kassim & Ramayah, 2015). Studies have found a strong correlation between perceived usefulness and users' intention to adopt or use a new system (Sagnier et al., 2020; Tahar et al., 2020; Tubaishat, 2018; Kalogiannakis & Papadakis, 2019). These studies have established that PU positively impacts users' attitudes towards acceptance or intention to use technology. In line with these findings, this study hypothesised that:

H1: Perceived usefulness positively impacts behavioural attitude towards the intention to use dashboards.

Perceived ease of use (PEU)

PEU, also derived from TAM, pertains to the relative easiness or effortlessness the user expects in a new system (Davis, 1989). A new system user expects such a system to be relatively easy to understand and use, failure to which they will be reluctant to use or have a negative attitude towards it. In support of this, Kalogiannakis and Papadakis (2019) established that users are likely to have a positive attitude towards a new technology or system and subsequently demonstrate the intention to adopt or use it if they discover that such a system is not complicated. Similar observations were made by Akhter et al. (2022), who found PEU to significantly determine users' intention to adopt Internet banking services in Bangladesh, as well as Hokroh et al. (2020), who observed that users' intention to use and adopt health wearables in Saudi Arabia was primarily influenced by their PEU. The above studies show that the likelihood of accepting technology is significantly high when the users perceive such technology as easy to use, hence leading to the formulation of the following hypothesis:

H2: Perceived ease of use positively impacts behavioural attitude towards intention to use dashboards.

Perceived functional risk (PFR)

Functional risk refers to the potentiality of a system failure or breakdown when carrying out a given task (Gunawan et al., 2022). Malfunctioning or breaking down of a system can significantly affect a user's performance and lead to other types of risks such as financial, information, and time losses (Tudu & Prakash, 2020). Studies show that functional risks significantly influence users' intention to use or adopt a system (Zhou et al., 2021; Gunawan et al., 2022; Tudu & Prakash, 2020). For instance, Gunawan et al. (2022) established that perceived functional risks negatively affected Indonesians' attitudes toward and intention to purchase electric cars. These findings are echoed in a study by Tudu and Prakash (2020), which established that consumers' fear of the potentiality of breaking down of luxury items purchased online negatively affected their attitudes and intention to purchase such products online. In this regard, it was hypothesised that:

H3: Perceived functional risk (PFR) negatively influences users' attitudes towards using BI dashboards.

Perceived Time loss risk (PTLR)

Technology users are time-conscious and hence more likely to consider potential time risks associated with implementing, learning, and troubleshooting a new technology or system (Ab Hamid & Cheng, 2020; Nguyen et al., 2022). Therefore, the likelihood of time-conscious consumers rejecting a system with high maintenance and time loss risks is high. This implies that dashboards that take more time to implement, learn, and troubleshoot are unlikely to attract the attention of time-conscious users. In support of this, Kassim and Ramayah (2015b) observed that time loss risk was among the factors that negatively affected users' intention to use the Internet banking system among Malaysians. Similar findings were reported by Amirtha et al. (2021), who found that time loss risk was a significant hindrance to adopting electronic shopping behaviour in Indian women. Though some studies have not found any significant relationship between time loss risk and intention to use innovation (for example, Tran, 2020; Al-Rawad et al., 2015), it is anticipated that business intelligence dashboards that require much time to implement, learn or troubleshoot are less likely to earn users' interests. Hence, it is hypothesised that:

H4: Perceived time loss risk (PTLR) negatively influences users' attitudes towards using BI dashboards.

Perceived informational risk (PIR)

Information risk pertains to the uncertainties users have regarding the system's ability to control and manage data and prevent it from unauthorised access and use (Li et al., 2020). An example of information risk is when unauthorised people illegally gain access to a system and use the legitimate user's identity to advance fraudulent activities. Information risks increase the likelihood of losing control over personal data. Information security is a crucial factor in selecting online technologies or information systems (Chen et al., 2020; Li et al., 2020). For instance, Li et al. (2020) reported that information security and privacy risks are crucial determinants of a user's decision to use online inquiry services provided by Chinese internet hospitals. Similar findings were reported by Ma et al. (2018) and Chen et al. (2020), who observed that a lack of control of personal data in online-based information systems could lead to a lack of trust and, consequently, the likelihood of users avoiding such systems because of fear of information loss.

H5: Perceived time loss risk (PTLR) negatively influences users' attitudes towards using BI dashboards.

Behavioural attitude (BA)

Behavioural attitude is the target user's desire to accept, adopt, and use new systems or technology (Rabaa'i, 2016; Mailizar et al., 2021). It refers to the user's view or feelings towards a new technology or system, which determines their behavioural intention to adopt or use a new system (Davis, 1989). This implies that if target users feel discomfort or are displeased by the system, they are more likely to develop a negative attitude towards it and consequently discontinue it or look for an alternative. Studies investigating the relationship between attitude and the intention to use or adopt information systems or technology have established that attitude is a significant predictor of the user's intention to use or embrace new technologies (Mailizar et al., 2021; Rabaa'i, 2016; Yu et al., 2021; Hsieh, 2015). For instance, Mailizar et al. (2021) observed that university students' positive attitudes towards e-learning significantly influenced their intention to use this learning mode during the COVID-19 pandemic. In this regard, it was hypothesised that:

H6: Behavioural attitude positively impacts users' intention to use BI dashboards.

3. Research Methods

This study utilised quantitative research methodology and applied the correlational research design, which are both aligned with the positivist research philosophy (Siedlecki, 2020; Tshabangu et al., 2021). The choice of research methodology, research philosophy, and research design was informed by the nature of the study, which aimed to objectively and empirically examine the factors that influence UAE government employees' decision to adopt BI dashboards. The correlational research strategy helped the researcher to measure and test the relationship between various technology acceptance factors proposed in the conceptual framework proposed above to produce generalisable research results that would help understand factors influencing users' intention to use dashboards (Siedlecki, 2020). Therefore, the correlational research design was suitable for the present study because it allowed the researcher to test the relationship between the hypothesised variables.

To enhance the generalisability of the findings, a large sample size of 350 respondents (working at executive levels) drawn from different government organisations in Dubai and Abu Dhabi was recruited. In this regard, a purposive sampling technique was utilised whereby the researcher identified high-rank employees (C-Level employees) from government institutions intending to adopt and implement BI dashboards. The researcher concentrated on the C-level executives because they are the targeted users of dashboards (for decision-making). Also, the study focused on organisations that had not implemented dashboards but were planning to implement them because it aimed to measure users' intention to use them, not their intention to continue using them.

The recruitment of the participants was preceded by the researcher's visit to various government organisations in Dubai and Abu Dhabi to identify those that had not implemented BI dashboards, despite their executive-level employees being exposed to them. The researcher's focus on the UAE (especially Dubai and Abu Dhabi) was based on the realisation that many business organisations in these emirates were quick to adopt new technologies, though the adoption of BI dashboards was relatively lower than other technologies. Also, the population in the two emirates is quite inclusive as it comprises of people from different nationalities and races. Besides, numerous cases of employees showing little interest in dashboards in the UAE have been reported (Forker, 2019; U.ae., 2021). In addition, UAE government organisations are easily accessible and have fewer approval bureaucracies, which made it easy for the researcher to access and identify the study population. Therefore, the above characteristics made UAE's organisations an ideal case study for the present study.

For an organisation to be considered, it also had to have at least 20 employees and operated for more than five years. The organisation was also supposed to be easily accessible with a few bureaucracies. After identifying organisations that met this criteria, the researcher collected contact details of employees at the executive level. However, before taking these details, they were asked whether they were knowledgeable about or had been previously exposed to BI dashboards; those not exposed to them were excluded from the study. These decisions aligned with the purposive sampling technique, which focuses on persons with specific characteristics (experience and knowledge) relevant to the research (Hennink et al., 2020). Before getting their contacts, the researcher explained the research topic and informed them that further information about the project, including data collection, would be shared later.

The participants' responses were collected using web-based survey questionnaires, which are less time-consuming, cheaper, and able to provide respondents with the space to express their true feelings and responses without fear of being identified, compared to conventional paper-based questionnaires (Kumar, 2019). The questionnaires were sent to respondents via links through emails or online platforms. They contained closed-ended questions, which allowed the respondents to select options that reflected their opinions. The questions were formulated based on the six hypotheses formulated above. Each statement/question examined how the identified variable influenced the intention to adopt/use dashboards based on the measurement items from the reviewed scholarly literature. A synopsis of how each variable was measured and the source from which it was derived is shown in Table 2 below. Each item's influence was measured using a 5- or 7-point Likert scale, depending on the construct.

Table 2: Survey questionnaire development and measurement

Construct	Original Items	Scale Used	Measurement Items Adapted	Source
Perceived Usefulness (PU)	• Using DSS gives greater control over our work. • Using DSS improves our work performance. • Using DSS enables us to accomplish tasks more quickly. • Using DSS supports critical aspects of our work. • Using DSS improves our work efficiency. • Using DSS improves the quality of our work. • Using DSS makes it more convenient to accomplish our strategies and goals. • Using DSS demonstrates our inventiveness to our business partners. • Overall, I find DSS useful for our work.	5 Point Likert Scale 1. Strongly disagree 2. Disagree 3. Neither agree nor disagree 4. Agree 5. Strongly agree	**PU01:** Using BI dashboard will give greater control over our work. **PU02:** Using BI dashboard will improve our work performance. **PU03:** Using BI dashboard will enable us to accomplish tasks more quickly. **PU04:** Using BI dashboard will improve our work efficiency. **PU05:** Using BI dashboard will make it more convenient to accomplish our strategies and goals. **PU06:** Overall, I will find BI dashboard useful for our work.	Dulcic, Pavlic, and Silic (2012)
Perceived Ease of Use (PEU)	• Using DSS is simple. • Using DSS is easy to understand. • Using DSS is intuitive. • Using DSS is flexible. • Using DSS does not require a lot of effort. • Using DSS does not require studying the manuals. • Using DSS is easy to predict. • Overall, I find DSS easy to use.	5 Point Likert Scale 1. Strongly disagree 2. Disagree 3. Neither agree nor disagree 4. Agree 5. Strongly agree	**PEU01:** Using BI dashboard will be simple. **PEU02:** Using BI dashboard will be easy to understand. **PEU03:** Using BI dashboard will be intuitive. **PEU04:** Using BI dashboard will be flexible. **PEU05:** Using BI dashboard will not require a lot of effort.	Dulcic, Pavlic, and Silic (2012)
Functional risk (PFR)	• The security systems built into the Internet Banking are not strong enough to protect my checking account Internet banking servers may not perform well and process payments incorrectly. • Internet banking servers may not perform well because of slow download speeds, the servers' being down or because the web site is undergoing maintenance. • Considering the expected level of service performance of the Internet Banking for you to sign up for and use it would be.	7 Point Likert Scale ranging from ―strongly disagree‖ (1) to ―strongly agree‖ (7)	**PFR01:** A BI dashboard may not perform well hence may hinder proper decision making. **PFR02:** A BI dashboard may not perform well because of slow download speeds, the servers' being down or because the system is undergoing maintenance. **PFR03:** A BI dashboard may not perform well hence may not process decisions correctly.	Kassim & Ramayah (2015b)
Perceived time loss risk (PTLR)	• If you had begun to use an Internet Banking, what are the chances that you will lose time due to having to switch to a	7 Point Likert Scale and a Semantic Differential	**PTLR01:** Switching to BI dashboards will make me lose a lot of time. **PTLR02:** Using a BI	Kassim & Ramayah (2015a)

Construct	Original Items	Scale Used	Measurement Items Adapted	Source
	different payment method? • My signing up for and using an Internet Banking would lead to a loss of convenience on me because I would have to waste a lot of time fixing payment errors. • Considering the investment of my time involved to switch to (and set up) Internet Banking makes them risky. • The possible time loss from having to set up and learn how to use Internet banking bill payment makes them risky.	Scale Likert scale used- ―strongly disagree‖ (1) to ―strongly agree‖ (7) Semantic Differential Scale- Improbable to probable	dashboard would lead to the loss of convenience on me because I would have to waste a lot of time fixing errors. **PTLR03:** The investment of my time involved to switch to (and set up) a BI dashboard makes it risky. **PTLR04:** The possible time loss from having to set-up and learn how to use a BI dashboard makes it risky.	
Perceived information risk (PIR)	• I believe my Internet banking transaction information will only be used for the purpose of the original transaction. • While using Internet banking, I believe that I control the use of my information. • I believe my Internet banking transaction information will not be lost during an online session. • I believe my Internet banking transaction information will only reach the target bank account	7 Point Likert Scale ―strongly disagree‖ (1) to ―strongly agree‖ (7)	**PIR01:** I believe the BI dashboard information will only be used for the purpose of the original purpose (facilitating decision making). **PIR02:** While using BI dashboard, I believe that I control the use of my information. **PIR03:** I believe the BI dashboard information will not be lost during an online session. **PIR04:** I believe the BI dashboard information will only reach the target users.	Kassim & Ramayah (2015a)
Behavioural Attitude (BA)	• I think that using online banking is a good idea. • I think that using online banking for financial transactions would be a wise idea. • I think that using online banking is pleasant • In my opinion, it is desirable to use online banking	7 Point Likert Scale ―strongly disagree‖ (1) to ―strongly agree‖ (7)	**BA01:** Using a BI dashboard is a good idea. **BA02:** In my opinion, it is desirable to use a BI dashboard. **BA03:** I think that using dashboard is pleasant. **BA04:** I like the idea of using a dashboard. **BA05:** In my view, using BI dashboard is a wise idea.	Rabaa'i (2016)

The quantitative data was analysed using the Statistical Package for Social Sciences (SPSS) 26.0 and partial least squares structural equation modelling (PLS-SEM) data analysis software. The analysis was done in two phases. The first phase involved assessing the measurement/outer model, which involved testing aspects such as the validity and reliability of the constructs (internal consistency reliability, indicator reliability, convergent validity, and discriminant validity. The second phase involved assessing the structural/inner model. It involved assessing the collinearity issue, path coefficients, and effect size.

The reliability and validity of the data collection and measurement instrument were ensured in various ways. First, the survey questionnaire development involved several pre-tests with different experts. The survey questionnaires were sent to the experts (executive levels employees working in organisations that have embraced dashboards or ought to be using dashboards), who reviewed them to ascertain their validity. The testers completed the survey online (since the actual project would use the same approach) and provided feedback on areas that needed improvements, as Ikart (2019) recommended. Second, studies show that common method variance (CMV), biases associated with the survey data collection method, can affect the significance, direction, and magnitude of coefficients, hence deflating or inflating the relationship between variables, consequently affecting the validity and reliability of the measurement instruments (Bozionelos & Simmering, 2022). To minimise CMV, the researcher kept the questions simple, specific, and concise, avoided vague or ambiguous concepts, and defined unfamiliar terms to enhance comprehension, a major problem when responding to survey questions (Tehseen et al., 2017). Also, based on the recommendations of Lin et al. (2015), CMV was controlled by introducing marker variables at the end of survey questionnaires as marker indicators. The three items included are: (1) “My views are very consistent over time;” (2) “I don’t change my mind easily;”, and (3) “Once I’ve concluded, I’m not likely to change my mind” (pp. 221). These marker indicators were used to create a method factor, which is an exogenous variable that was used to predict each endogenous variable in the research model. The method factor model was compared with the baseline model to establish whether significant path models in the latter remained significant in the former (Lin et al., 2015). Third, the measurement and structural model were assessed using the SPSS and PLS-SEM software (see the following section).

Various ethical guidelines were observed during data collection. To begin with, the researcher sought ethical approval of the research from the university before commencing recruitment and data collection processes. After recruiting the research participants, the researcher emailed them an invitation to participate in the study. The letter/email included information on the research topic, purpose, significance of the research, data collection instrument and mode of administration and estimated duration. Before sending the survey questionnaires, the researcher emailed the informed consent form, where the participants were required to read and confirm their agreement with the statements by ticking the checkbox labelled “I accept”, which automatically submitted the form to the researcher. The researcher emailed survey questionnaires to only those who submitted back their informed consent forms. In the informed consent form, the respondents were informed that their responses and identity would be treated with utmost confidentiality. They were reminded that their participation was voluntary and had the right to withdraw from the study at any stage without any fear of victimisation. Furthermore, their identities were anonymised by assigning unique identifiers to each survey questionnaire.

4. Results

4.1. Respondents’ profile

Studies show that age and gender can significantly moderate the user’s perception and use of information technologies and systems in the workplace, whereby younger workers were found to be more open to adopting and experimenting with new technological innovations than older adults (Moris et al., 2005). In this regard, it was important to capture the two demographic characteristics of the respondents to establish whether there was any association between gender and age and intention to use dashboards. Another demographic characteristic captured was the educational level of the participants. Studies show that people with higher levels of education are more likely to adopt new technologies (Muriithi et al., 2016; Riddell &Song, 2017).

Table 3: Respondents’ Demographic Profile

Demographic characteristic	Category	Frequency	Valid Percentage %
Voluntariness of use	Yes	180	51
	No	170	49
Gender	Female	239	68.4

	Male	111	31.6
Age (Years)	21 - 30 year	132	37.6
	31- 40 years	111	31.6
	41 - 50 years	47	13.5
	51 - 60 year	32	9.0
	Under 21 years old	29	8.3
Educational Levels	Bachelor's degree	205	58.6
	Doctor's degree	18	5.3
	High school/ vocational	37	10.5
	Master's degree	89	25.6
Occupation	Government employee	350	100
	Company employee	0	
	Self-employment	0	
	Other (Please specify)	0	

As demonstrated in Table 3 above, most respondents were females (68.4%). In terms of age, the majority of the respondents were young executives (below 40 years) (69.2%). Regarding educational levels, most respondents had a bachelor's degree (58.6%), while a quarter had a master's degree (25.6%). Notably, about 10% of the respondents had only a high school certificate but served at executive-level positions in their organisations.

4.2. Assessment of the measurement model

The first assessment of the measurement model involved internal consistency, reliability, and convergent validity. The internal consistency was determined using composite reliability (CR), while AVE was used to determine convergent validity. The recommended minimum threshold values for convergent validity and internal consistency reliability are 0.50 and 0.70, respectively (Hair et al., 2017; Fornell & Larcker, 1981). Results presented in the table below show that the minimum CR value was 0.877 while the minimum AVE value was 0.795. This confirms that all constructs utilised in the present study met the CR and AVE values.

Table 4: Internal consistency reliability and convergent validity for all constructs

Variable	Item	Loading	CR	AVE
Behavioural Attitude	BA01	0.912	0.95	0.834
	BA02	0.903		
	BA03	0.925		
	BA04	0.944		
	BA05	0.881		
Behavioural Intention	BI01	0.900	0.877	0.803
	BI02	0.910		
	BI03	0.878		
Perceived Ease of Use	PEU01	0.915	0.936	0.798
	PEU02	0.898		
	PEU03	0.940		
	PEU04	0.903		
	PEU05	0.805		
Perceived Financial Risk	PFR01	0.938	0.925	0.869
	PFR02	0.921		
	PFR03	0.938		
Perceived Informational Risk	PIR01	0.882	0.914	0.795

	PIR02	0.898		
	PIR03	0.902		
	PIR04	0.884		
Perceived Time Loss Risk	PTLR01	0.903	0.95	0.871
	PTLR02	0.955		
	PTLR03	0.939		
	PTLR04	0.935		
Perceived Usefulness	PU01	0.916	0.957	0.824
	PU02	0.922		
	PU03	0.899		
	PU04	0.905		
	PU05	0.900		
	PU06	0.903		

The second assessment of the measurement model involved determining the discriminant validity. In this regard, the Fornell and Larcker (1981) criterion and the Heterotrait-Monotrait (HTMT) ratio methods were used. Through the Fornell-Larcker criterion, the AVE values of each construct were compared with other constructs' correlation values. According to Hair et al. (2014), discriminant validity is considered positive if the square root of the AVE value of each construct is higher than the correlation value of AVE for other constructs. Similar observations were made in the present study (as demonstrated in the Table below), which implies that discriminant validity was achieved.

Table 5: Discriminant validity based on the Fornell-Larcker criterion

	BA	BI	PEOU	PFR	PIR	PTLS	PU
BA	0.913						
BI	0.785	0.896					
PEOU	0.826	0.769	0.893				
PFR	0.492	0.438	0.531	0.932			
PIR	0.815	0.729	0.761	0.690	0.892		
PTLS	0.340	0.302	0.365	0.720	0.557	0.933	
PU	0.822	0.771	0.829	0.449	0.652	0.286	0.908

Note : BA = Behavioural Attitude, BI = Behavioural Intention, PEOU = Perceived Ease of Use, PFR = Perceived Financial Risk, PIR = Perceived Informational Risk, PTLR = Perceived Time Loss Risk, PU = Perceived Usefulness

The second approach, the HTMT ratio, measures similarities between latent variables (Henseler et al., 2015). HTMT shows higher accuracy and preciseness in discriminant validity estimation (Hair et al., 2022). This method achieves discriminant validity when the HTMT ratios are below 0.90 (Hair et al., 2022). As demonstrated in the table below, all HTMT ratios were below this threshold value (the highest was 0.857), which implies that discriminant validity was achieved.

Table 6: Discriminant validity (HTMT ratios)

	BA	BI	PEOU	PFR	PIR	PTLS	PU
BA							
BI	0.857						

PEOU	0.871	0.847					
PFR	0.523	0.484	0.571				
PIR	0.872	0.814	0.822	0.753			
PTLS	0.357	0.331	0.389	0.767	0.600		
PU	0.861	0.840	0.870	0.475	0.696	0.299	

Note: BA = Behavioural Attitude, BI = Behavioural Intention, PEOU = Perceived Ease of Use, PFR = Perceived Financial Risk, PIR = Perceived Informational Risk, PTLR = Perceived Time Loss Risk, PU = Perceived Usefulness

4.3. Assessment of the structural model

The structural model tested the hypothesised relationships between the constructs used in the theoretical framework of this study. In this regard, a bootstrapping procedure involving 5000 re-samples was used to determine the path coefficients based on the suggestions of Hair et al. (2022). The results are illustrated in Figure 3 and Table 7 below.

Table 7: Path coefficients

Hypothesis	Relationships	**std.Beta**	**std.Dev**	**T-value**	**P-value**	**BCI LL**	**BCI UL**	**Decision**
H1	PU --> BA	0.403	0.044	9.120	*p*<.001	0.702	0.845	Accepted
H2	PEOU --> BA	0.163	0.054	3.043	0.002	0.056	0.264	Accepted
H3	PFR --> BA	-0.102	0.039	2.541	0.011	-0.180	-0.026	Accepted
H4	PIR --> BA	0.532	0.050	10.627	*p*<.001	0.428	0.623	Rejected
H5	PTLR --> BA	-0.058	0.027	2.089	0.037	-0.110	-0.005	Accepted
H6	BA --> BI	0.784	0.037	21.265	*p*<.001	0.316	0.491	Accepted

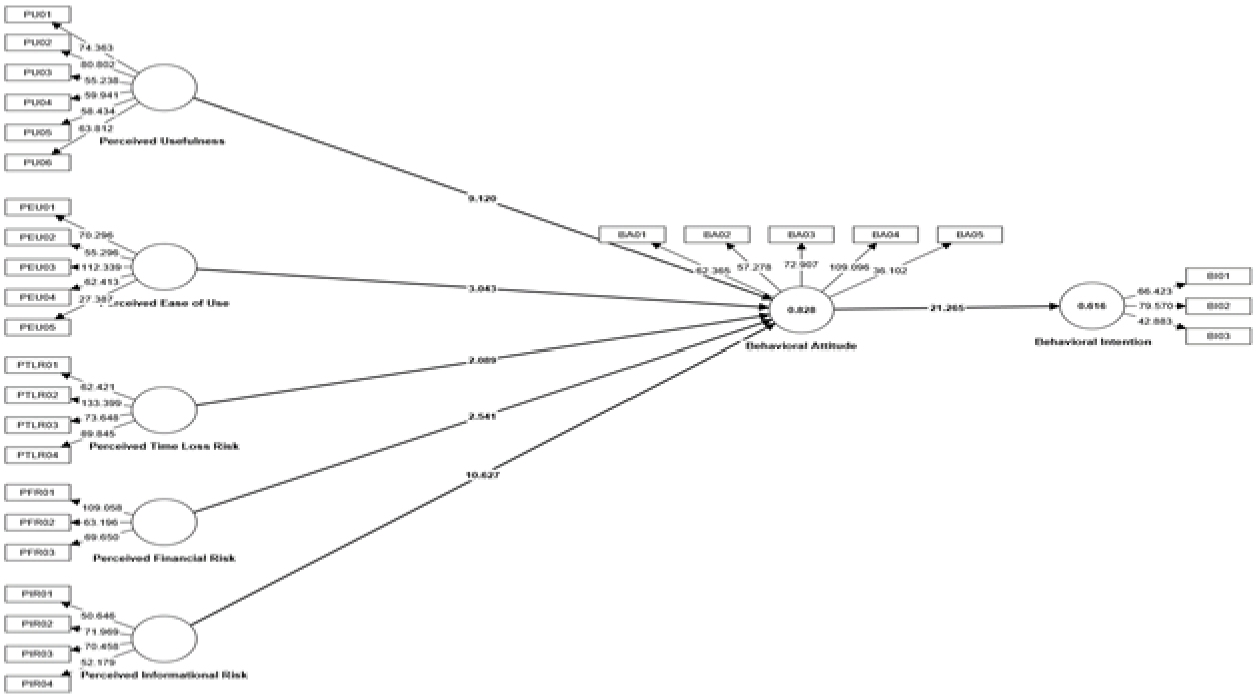
Note: BA = Behavioural Attitude, BI = Behavioural Intention, PEOU = Perceived Ease of Use, PFR = Perceived Financial Risk, PIR = Perceived Informational Risk, PTLR = Perceived Time Loss Risk, PU = Perceived Usefulness

Significance testing results show that there was a significant relationship between perceived usefulness (PU) and behavioural attitude (BA) ($\beta = 0.403$, $t = 9.120$, $p < 0.001$) as well as between perceived ease of use (PEOU) and behavioural attitude (BA) ($\beta = 0.163$, $t= 3.043$, $p< 0.01$). Thus, the hypotheses, H1 and H2, which were based on the TAM, were accepted.

On the perceived risks, the results show that the three perceived risk dimensions have a significant relationship with behavioural attitude (BA). In particular, the study shows that perceived functional risks (PFR) and perceived time loss risks (PTLR) have a significant negative relationship on behavioural attitude ($\beta = -0.102$, $t = 2.541$, $p < 0.05$ and ($\beta = -0.058$, $t = 2.089$, $p<0.05$, respectively), leading to the acceptance of H3 and H5. However, the findings show that perceived information risk (PIR) positively relates to behavioural attitude ($\beta = 0.532$, $t = 10.627$, $p < 0.001$), leading to the rejection of H4, which indicated that the relationship between the two variables is negative. Lastly, the behavioural attitude was found to have a strong positive relationship with the behavioural intention to adopt BI dashboards (β = 0.784, t = 21.265, p < 0.001), hence confirming H6.

Fig.3: PLS structure model

5. Results



This study examined factors influencing the intention to adopt and use dashboards among C-level employees in UAE government organisations. The study particularly aimed to achieve these two objectives: (1) To identify the factors that influence behavioural attitudes towards the intention to use business intelligence dashboards in the UAE, and (2) To investigate the influence of risk dimensions on behavioural attitudes towards users' intention to use business intelligence dashboards in the UAE. These objectives were achieved by extending Davis (1986)'s TAM model to include perceived risk as a multidimensional construct comprising perceived functional risk, perceived informational risk, and perceived time loss risk.

On factors influencing users' behavioural attitudes towards the intention to use BI dashboards, five variables/factors, namely perceived ease of use (PEOU), perceived usefulness (PU), perceived financial risk (PFR), perceived informational risk (PIR), and perceived time loss risk (PTLR), were identified and their relationship on behavioural attitude (BA) tested. As reported above, PU and PEOU had a positive and significant impact on behavioural attitude, implying that the executives were more likely to have positive attitudes towards dashboards and even consider adopting them if they perceived them to be useful or easier to implement, learn, and use in their decision-making roles. Similar findings were made by Pertami and Sukaatmadja (2021) and Saparudin et al. (2020), which found PEU and PU to positively and significantly influence individual's attitudes towards using TikTok application and mobile banking, respectively.

Regarding the multidimensional perceived risks, the study found that PTLR and PFR negatively influenced the users' BA towards the implementation of BI dashboards. These findings echo those made in studies such as Leowarin and Thanasuta (2021) and Liou et al. (2015) which showed that functional risks negatively affect targeted users' intention to adopt or use new technology. However, some studies (for example, Kartono &Tjahjadi, 2021; Kim et al., 2021) have shown that, though PFR negatively affects users' attitudes, the impact is insignificant. This study's findings on the relationship between

TMLR are also consistent with Featherman et al.'s (2021) and Hwang et al.'s (2021), which demonstrated that time loss risks have a significant and negative impact on user's intention to use new technologies or information systems. While this study initially hypothesised that perceived information risks negatively affect users' attitudes towards the adoption or use of dashboards, the results were contrary, showing a positive relationship, leading to the rejection of this hypothesis. This finding is also contradictory to what has been reported in the previous studies (for example, Chuah et al., 2022; Choe et al., 2021; Klobas et al., 2019; Yi et al., 2020), which showed that informational risks negatively affect user's behavioural attitudes, and hence their intention to use or adopt emerging technologies. Informational risk is expected to be a significant factor in information security-related systems or applications than visualisation technologies such as dashboards. This could probably explain why this construct did not have a significant negative impact on users' BA towards the intention to use dashboards. Nonetheless, such contradictory findings necessitate further investigation into how functional and informational risks influence the intention to use emerging technologies such as dashboards.

The above findings in perceived risks also address the second research objective, which sought to investigate the influence of risk dimensions on the BA towards the intention to use dashboards. As reported above, the study found that PTLR and PFR had a significant negative impact on the behavioural attitude, implying that a target user's attitude towards BI dashboards can be negatively affected if they feel or perceive that such a system poses some technical/functional risks or consumes more time in training, implementing or using it (high time loss risks). However, informational risks were unexpectedly found to correlate positively with behavioural attitude, contrary to the hypothesis formulated and the existing literature. This calls for further investigation to understand the relationship between informational risks and behavioural attitudes towards the intention to adopt dashboards.

This study makes significant theoretical and practical contributions. Theoretically, the study enriches the current literature on users' intention to adopt dashboards. As mentioned in the introduction, this area has received little scholarly attention, with much of the information being on tactical and operational aspects of dashboards and mostly on non-scholarly sources. This study, therefore, enhances the already scanty body of knowledge on factors motivating users to use dashboards. Besides, the study contributes to the improvement of the TAM framework, which is criticised for its narrow perspective on technology acceptance, as it assumes that behavioural attitudes towards new technology are influenced by PEU and PU (Ajibade, 2018). Therefore, including perceived risks as a multidimensional factor improves this model's exploratory and predictive power.

From a practical perspective, this study's findings provide various paths for action to improve the use and adoption of dashboards in the UAE, which is relatively lower compared to other technologies. Having established that PU and PEU significantly influence behavioural attitudes towards intention to use and adopt BI dashboards, this study enlightens organisations to ensure that they impart their employees with the relevant skills and knowledge and create awareness on BI dashboards to positively influence their perceptions of the usefulness and ease of use of dashboards and consequently develop positive attitudes towards them. Therefore, these findings suggest that the UAE government should focus on changing employees' attitudes towards BI dashboards by implementing awareness and training programs that demonstrate the usefulness of the BI dashboards, equip target users with knowledge and skills on how to implement and use these systems as well as dispel fears on functionality and time loss risks, which have been found to affect their intention to adopt or use dashboards negatively. Also, these findings are crucial to BI dashboard developers as they demonstrate key areas they need to consider when designing them to enhance the confidence of new users and encourage more individuals and organisations to implement BI dashboards.

6. Conclusion

This study has shown that, among the factors investigated, behavioural attitude and perceived usefulness have the highest impact on the intention to use dashboards. This implies that executives' decision to use or adopt BI dashboards is significantly informed by their evaluation of their (dashboards) usefulness in their decision-making roles. The findings have also shown that time loss and functionality risks partly influence such decisions. Therefore, the study contributes to the scanty body of literature on the adoption and use of dashboards by executives in the UAE and enriches the TAM's theoretical framework by including risk as a multidimensional construct, hence improving its predictive and exploratory power. The study enlightens organisations and dashboard developers on what issues or factors to consider to enhance the adoption and use of dashboards in UAE organisations. The study suggests that creating awareness and training employees on dashboards equips them with knowledge and skills that positively influence their attitudes towards the intention to use dashboards in decision-making.

However, despite making the above contributions, this study has some limitations that can be used as a foundation for future research. To begin with, the study utilised a quantitative research design, allowing for testing hypothesised relationships between variables derived from the existing literature and theoretical models. While this design allowed for the quantification of the findings, it does not allow for a broader and in-depth coverage of the research topic. Therefore, future research should consider a mixed-method approach that allows the researcher to use both qualitative and quantitative approaches, hence exploring the research problem in depth and breadth. Secondly, the study's scope was limited to the UAE setting, particularly Dubai and Abu Dhabi Emirates. While focusing on these two emirates allowed the researcher to analyse collected data comprehensively, it reduced the generalisability of the findings because the results reflect only two emirates. In this regard, future studies can consider covering a broader scope, for example, including other emirates or other countries in the Middle East or even include both private and public organisations to enhance the generalisability of the study's findings.

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