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Examining the Psychological Factors Influencing Intention to Use Business Intelligence Dashboards in the UAE

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Abstract: In spite of the manifold benefits associated with dashboards, their widespread adoption and individual-level usage in the United Arab Emirates (UAE) have remained limited. To address this gap, the present study employed quantitative research methodologies, specifically utilizing purposive sampling techniques and a survey instrument for data collection. The analysis employed the SmartPLS technique, which unveiled several factors that influence the intention to use dashboards, including perceived ease of use (PEOU), perceived usefulness (PU), perceived relative advantage (PRA), and perceived quality across multiple dimensions (informational, service, and system). Among these factors, PU exerted the most substantial impact on the intention to use dashboards, followed by PRA, PEOU, perceived service quality, and perceived information quality. Although perceived system quality demonstrated a positive association with the behavioral intention to use dashboards, its effect did not reach statistical significance. The findings of this study offer valuable insights for dashboard developers, furnishing evidence-based guidance on how to design dashboards that augment user acceptability and usage. By empirically testing a research framework based on the Technology Acceptance Model (TAM) and extending it to encompass quality as a multidimensional construct, this study elucidates the factors that influence users' intention to use dashboards in the UAE.

Keywords-Psychological Factors, Business Intelligence, Contemporary business environment

1. Introduction

The contemporary business environment is marked by a plethora of intricacies, imposing the imperative upon managers and decision-makers to render accurate and timely decisions that contribute to the enhanced competitiveness and overall success of their respective organizations. (Martins, Martins, Caldeira, & Sá, 2020) observed that the contemporary business changing is witnessing rapid technological advancements and increased globalization, resulting in a growing necessity for top management to engage in extensive data analysis to maintain a competitive advantage. In response to these challenges and complexities, organizations are increasingly turning to decision support systems and analytics tools, such as dashboards, for assistance. According to Smartsheet (2019), dashboards are data visualization tools that facilitate real-time visibility by presenting graphical displays of performance-related indicators within an organizational context. These dashboards are intricately designed to offer a customized interface that enables the retrieval of real-time data from diverse sources, including business intelligence (BI) systems, customer resource management (CRM) systems, and other relevant platforms.

In recent years, BI have witnessed a substantial upsurge in their adoption and popularity within the corporate realm. Notably, empirical studies, including the research conducted by Humphries (2017), have revealed that dashboards and scorecards rank among the most in-demand software tools among both corporate entities and individuals. This growing preference can be attributed to the recognition that BI systems play a pivotal role in enhancing organizational decision-making processes by presenting business intelligence in a visually engaging graphical format, as emphasized by Smartsheet (2019). Fundamentally, BI dashboards empower executives and decision-makers to make prompt and accurate data-driven decisions. Smartsheet (2019) contends that this technological tool enables users to effectively analyze voluminous datasets and make real-time, evidence-based decisions. Achieving this is made possible through the consolidation of key performance indicators (KPIs) and scorecards onto a unified interface, which is meticulously customized to cater to the distinct needs of C-level managers, executives, and other decision-makers. Consequently, such individuals are equipped with the ability to visualize their organization's current performance, identify areas of strength and weakness, and explore potential opportunities for expansion.

Despite the escalating popularity of BI and their associated advantages, research indicates that users' acceptance and intention to use these tools remain remarkably low. Bastedo et al. (2017) assert that employees' interest and utilization of BI dashboards have yet to reach the anticipated levels. Insights gathered from various organizations in the UAE corroborate this finding, revealing that despite the widespread adoption of BI dashboards by many organizations, numerous employees exhibit minimal usage and express a preference for maintaining conventional decision-making approaches. This prevailing trend is also evident in my current workplace, where a substantial portion of employees does not incorporate BI dashboards in their decision-making processes or daily activities. Consequently, there is a pressing need for a comprehensive investigation to explore the factors influencing the acceptance and intention to use dashboards at the individual level. The primary impetus behind the present study stems from the imperative to ascertain the underlying reasons for this apathy towards dashboard usage, despite their proven organizational and individual benefits.

Due to the absence of prior research on the factors influencing users' intention to use BI dashboards, it was not possible to establish these factors based on existing knowledge. The limited information available on dashboard adoption mainly comes from non-academic sources like blogs and websites. Moreover, studies examining the factors influencing the acceptability and use of related decision support systems, such as BI systems, have produced inconsistent findings. It is important to note that extrapolating these results to the context of dashboards may not be appropriate due to the distinct functionalities and features of these technologies. Additionally, previous studies on BI systems adoption have been conducted in diverse social contexts, highlighting the need for a new empirical investigation to identify the specific factors influencing users' intention to adopt dashboards in the UAE context.

Hence, this study aims to fill the existing gap in the literature and address the issue of low users' intention to use dashboards by extending the Technology Acceptance Model (TAM). In this study, perceived quality is introduced as a multidimensional construct. While previous studies have explored the inclusion of perceived quality in the TAM framework, none of them have specifically examined quality as a multidimensional construct during the time of this study. Consequently, this research contributes to the advancement of the technology acceptance literature by incorporating quality as a multidimensional construct. Additionally, it expands the current understanding by providing new insights into the factors that influence the adoption of dashboards in the UAE context, an area that has been largely overlooked thus far.

2. Literature Review

While the factors influencing technology adoption differ from one technology to another, studies have shown that these factors can be divided into two broad categories: individual and organizational (Ahmad, 2018, pp. 11-12; Badi, Ochieng, Nasaj, &Papadaki, 2021, p. 36). Individual factors refer to people's cognitive understanding and interpretation of technologies, including perceived usefulness, enjoyment of the new technology/innovation, personality traits (for example, extraversion), risk aversion, values, , personal beliefs, , performance expectations, and perceived benefits, among other factors (Ahmad, 2018, pp. 11-12; Badi et al., 2021, p. 36). On the other hand, organizational factors refer to organizational-related issues such as facilitating conditions, organizational structure and size, industry type, culture, policies, and capacity, among others (Ahmad, Miskon, Alkanhal, &Tlili, 2020, p. 11).

A plethora of models and theories have been developed to explore the intricate factors that shape the adoption of new technologies, both at organizational and individual levels. Prominent frameworks in this domain include the TAM, diffusion of innovation (DOI) theory, TPB, Theory of Reasoned Action TRA, PMT, UTAUT, and DeLone and McLean ISSM. These models have been extensively employed in research investigating technology adoption. Through an exhaustive examination of the existing literature pertaining to these models, the TAM framework emerged as the most suitable choice for the present study. This selection is grounded in its extensive

utilization and empirical substantiation, particularly within the context of decision support systems and other technologies.
However, to enhance TAM's predictive power regarding users' intention to adopt and use dashboards in UAE organizations, the model was expanded by introducing a multidimensional construct known as perceived quality. This extension aims to address the criticism of oversimplification that TAM has more understanding factors influencing dashboard adoption. By incorporating perceived quality, the expanded model seeks to offer valuable insights into the adoption and utilization of dashboards in the specific context of the UAE. This research aims to contribute to the existing knowledge by exploring the multidimensional aspects of perceived quality and their impact on users' intention to adopt and utilize dashboards effectively.

Technology Acceptance Model

In 1986, Fred Davis introduced the initial version of the model, which was a modification of the TRA developed by Fishbein and Ajzen in 1975 (Lim, 2018; Wallace & Sheetz, 2014). Davis proposed this model as a framework to understand the factors influencing the acceptance and adoption of IS and computer technologies by end-users. While the TRA aimed to explain general behaviors, Davis specifically tailored the TAM to elucidate the factors that impact technology acceptance and user behaviors across various information systems and user populations (Lim, 2018).

TAM expands on the attitude construct of TRA by introducing two user-motivation concepts: PU and PEU, as depicted in Figure 1. Davis's research revealed that these constructs significantly influence the intention to use new technologies, such as e-mail systems and data editing tools. PEU refers to the extent to which target users believe that adopting a new technology will be effortless or require minimal effort. On the other hand, PU refers to the subjective belief of target users that a new technology or system will enhance their job performance and overall quality of life (Alrifae et al., 2021). Davis also recognized external variables on these beliefs, which he termed as additional factors in the model (Lim, 2018).

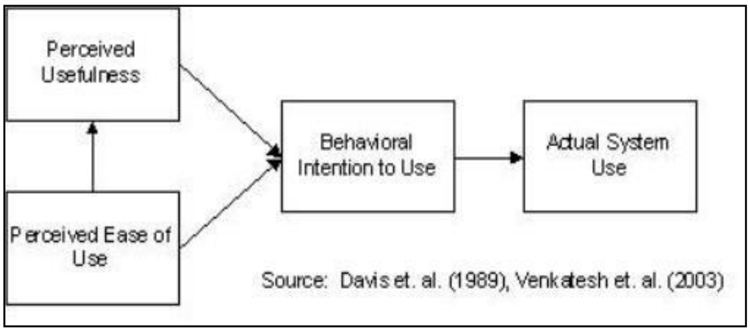

Figure 1. Original TAM by Davis (1989)

TAM has been widely used in numerous studies and has established itself as a robust theoretical framework for explaining users' behavioral intention to utilize information systems. The model's popularity among researchers in the field of IS can be attributed to its relative simplicity and the extensive empirical support it has garnered. Its high predictive power has been demonstrated across various domains.

Notable examples of domains where TAM has been extensively applied and proven to possess strong predictive capabilities include the internet and electronicbanking sector electronic payment and mobile payment (Daştan & Gürler, 2016; Kelana, Riskinanto, & Hilamawan, 2017; Lai, 2016; Teoh, Chong, Lin, & Chua, 2013), e-learning (Elkaseh, Wong, & Fung, 2016; Punnoose, 2012), e-commerce (Juniwati, 2014) mobile and electronic health records technology (Hoque, 2016), and e-government (Rabaai, Zogheib, AlShatti, & AlJamal, 2015).
Existing studies have indicated that the Technology Acceptance Model (TAM) demonstrates an accuracy rate of approximately 40% in predicting users' intention to accept and utilize a new system. (Ahmad, 2018). This

evidence further reinforces the model's reliability and effectiveness in understanding user behavior and technology acceptance.

3. Materials and Methods

In this study, a quantitative research methodology was utilized., utilizing a correlational research design. The selection of this method was based on the positivism research philosophy adopted, which aimed for an objective approach to addressing the research problem through inductive reasoning. To obtain research results that can be generalized, a quantitative research methodology was employed in this study. The aim was to investigate the factors that influence users' intention to use dashboards specifically in the UAE.It was necessary to collect data from a relatively large sample, as was done in this study. The correlational research design was deemed appropriate due to its focus on examining relationships between variables. Furthermore, the cross-sectional study to be collected in a single instance, thereby enhancing the method's relevance.

The study population was selected using a purposive sampling technique, specifically targeting high-ranking employees who were anticipated to utilize dashboards. This selection criterion was applied because the primary focus of the study was to assess users' intention to initially use dashboards, rather than their intention to sustain their usage over time.. To gather data, web-based survey questionnaires were used. This approach made the data collection and analysis process cheaper and less time-consuming while at the same time improving the response rate. As noted by Kumar (2019), using web-based questionnaires encourages the respondents to provide their true feelings/genuine responses since they are more assured of their identity being concealed than the conventional paper-based questionnaire. Another point worth noting regarding the data collection approach is that all the questions were closed-ended, meaning the respondents only selected a choice from the limited number of options provided. Using closed-ended questions, the responses’ uniformity made it easier to mathematically analyse the collected data using the necessary quantitative data analysis software programs. It also minimized several issues, including misunderstanding from the respondents, chances of getting irrelevant answers, and researcher biases.

The collected data was processed and organized using the SPSS 26.0 to ensure its cleanliness and proper arrangement. Subsequently, the data underwent analysis using PLS-SEM software, enabling a comprehensive examination of the relationships within the model. The analysis involved two main phases: the assessment of the measurement model and the evaluation of the structural model.

As part of the measurement model assessment, several tests were conducted to evaluate the reliability and validity of both reflective and formative constructs. These tests encompassed assessments of internal consistency, indicator reliability, discriminant validity and convergent validity.

In the subsequent phase, the structural model assessment was performed to determine the degree to which the model explained the variances in the dependent/endogenous constructs. This phase included examinations of effect sizes and the predictive relevance of the model. Key tests conducted during this phase encompassed assessing collinearity issues were addressed in the structural model by examining the path coefficients, testing the coefficient of determination (R2), assessing the effect size of f2, and evaluating the predictive relevance of Q2.

By conducting these rigorous analytical procedures, a comprehensive understanding of the collected data was achieved, elucidating the relationships and predictive capabilities within the model of the study.

Theoretical Framework

After conducting a comprehensive review in the introduction section, it was determined that the TAM is the appropriate framework for this study. The existing empirical literature, research problem and the examination of prominent theories and models of technology acceptance at the individual level all converged on TAM as the ideal theoretical foundation. The model's wide application and the supporting empirical evidence further solidified its suitability for the study. To enhance its predictive and explanatory power regarding users' intention to adopt a dashboard, a multidimensional construct called perceived quality was introduced. This inclusion aimed to provide a comprehensive perspective to guide the decision-making process in adopting dashboards as decision aid tools. Importantly, this integrated framework, which incorporates perceived quality, is a novel

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contribution as previous studies have primarily focused on single dimensions of quality within TAM. In contrast, this study incorporates three dimensions: perceived system quality, perceived service quality, perceived information quality. Figure 2 below presentscapturing the interplay of variables within the TAM framework enhanced by perceived quality.

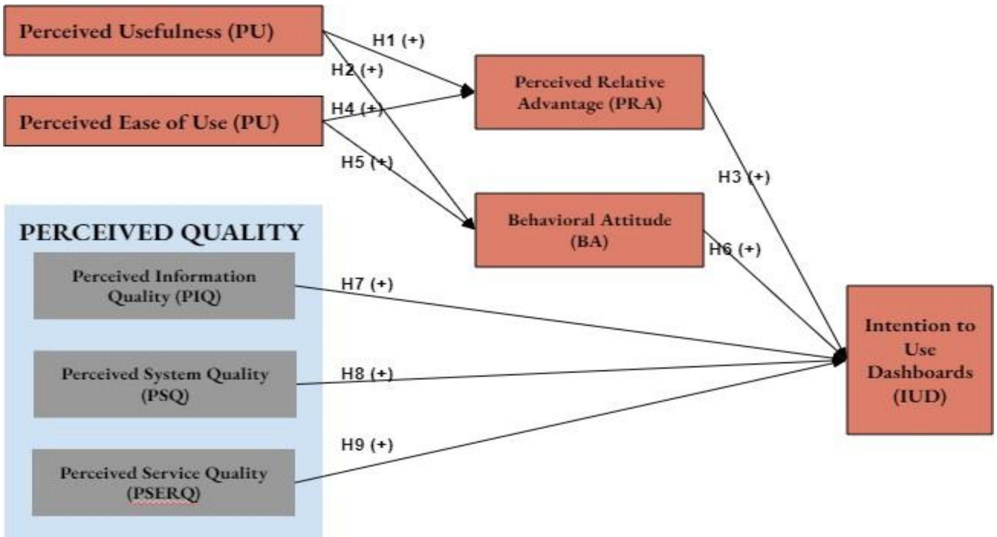

Figure 2. ResearchModel

The research depicted in the provided figure aims to investigate nine hypotheses that explore the relationships among eight variables. The model comprises five independent variables: perceived ease of use, perceived usefulness, perceived information quality, perceived system quality, and perceived service quality. The dependent variables include behavioural intention and perceived relative advantage. The connections between these variables and the relevant literature have been extensively reviewed in the subsequent subsections, albeit concisely.

3.1 Hypotheses development

Perceived usefulness

PUis a central concept in the TAM model, which is used to understand the acceptance of technology. PU refers to an individual's subjective assessment of how beneficial a new system is in enhancing their job performance and overall quality of life (Davis, 1989). This implies that PU primarily relates to the system's ability to improve productivity and effectiveness in tasks. To determine the advantages of the new system, users often compare it with previous systems they have used. E.g., in banking industry, customers may compare the convenience of A novel 24-hour internet banking system was introduced, alongside the traditional face-to-face transaction methods at physical branches. If customers perceive the new system as more convenient and user-friendly, their intention to accept and use it increases.

Extensive research within the field of IS has investigated the impact of perceived usefulness on users' intention to adopt and utilize new technologies. The findings consistently indicate that perceived usefulness serves as a significant predictor of users' intention to adopt and use a new system. Various studies have revealed a positive association between perceived usefulness and users' attitudes toward technology usage (Šumak, Heričko, Pušnik, &Polančič, 2011). Additionally, other research has highlighted the importance of perceived usefulness in predicting users' intention to adopt technology (Sagnier et al., 2020). These findings suggest that when users perceive a dashboard or system as valuable in enhancing their job performance, their intention to adopt and utilize it becomes stronger. Based on these observations, we propose the following hypothesis:
H1: Perceived usefulness has a positive impact on perceived relative advantage.
H2: Perceived usefulness positively impacts behavioural attitude towards the intention to use dashboards.

Perceived relative advantage.

Perceived relative advantage refers to how an individual perceives a new system to be better than the one intended to succeed or replace (Ifinedo, 2011). This definition implies that if a new system is perceived as having more benefits than the existing one, the probability of accepting that such a system will be significantly high. Previous studies (Deng et al., 2021; Dwivedi et al., 2009; Li et al., 2011) have established a positive relationship between relative advantage and the adoption of new technologies, especially in small- and medium-sized enterprises (SMEs). For example, Deng et al. (2021) noted that relative advantage had the most robust direct relationship with physicians' attitudes and intention to use clinical practice guidelines (CPGs) on antimicrobials. The authors pointed out that the physicians were more interested in using the new CPGs on antimicrobials because they considered them better than the previous practices (Deng et al., 2021). Building upon the aforementioned findings, the following hypothesis was formulated:

H3: Perceived relative advantage (PRA) positively affects users' intention to use BI dashboards.

Perceived ease of use

PEU is a fundamental component of the TAM model, which refers to the user's perception of the system's simplicity and minimal effort required for its use. PEU represents users' perception of how easy it is to comprehend and navigate the dashboard in their daily tasks. Previous research has consistently highlighted the complementary relationship between PEU and perceived usefulness (PU). For instance, studies by Venkatesh and Davis (2000), Teo and Noyes (2014), and Tan et al. (2014) have shown that when a system is perceived as effortless and less complex, it positively influences users' attitudes and intention to adopt and use the technology. These findings underscore the significance of PEU in shaping users' acceptance and adoption of technology. Therefore, based on these insights, this study formulated the following two hypotheses to investigate the relationship between PEU and users' intention to adopt dashboards:

H4: Perceived ease of use has a positive impact on perceived relative advantage.

H5: Perceived ease of use positively impacts behavioural attitude towards intention to use dashboards.

Behavioural attitude

Behavioral attitude refers to the inclination of individuals to accept, adopt, and utilize a new system or technology (Rabaai, Zogheib, AlShatti, &AlJamal, 2015). In the context of the Technology Acceptance Model (TAM), attitude plays a crucial role in mediating the relationship between perceived usefulness, perceived ease of use, and the intention to adopt and use a new technology. Numerous studies have consistently shown that users' positive attitudes towards a system or technology significantly increase the likelihood of its adoption and use. Research conducted by Hsieh (2015), Presseau, Francis, Campbell, and Sniehotta (2011), and Yu et al. (2021) have examined the association between attitude and behavioral intention in the context of information technology systems among healthcare professionals, and their findings support the significant impact of attitude on acceptance and use behavior. These studies highlight that the attitude developed by users towards a new system or technology strongly influences their intention to adopt and use it. Building upon this knowledge, this study proposes the following hypothesis:

H6: Behavioural attitude has a positive impact on user’s intention to use BI dashboards.

Perceived information quality

Perceived information quality is defined as the desirable properties of an information system's output (Tam & Oliveira, 2017, p. 544). It includes measures demonstrating the quality and usefulness of information generated by a new system. Research on the success of information systems has shown that this construct is one of the critical precursors of user satisfaction. For instance, Cheung, Lee, and Rabjohn (2008) and Zhou (2011) established that information quality plays a crucial role in the users' experience using M-banking services. They noted that when the information is irrelevant, imprecise, or outdated, users tend to doubt the system’s integrity and the ability to provide quality services. Furthermore, if the information is produced in a way that unnecessarily increases users’ workload, the usage would be adversely affected. Weak and unhelpful information is also likely to frustrate users, thus reducing their satisfaction levels and use. These findings led to the following hypothesis.

H7: Perceived information quality positively impacts users' intention to use BI dash- boards.

Perceived system quality

The perceived system quality is defined as the degree to which a user perceives a system as helpful to their work performance (Zhou, 2011, p. 71). It is assessed based on availability, dependability, adaptability, usability, and response time (Tam & Oliveira, 2017, p. 544). In the e-commerce context, for instance, DeLone and McLean (2003, pp. 9-30) established that the influence of a website on consumer purchases could only be understood by evaluating its usability and the relevance of the information it presents to potential buyers. To emphasize the role of system quality in users' intention to use a system, the internet was used as an example. They noted that the slow response time due to poor website design and heavy traffic or the inaccessibility of a system could cause people to stop using the internet despite its popularity. This observation suggests that the quality of a system (in this case, dashboards) is a critical determinant of users' perceptions and behavioral intention to use. If it is perceived as high quality, users are likely to trust its capability, integrity, and friendliness, thus developing the intention to use and continue depending on it. In support of this view, Sabarudin and Razak (2021, p. 4) found that system quality strongly affected students' intention to use and continue using information system management. These findings prompted the following hypothesis:
H8: Perceived system quality positively impacts the user's intention to use BI dashboards.

Perceived service quality

The perceived service quality focuses on the support given to users by service providers or system developers. Most studies that have investigated this construct's influence on the acceptance and use of information system innovations have evaluated it based on measures such as assurance and responsiveness of the support team and the provision of valuable training (Dhingra, Gupta, & Bhatt, 2020, p. 44; Tam & Oliveira, 2017, p. 544). Their findings show that providing high-quality services and assuring user satisfaction is critical to a system's continued application and success. In the banking sector, for instance, it was established that service quality considerably affected users' satisfaction and their subsequent emotional response to M-banking services (Marinkovic&Obradovic, 2015). This observation suggests that if the service quality is deemed poor, users will become frustrated and dissatisfied with the system, thus distrusting it (Dhingra et al., 2020, p. 44). Consequently, the overall service quality from the mobile-banking service provider should be consistent with users' expectations and the industry standards to yield the desired positive impacts on their satisfaction and the intention to use. It was, therefore, hypothesized that:
H9: Perceived service quality positively impacts the user's intention to use BI dashboards.

4. Results

4.1 Profile of Respondents

Age and gender are significant moderators of user perception, adoption and sustained use of technology at the workplace. Studies (for example, Wahdain and Ahmad, 2014) have found significant gender differences in the adoption of technology among older workers. Also, these studies have shown that younger employees are more likely to adopt technological innovations at the workplace than older employees. Therefore, it was imperative to capture the age and gender characteristics of the participants in order to establish whether there is any relationship between age and gender and the intention to use BI dashboards. In this regard, the study established that most of the respondents were females (68.4%), while the rest were males (31.6%). Regarding age, most of the respondents (69.2%) were young (aged below 40 years). Those aged above 40 were only 22.5% (See the Table 1 below). All of the participants worked at executive levels in government organisations.

Table 1: 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)	Under 21 years old	29	8.3
	21-30 year	132	37.6
	31-40 year	111	31.6
	41-50 year	47	13.5
	51-60 year	32	9.0
Educational Levels	Bachelor’s degree	205	58.6
	Doctor’s degree	18	5.3
	High School/voca-tional	37	10.5
	Master’s degree	89	25.6
Occupation	Government em-ployee	350	100
	Company em-ployee	0	
	Self-employment	0	
	Other (please specify)	0	

Another demographic factor captured in the questionnaire because of its role in the perception and adoption of technology at the workplace is education level. Previous research has demonstrated that education increases the probability of using different technologies at the workplace and that employees with more education have longer experiences with different technologies than those with less education (Muriithi, Horner, & Pemberton, 2016; Riddell & Song, 2017). Therefore, in this study, it was found that the majority of the respondents (58.6%) had Bachelor's degree, followed by a Master's degree (25.6%), then high school/vocational (10.5%). Only 5.3% of the respondents had Doctor’s degree (See Table 4.2 above). Interestingly, a significant percentage of respondents had only high school/vocational training certificates, yet they held executive positions in organisations. 4.5 Measurement Model The measurement model basically established unidirectional.

4.2 Assessment of Measurement Model

The internal consistency and convergent validity were determined using Composite Reliability (CR) and AVE, respectively. According to methodology scholars, the recommended threshold values for internal consistency reliability is at least 0.70 and 0.50 for convergent validity (Fornell&Larcker, 1981; Hair, Hult, Ringle, &Sarstedt, 2017). As demonstrated in Table 2 below, all constructs met the threshold values for internal consistency reliability as the CR values ranged from 0.924 to 0.971, which was far above the 0.70 cut off value. Also, the AVE values ranged between 0.798 and 0.892, which were also above 0.50 threshold value.

Table 2: Internal consistency reliability and Convergent validity

Variable	**Item**	**Loading**	**Cronbach's alpha**	**CR**	**AVE**
behavioralattitude	BA01	0.912	0.950	0.962	0.834
	BA02	0.903			
	BA03	0.925			
	BA04	0.944			
	BA05	0.881			
IntentiontouseBI	IUD1	0.904	0.877	0.924	0.803

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	IUD2	0.911			
	IUD3	0.873			
Perceivedeaseofuse	PEU01	0.915	0.936	0.952	0.798
	PEU02	0.897			
	PEU03	0.939			
	PEU04	0.903			
	PEU05	0.806			
Perceivedinformationquality	PIQ01	0.914	0.964	0.971	0.849
	PIQ02	0.894			
	PIQ03	0.932			
	PIQ04	0.939			
	PIQ05	0.921			
	PIQ06	0.928			
Perceived relativeadvantage	PRA01	0.929	0.959	0.968	0.858
	PRA02	0.934			
	PRA03	0.927			
	PRA04	0.911			
	PRA05	0.932			
Perceived servicequality	PSERVQ01	0.953	0.960	0.971	0.892
	PSERVQ02	0.933			
	PSERVQ03	0.938			
	PSERVQ04	0.954			
Perceived systemquality	PSQ01	0.898	0.949	0.961	0.832
	PSQ02	0.895			
	PSQ03	0.924			
	PSQ04	0.923			
	PSQ05	0.919			
Perceivedusefulness	PU01	0.916	0.957	0.966	0.824
	PU02	0.923			
	PU03	0.899			
	PU04	0.905			
	PU05	0.900			
	PU06	0.904			

Note: IUD = Intention to use BI, PEU = Perceived ease of use, PIQ = Perceivedinformationquality,PRA=Perceivedrelativeadvantage,PSERV=Perceivedservicequality,PSQ=Perceivedsystemquality,PU=Perceivedusefulness,BA=behavioral attitude.

To assess the discriminant validity, two methods were employed: the Fornell-Larcker criterion (Fornell & Larcker, 1981) and the Heterotrait-Monotrait (HTMT) ratio. According to the Fornell-Larcker criterion, the square root of the Average Variance Extracted (AVE) for each construct was compared with the correlation

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values of other constructs. If the square root of the AVE for a construct was greater than the correlation values with other constructs, it indicated discriminant validity (Hair, Sarstedt, Hopkins, & Kuppelwieser, 2014, pp. 139).

The results presented in Table 3 demonstrate that the square root of the AVE for each construct exceeds the correlation values with other constructs, providing evidence of discriminant validity.

Table3: Discriminantvalidity(FornellandLarckerCriterion)

	BA	IUD	PEU	PIQ	PRA	PSERV	PSQ	PU
BA	0.913							
IUD	0.784	0.896						
PEU	0.825	0.770	0.893					
PIQ	0.943	0.814	0.865	0.922				
PRA	0.850	0.791	0.863	0.854	0.926			
PSERV	0.844	0.773	0.848	0.882	0.793	0.944		
PSQ	0.905	0.805	0.876	0.946	0.872	0.882	0.912	
PU	0.822	0.770	0.828	0.832	0.906	0.788	0.844	0.908

Note:IUD=IntentiontouseBI,PEU=Perceivedease ofuse,PIQ=Perceivedinformationquality, PRA =Perceivedrelativeadvantage,PSERV=Perceived servicequality,PSQ=Perceivedsystemquality,PU =Perceivedusefulness,BA=behavioralattitude.

The HTMT ratio method is considered more precise and accurate in estimating discriminant validity (Hair, Hult, Ringle, &Sarstedt, 2022). As per this method, values above 0.90 demonstrate a discriminant validity problem (Henseler, Ringle, &Sarstedt, 2015; Franke&Sarstedt, 2019). However, results presented in Table 4 below show all the HTMT ratios were below 0.90, hence demonstrating the absence of discriminant validity problem across the constructs of the measurement model.

Table4: Discriminantvalidity

Construct	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
1.BA								
2.IUD	0.857							
3.PEU	0.871	0.847						
4.PIQ	0.985	0.883	0.908					
5.PRA	0.891	0.862	0.908	0.888				
6.PSERV	0.883	0.840	0.894	0.917	0.826			
7.PSQ	0.952	0.881	0.928	0.988	0.914	0.923		
8.PU	0.861	0.840	0.870	0.866	0.945	0.821	0.884	

Note: IUD = Intention to use BI, PEU = Perceived ease of use, PIQ = Perceived information quality, PRA = Perceived relative advantage, PSERV = Perceived service quality, PSQ = Perceived system quality, PU = Perceived usefulness, BA = behavioral attitude.

4.3 Assessment of Structural Model

Structural model tests were conducted to establish the association or the relationship between constructs (hypothesized relationships). Therefore, the significance of path coefficients was determined through a

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bootstrapping procedure with 5000 re-samples, based on recommendations by Hair, Hult, Ringle, and Sarstedt (2022). The results are demonstrated in Figure 3 and Table 5.

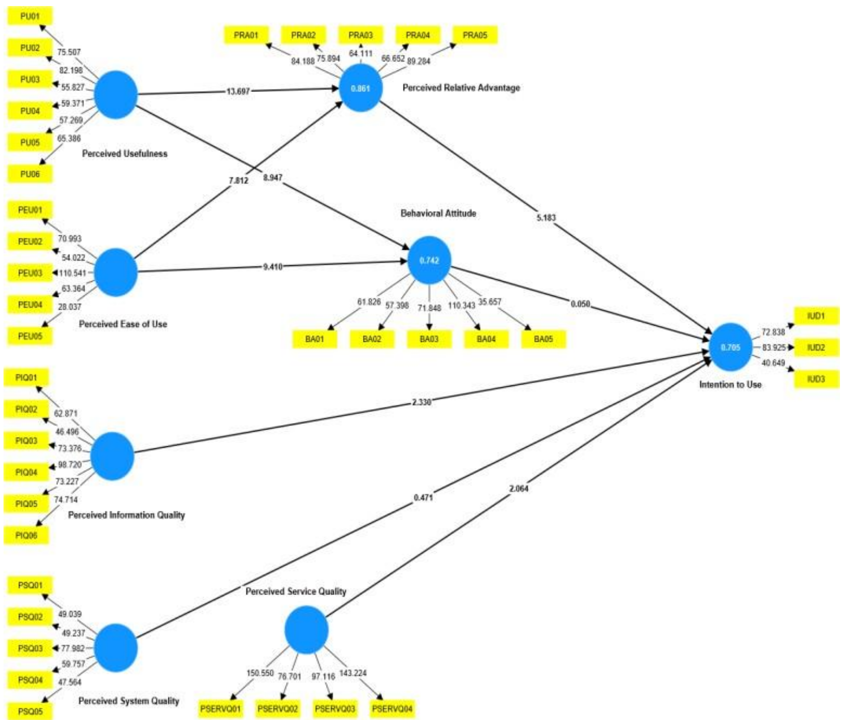

Figure3:PLSstructure model

The results obtained indicated that perceived usefulness (PU) had a significant effect on perceived relative advantage (PRA) ($\beta = 0.608$, $t = 13.697$, $p < 0.001$) and Behavioural Attitude ($\beta = 0.401$, $t = 9.088$, $p < 0.001$), leading to the acceptance of H1 and H2. Similarly, perceived ease of use (PEOU) was found to have a positive significant relationship with PRA ($\beta = 0.359$, $t = 7.811$, $p < 0.001$) and Behavioural Attitude ($\beta = 0.169$, $t = 3.187$, $p<0.001$), implying that hypotheses H4 and H5 were accepted. PRA significantly and positively influenced targeted Users intention to use dashboards (IUD) ($\beta = 0.316$, $t = 5.183$, $p < 0.\ 001$), meaning that H3 was supported.

Pertaining to perceived quality factors, the findings showed that only perceived in-formation quality (PIQ) ($\beta = 0.336$, $t = 2.330$, $p<0.05$) and perceived service quality (PSERQ) ($\beta = 0.177$, $t = 2.064$, $p<0.05$) had a significant positive effect on the intention to use dash-boards, implying that the findings supported hypotheses H7 and H9. However, perceived system quality (PSQ) was found to have an insignificant influence on the intention to use dashboards ($\beta = 0.060$, $t = 0.471$), leading to the rejection of H8. Similarly, behavioural attitude was found to have an insignificant negative influence on the intention to use dashboards ($\beta = -0.005$, $t = 0.050$), meaning that hypothesis H6 was not supported. Therefore, all hypotheses, except H6 and H8, were accepted in this study (see Table 4 below).

Table 5: Path coefficient significance levels

Hypothesis	**Relationships**	**std.Beta**	**StdEr-ror**	**T-value**	**P-value**	**BCILL**	**BCIUL**	**Decision**
H1	PerceivedEaseofUse->Per-ceivedRelative Advantage	0.359	0.046	7.812	*p*<.001	0.284	0.435	Accepted

H2	PerceivedEaseofUse->Be-havioralAtti-tude	0.460	0.049	9.410	*p*<.001	0.379	0.540	Accepted
H3	PerceivedRela-tiveAdvantage ->Intentionto Use	0.316	0.061	5.183	*p*<.001	0.219	0.420	Accepted
H4	PerceivedUse-fulness->Per-ceivedRelative Advantage	0.608	0.044	13.697	*p*<.001	0.535	0.680	Accepted
H5	PerceivedUse-fulness->Be-havioralAtti-tude	0.441	0.049	8.947	*p*<.001	0.360	0.521	Accepted
H6	BehavioralAt-titude->Inten-tiontoUse	-0.005	0.095	0.050	0.480	-0.160	0.157	Rejected
H7	Perceived In-Formation Quality -> In-tention to Use	0.336	0.144	2.330	0.010	0.090	0.566	Accepted
H8	Perceived Sys- tem Quality -> Intention to Use	0.060	0.127	0.471	0.319	-0.154	0.264	Rejected
H9	Perceived Ser- vice Quality -> Intention to Use	0.177	0.086	2.064	0.020	0.049	0.331	Accepted

4. Discussion and Conclusion

The objective of this research was to examine the factors influencing users' intention to utilize dashboards in the UAE.A comprehensive model was employed, considering various constructs as key determinants of behavioral attitude and intention to use dashboards. The study examined how these constructs influenced users' attitudes towards dashboards and their intention to use them. The findings indicated that PU, PIQ, PRA, PSERVQ, and PEOU had positive and significant impacts on users' behavioral intention to use dashboards. This means that when users perceive dashboards as relevant to their work, capable of delivering desired outcomes, superior to previous technologies, offering high-quality services, and easy to use or requiring minimal effort. However, the influence of PSQ and BA on the intention to use dashboards was positive but not statistically significant, suggesting that these factors may have a relatively weaker influence compared to other factors in users' decision-making process when adopting a new application. It is worth noting that previous studies, such as Chang and Tung (2008) and Liou, Hsu, and Chih (2015), have reported significant and positive effects of PSQ on technology acceptance. The divergent results underscore the necessity for additional exploration into the influence of PSQ and BA on the intention to use dashboard technologies, in order to attain a more comprehensive understanding of their effects.

5. Recommendations and Practical Implications

The significant impact of perceived usefulness on the intention to use dashboards implies that enhancing awareness regarding the usefulness of this technology can be an effective measure to promote its acceptance and utilization in the UAE. This awareness should also focus on the ease of use, relative advantage, and quality (informational, service, and system) of dashboards because these constructs were also significant predictors of users' intention to use dashboards. Apart from the awareness, the designers and developers should invest their time and resources in improving the quality of dashboards since quality is significantly influential. This study also provides evidence-based insights that UAE organizations can use to enhance the acceptance and use of dashboards at an individual level.

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