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Adoption of Business Intelligence Among Iraqi SMEs Culture: Impact of Technology Acceptance Model, Information Quality, And Organizational Readiness

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Abstract: Effective use of business intelligence has become essential for small and medium-sized organizations (SMEs) in the era of digitalization due to the introduction of new technologies. Therefore, this study aims to measure the influence of the Technology Acceptance Model (TAM) and other factors, for example, the quality of information, organization readiness and technology infrastructure, on business intelligence. A quantitative research methodology was used, with a sample size of 281 participants who were owners, managers and information system staff in Iraqi SMEs who had experience using business intelligence. The findings of this study indicated that the quality of information has a significant impact on perceived usefulness (PU) and perceived ease of use (PEOU). Similarly, PU, PEOU, organization readiness and technology infrastructure positively and significantly impact business intelligence adoption. This study offers a comprehensive analysis of the crucial aspects that contribute to the successful deployment of business intelligence, thereby influencing the outcomes of SMEs. The results of this study will help entrepreneurs, SME owners managers, and academics develop a business intelligence system that can enhance overall organizational efficiency in a dynamic economic setting. Putting in place a good business intelligence system will help managers make better decisions, boost economic growth for businesses, support new ideas in businesses, and improve their overall performance and output.

Keywords: Technology Acceptance Model, Business intelligence, information quality, Technology infrastructure, organization culture

1. Introduction

In the contemporary era of digitalization, there is a growing expectation within organizations for employees to participate in data-driven decision-making processes to achieve a competitive edge. This advancement requires enhanced adaptability and rapid decision-making assistance. BI has undergone significant development since its inception as a decision support system. They now serve as a crucial tool for businesses grappling with the overwhelming volume of structured and unstructured data created internally and externally, continuously, and across organizational borders (Al-Okaily, Teoh et al., 2023).

SMEs should be vigilant in managing their businesses within the current dynamic environment characterized by increased rivalry, improved innovative flexibility, advancements in information technology (IT), and ever-growing consumer demands (Gomwe et al., 2022). The use of business intelligence is widely recognized for its ability to improve the quality of decision-making processes by transforming organizational data into valuable data (Chen & Lin, 2021). In the contemporary and ever-evolving environment, attaining a competitive edge is contingent upon pursuing technological innovation and its subsequent implementation within the context of business operations. The recognition of the importance of SMEs is widely acknowledged by numerous studies in different developing countries such as Saudi Arabia (Maghsoudi & Nezafati, 2023), Iraq (Jameel & Alheety, 2022), Nigeria (Lateef & Keikhosrokiani, 2023) Jordan (Masa'Deh et al., 2021) as well as industrialized nations (Guo et al., 2021; Stjepi et al., 2021). Today in highly competitive markets, SMEs are looking to continue to thrive to gain more customers. the market environment requires SMEs to make and take effective decisions on time, which should be in line with the business model.

SMEs in developing countries play an essential role in developing the economies of countries. At the same time, these SMEs in developing countries face several challenges in getting good data for sound decision-making (Adeyelure et al., 2018). Other challenges facing SMEs in implementing BI are that management activity is ineffective and planning resources are not enough (Lateef & Keikhosrokiani, 2023). BI systems in SMEs must be effective and seamless and be able to interact with other systems (Gonzales et al., 2019). The study by Wong et al. (2020) reported that a num-

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-ber of SMEs made an excellent investment to reach effective BI systems, reduce the cost of production, and maintain effective systems. usually implementing BI systems in the workplace to support decision-making, which may lead to an increase in profitability and a decrease in expenses as well as to improve customer interactions (Lateef & Keikhosrokiani, 2023). Due to poor planning and management, some organizations face several problems in using and adapting the BI in the workplace, leading to failure. As a result, these organizations face financial losses (Jameel et al., 2023). Because it has a notable effect, BI has attracted good attention among organizations around the world. (Kohnke et al., 2011; Seo & Lee, 2021). However, in developing countries such as Iraq, the situation is different due to the challenges that still exist related to culture and economics.

Using BI leads to improving the effectiveness of business operations and simplifying the decision-making process by providing easy and fast access to data and information recently, several studies emphasized the vital role of BI in the market environment and strengthened the competitive advantage of organizations through the easy identification of threats and opportunities in markets (Al-Okaily, Teoh et al., 2023; Arefin et al., 2021). For instance, Al-Okaily et al. (2023) demonstrated how the adoption of BI systems leads to high adaption for organizations in dynamic markets and environments, which will help organizations gain a competitive advantage. In addition, Arefin et al. (2021) emphasized the important link between BI and decision-making within organizations and focused on responsiveness and agility when using BI. BI is considered a cornerstone for organizations to make sound decision-making and empower their organizations to survive in the marketplace.

Although there are potential advantages and a significant increase in the BIS market, which surpassed US$23.1 billion in 2020 and is projected to reach US$33.3 billion by 2025 with a compound annual growth rate (CAGR) of 7.6% between 2020 and 2025 (Al-Okaily, Teoh et al., 2023). In fact, numerous firms have failed to attain the expected and likely advantages of their investments in BIS. For instance, Gartner Inc. has demonstrated that more than 87% of firms have been categorized as having a poor level of BIS technological maturity. A recent poll among executive managers of major corporations such as Ford Motor Co., American Express, Johnson & Johnson, and General Electric reveals that 77% of them consider business analytics to be a serious challenge (Choi et al., 2022). Previous research has indicated that between 70 and 85% of business information systems (BIS) initiatives do not achieve the anticipated returns, as evidenced by Trieu (2022) and Ain et al. (2019). A study by Ahmad et al. (2021) in developing countries found that the failure rate, attributed to a combination of technological and management challenges, was approximately 80%. (Ain et al., 2019; Trieu, 2023). In Iraq, a number of small businesses face challenges to effectively adapt the BI to improve their decision-making, which can lead to failure to build a good competitive advantage (Jameel et al., 2021; Thabit & Abdullah, 2023). This study seeks to find the impact of TAM on BI in Iraqi SMEs, as well as to include new variables such as technology infrastructure, quality of information, and organization readiness.

2. Literature Review and Hypothesis Development

2.1. Business Intelligence

In 1989, Gartner Group introduced the concept of BI for the first time and has been continuously developed over the years, particularly in terms of technological advancements and changing business landscapes (Maghsoudi & Nezafati, 2023; Saeed et al., 2023). BI was defined by Peters et al. (2016). According to Peters et al. (2016), business intelligence is the term used to describe a range of actions that are intended to gather, store, analyze, and extract high-quality data from various business domains. Although data analysis was prioritized in the past, modern viewpoints acknowledge that business intelligence is complex and involves organizational, technological, and strategic components (Ranjan & Foropon, 2021).

The importance of business intelligence in improving decision-making processes at all organizational levels, from strategic to operational, has been highlighted by recent research (Maghsoudi & Nezafati, 2023; Jasim et al., 2022). But even with the increasing number of studies on business intelligence, there is still a significant knowledge gap on how exactly it affects competitive advantage and organizational performance, especially when it comes to small and medium businesses (SMEs).

In the words of Chen and Lin (2021), business intelligence can improve decision-making processes at all organizational levels by means of a methodical methodology to turn unprocessed data into actionable insights. Al-Eisawi et al. (2020) also stress that the main goal of business intelligence is to enhance decision-making by gathering, analyzing, and using data. However, even if these studies provide light on the theoretical foundations of business intelligence, more empirical studies are required to explore its applications, particularly in the context of SMEs.

Business intelligence has been shown to provide significant advantages for SMEs in recent research, including increased operational effectiveness, cost savings, revenue growth, and the discovery of new prospects (Niu et al., 2021; Nithya & Kiruthika, 2021). However, there is a paucity of empirical data on the efficient application of business intelligence by SMEs to secure a long-term competitive edge in changing market conditions. Furthermore, although research like that of Gauzelin and Bentz (2017) highlights the beneficial effects of business intelligence on SME performance and decision-making, there is still a knowledge vacuum regarding the precise mechanisms by which business intelligence affects organizational outcomes in various contexts, such as the Republic of Iraq.

In conclusion, more and more extensive research is needed to bridge the gap between theory and reality, especially in the context of small businesses. Although existing research sheds light on the theoretical foundations and potential benefits of business intelligence, future studies should focus on the complex relationships between business intelligence, organizational strategy, and performance outcomes, taking into account industry-specific dynamics and contextual factors.

2.2. Technology Acceptance Model (TAM)

The original form of TAM was proposed by Fred Davis in 1989 and is a product of TRA, the Theory of Reasoned Action (Fishbein and Ajzen, 1975), modified. This is a core framework that focuses on the elements that affect end-user acceptance and adoption of information systems and computer technologies (Thabit & Abdullah, 2023; Jameel et al., 2021). This has generated a great deal of interest in the IS community, and many innovative improvements have been made to enhance its explanatory power and operationalization (Bach et al., 2022).

In recent years, the TAM model has been expanded to various different sectors including higher education, health, banking, etc. in order to see or understand the better technology adoption behaviours of every society (Bany Mohammad et al., 2022; Arefin et al.,2021). Despite the value of the model for understanding how users engage with technologies at work, there is a dearth of research specifically related to TAM and its use on the topic of Business Intelligence (BI) Technology, especially when it is used by small and medium enterprises (SMEs) in Iraq.

Although previous research examined the impact of TAM on IT usage intentions in a number of fields, such as education and banking, there has been little or no focus on BI adoption within SMEs, especially those located in Iraq. This study will contribute to filling this gap by extending the TAM model by incorporating new research results as technology infrastructure, organization readiness, and information quality (Bany Mohammad et al., 2022; Bhatiasevi & Naglis, 2020; Jameel et al., 2021). The focus of this research is to provide a better understanding of different aspects which can affect the adoption and usage levels of BI tools in SMEs, resulting in both additions to theoretical progressions as well as providing insights for practical applications among the organizational decision-makers.

2.3. Hypotheses Development

2.3.1. Perceived Usefulness

PU stands for "the extent to which an individual believes that utilizing a specific system would improve their job performance." (Davis, 1989, p.320). The level at which users think that using a particular system will improve their jobs and lead to better performance is called PU (Jameel et al., 2021). It is indicated that the benefits offered by managers can facilitate the promotion of configuration management adoption, the system's usefulness in the workplace, and the anticipated productivity gains resulting from its implementation (Jameel et al., 2021).

previous studies reported on the importance of end-users and PU in BI systems. These perceptions play a vital role in the development and shaping of business goals and the improvement of organizational performance of organizations (Masa'Deh et al., 2021). When the data offered by BI is perceived as useful, the utilization of information systems such as BI has the potential to enhance operational efficiency within the organization, thus leading to increased productivity (Maghsoudi & Nezafati, 2023). Users evaluate the efficacy of using BI. Users would be encouraged to engage with and accept BI information if they perceive it to be useful, relevant to their professional responsibilities, aligned with their established usage patterns, beneficial compared to alternative resources, inspiring their work, and supportive of their job performance (Guo et al., 2021). In this scenario, users will show improved levels of participation in utilizing BI data and demonstrate more receptiveness toward embracing and implementing such information.

Based on the results previously reported, PU was able to increase the reliability of BI systems, and PU had a significant impact on BI (Bach et al., 2022; Guo et al., 2021; Hou, 2016). However, previous results suggest that PU had an insignificant impact on BI adoption (Masa'Deh et al., 2021). the current study based on previous work proposed that BI enhance the efficiency and reliability of the usefulness of systems, thus BI is able to improve decision-making.

H1: *PU has a positive and significant impact on BI adoption among SMEs.*

2.3.2. Perceived ease of use

Davis (1989) proposed that, while potential users may see a certain system as valuable, they may also experience the system as too complex and believe that the advantages gained from using the system are not worth the work expended. Perceived ease of use is the degree to which an individual feels that utilizing a specific technology would require minimal effort, according to Davis (1989). This may be deduced from the definition of "ease", which states that it refers to the absence of difficulty or significant effort. Effort is a limited resource that individuals may allocate to the several tasks they are accountable for (Radner & Rothschild, 1975, as referenced in Davis, 1989). Assuming that all other factors are the same if one system is viewed as more user-friendly than another, it is more probable that people will adopt it.

PEOU and BI play vital roles in helping decision-makers in the workplace to make sound decisions; the SME staff should take proactive action when using BI to improve the decision (Guo et al., 2021; Hou, 2016). BI empowers users effectively using the data and analyzes it with less effort and cost (Guo et al., 2021). the success of BI in achieving the goals of the organization is proportional to PEOU, which all the users looking for simplified systems. When PEOU and BI have a good relationship, it will lead to benefits for system users and will lead to effective achievement of organization goals (Masa'Dh et al., 2021). Previous results reported that PEOU has a significant impact on BI. However, PEOU is considered an important factor in the adoption of BI (Bach et al., 2022; Guo et al., 2021; Masa 'Deh et al., 2021). Other previous results reported that BI was negatively and insignificantly affected by PEOU (Guo et al., 2021; Hou, 2016). This study proposed that the end user's perception regarding BI leads to easy and simple systems and BI adoption.

H2: *PEPU has a positive and significant impact on the adoption of BI among SMEs.*

2.3.3. PEOU and PU

The proposed hypothesis posits that the PEOU will positively affect the PU of the BI system. It indicates that if the BI system is user-friendly, the end user will perceive it as a tool that may improve task efficiency, accuracy, and overall effectiveness (Davis, 1989). This study postulates that there is a positive relationship between the PEOUs of BI users and their possibility of perceiving it as beneficial and subsequently using it.

In their study, Hou (2016) reported empirical findings supporting the theory that business intelligence PEOU positively affects individuals' perception of its PU. Other Previous results showed that PEOU has a significant impact on business intelligence PU (Bach et al., 2022; Guo et al., 2021; Masa'Deh et al., 2021).

H3: *PEOU has a positive and significant impact on the adoption of PU among SMEs.*

2.3.4. Information Quality

BI tools have become necessary for companies seeking a competitive advantage and improving operational effectiveness. However, the efficacy of these systems is contingent on the quality of information inputted into them (Hmoud et al., 2023). Hence, the primary aspect of BI systems is QI, and BI may include modern tools and reports, while the absence of QI may lead to poor reports and analysis, results insufficient (Jameel et al., 2021).

Nevertheless, getting high-quality information is considered vital to the success of BI and the acquisition of a clear vision capable of implementing it, leading to high performance. According to Popovi et al. (2012), the QI can improve the efficacy of decision-making, increase the level of operation, and improve the return on investment. the systems with high quality and provide a high level of communication, accuracy, and up-to-date information are considered, from the user's perspective, useful systems (Kohnke et al., 2011).

The determination of PU and PEOU usually depends on the level of IQ requested by the business, in addition to providing support from the social and simplified adoption of BI in SMEs (Alsibhawi et al., 2023). The efficiency of IT management is important to implement BI within the organization. This includes the BI introduction to business and leads to the high adaptability of BI adoption. PU will increase when the IQ exists; Kohnke et al. (2011) indicated that IQ statistically impacts on PU if it exists. Similarly, when BI exists in the workplace, IQ can improve PEOU (Guo et al., 2021; Masa 'Deh et al., 2021).

H4: *IQ has a positive and significant impact on the adoption of PU among SMEs.*

H5: *IQ has a positive and significant impact on PEOU adoption among SMEs.*

2.3.5. Technology infrastructure

An organization's technology resources encompass its IT infrastructure, which encompasses a range of technologies, applications, and systems (Alzoubi et al., 2023). Ritter and Gemünden (2004) indicated that technology resources empower enterprises to effectively use and manage technology inside their internal operations, enabling them to both utilize and comprehend its functionalities.

Technology Infrastructure refers to a collection of technologies and established protocols that facilitate the exchange of data and allocation of resources inside organizations, ensuring compatibility and interconnectedness (Bany Mohammad et al., 2022). This technology gives organizations real-time access to information, conducts customer data analysis, facilitates product development, assesses competitive marketplaces, and streamlines resource allocation across different business divisions (Al-Okaily Al-Okaily, et al., 2023).

The technology infrastructure improves the use and adoption of BI among employees, and empirically, technology infrastructure significantly impacts BI use (Bany Mohammad et al., 2022). The study was conducted among different levels of SME employees in Nigeria and reported that the technology factor significantly impacts the implementation of BI (Lateef & Keikhosrokiani, 2023).

H6: *Technology Infrastructure positively and significantly impacts BI adoption among SMEs.*

2.3.6. Organization Readiness

Organizational readiness is the availability of enough resources within an organization, including human, financial, technological, knowledge, skills, and other relevant factors (Stjepić et al., 2021). Organizational readiness refers

to the technological infrastructure and the people resources possessing proficient IT abilities (Bhatiasevi & Naglis, 2020). The existence of readiness in the organization is important for the success of BI adoption in any organization (Bany Mohammad et al., 2022). According to Bhatiasevi and Naglis (2020), the success level of BI adoption in an organization highly depends on the readiness of the organization. There are several indicators of readiness, such as leaders' support, IT infrastructure in the workplace, and the values and attitude of the company. the adoption of BI led to good decisions and results in most of the organizations that adopted the BI (Bany Mohammad et al., 2022). Thus, as a result, SMEs need to ensure readiness in the workplace for the adoption and implementation of BI. Stjepić et al. (2021) indicated that readiness in the organization has a significant role in BI adaption. Bhatiasevi and Naglis (2020) indicated that the organization's readiness is able to improve BI in SMEs and statistically, BI is impacted by readiness. Similarly, Stjepić et al. (2021) showed in the study results readiness of the organization has a significant impact on the use of BI in Croatian SMEs.

H7: *Organizational readiness has a positive and significant impact on BI adoption among SMEs.*

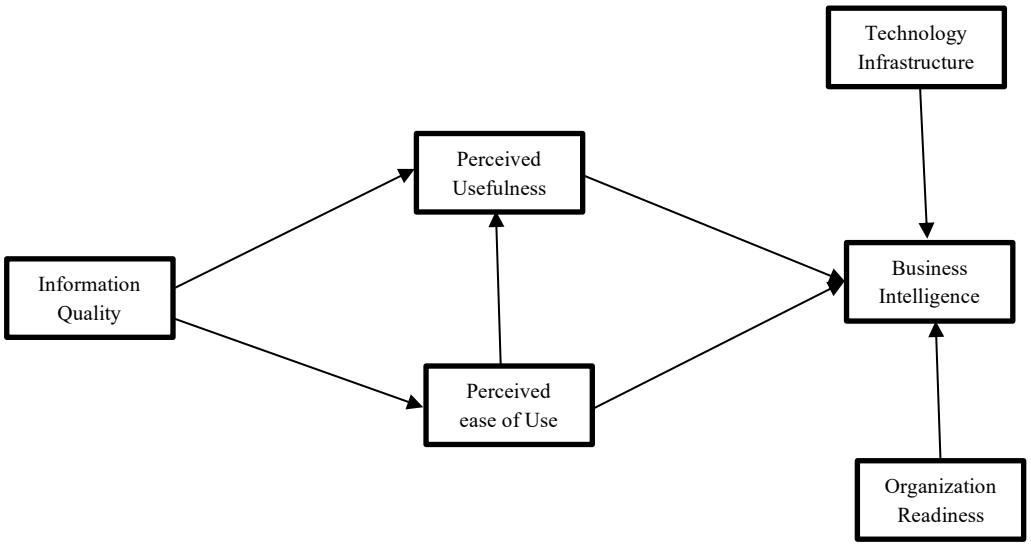

Figure 1: A proposed model

3. Methodology

The study adopted the positivist approach due to the nature of the survey, which was quantitative, and the data collected by questionnaire. The population of this study is the managers, owners and information system staff of SMEs in Erbil, Iraq. Respondents were asked to assess their level of awareness of BI and respondents who lacked understanding of BI were not part of this survey.

The study used a convenience nonprobability sample due to the sample frame of the population unavailable (Hasan et al., 2021; Hmoud et al., 2023). The study used 'structural equation modeling' (SEM) to analyze the collected data; the valid returned questionnaire was 281. According to Kline (2013), the minimum required of questionnaires is 200 to fit this type of research; thus, the sample size of this study aligns with Kline's recommendations.

The questionnaire was administered in Arabic and underwent a double translation process from English to Arabic and then from Arabic back to English, ensuring that it remained consistent with the original, following the methodology described by Ataseven et al.(2013). Four experts from Iraqi higher education institutions specializing in BI and management information systems thoroughly analyzed each measurement item's language and meaning to validate the questionnaire and ensure its content validity. Some elements were eliminated due to their repetitive nature, and modifications were implemented to resolve any potential concerns about comprehension and ambiguity.

The number of items is 28 items distributed among 6 main variables, as illustrated in Table 1, and a five-level Likert scale was used in the questionnaires from “strongly disagree” (1) to “strongly agree” (5). The SMART PLS 4 is used to analyze the valid data; this software enables the researcher to analyze complex models.

Table 1: Research Instrument

Variable	No. of Items	Source(s)
Information Quality	4	(Guo et al., 2021; Hmoud et al., 2023)
Perceived Usefulness	4	(Davis, 1989)
Perceived ease of use	4	(Davis, 1989)
technology infrastructure	4	(Bany Mohammad et al., 2022)
Organization readiness	6	(Hmoud et al., 2023; Puklavec et al., 2018)
Business intelligence	6	(Bach et al., 2022; Guo et al., 2021)

4. Results

4.1. Validity of measurement model

The accuracy with which a measurement model captures the intended construct or notion determines its validity. This is an important part of the research since it ensures the reliability and importance of the measurements used in a study. A measurement model, as defined by Kline (2013), analyzes latent or composite variables. Furthermore, Hair et al. (2019) suggest three criteria for measuring the validity of a measurement model: construct validity, convergent validity, and discriminant validity.

4.2. Convergent validity

To assess the convergence of the construct, factor loadings, 'composite reliability' (CR), 'Cronbach's Alpha' (CA) and 'average variance explained' (AVE) were calculated using the method described by Fornell and Larcker (1981). Convergent validity is considered to be established when all three of the following conditions are met: (a) CR values of 0.7 or higher, (b) factor loadings of 0.7 or higher, and (c) AVE values of 0.5 or higher (Hair et al., 2019).

According to the findings in Table 2, the measurement model appears to meet the criteria for construct reliability CR, CA, factor loading, and AVE. The CR values, which range from 0.945 to 0.912, indicate the good internal consistency and reliability of the measurement model. A higher CR value indicates that the indicators accurately measure the underlying components.

Standard loading levels range from 0.754 to 0.936. The strength of the link between the observed indicators and their related latent constructs is reflected in these values. Higher standardized loadings imply a stronger link between the indicators and the underlying components. CA ranges from 0.872 to 0.930. Thus; no issue in the reliability.

Table 2: Construct validity and reliability

Constructs	Items	Factor Loading	Cronbach's alpha	Composite reliability	(AVE)
Business Intelligence	BI1	0.790	0.913	0.916	0.698
	BI2	0.869			
	BI3	0.796			
	BI4	0.778			
	BI5	0.901			
	BI6	0.873			
Information Quality	IQ1	0.881	0.900	0.902	0.770
	IQ2	0.884			
	IQ3	0.864			
	IQ4	0.881			
Organization Readiness	OR1	0.754	0.930	0.930	0.742
	OR2	0.872			
	OR3	0.872			
	OR4	0.896			
	OR5	0.895			
	OR6	0.871			
PEOU	PEOU1	0.869	0.872	0.881	0.722
	PEOU2	0.867			
	PEOU3	0.872			
	PEOU4	0.789			
PU	PU1	0.798	0.912	0.916	0.794
	PU2	0.912			
	PU3	0.936			
	PU4	0.912			
Technology Infrastructure	TI1	0.847	0.886	0.887	0.745
	TI2	0.866			
	TI3	0.891			
	TI4	0.848			

Source: Calculated by the author

4.3. Discriminant validity

The discriminant validity is measured by the “Heterotrait-Monotrait ratio of the correlation (HTMT)”. The HTMT is calculated by taking the average of the correlations between items across different variables and comparing it to the average correlations between items within the same variables. According to Henseler et al. (2015), HTMT obtained greater than 0.90 indicates the absence of discriminant validity. Based on Table 3 all the HTMT values are less than 0.90 thus there is no issue with discriminant validity.

Table 3. HTMT

	BI	IQ	OR	PEOU	PU	TI
BI						
IQ	**0.528**					
OR	0.734	**0.439**				
PEOU	0.569	0.526	**0.480**			
PU	0.580	0.668	0.529	**0.528**		
TI	0.580	0.555	0.480	0.548	**0.564**	

BI: Business Intelligence; IQ: Information Quality; OR: Organization Readiness; TI: Technology Infrastructure
Source: Calculated by the author

4.4. Assessment of structural model

The second step is to omit executing the structural model, which includes assessing the importance of routes, as well as R2 and Q2 for suggestive value. According to Fig. 2, the R2 value for the model is 0.561, suggesting that the independent variables in the model account for about 56.1% of the variability in the dependent variable. The robustness of each structural path, represented by the R2 value for the dependent variable, is used to assess the model quality or goodness. According to Falk and Miller (1992), an R2 value equal to or greater than "0.1" is considered an acceptable requirement for structural path strength. As shown in Figure 2 and Table 4, the R2 value of 0.561 above the 0.1 criterion confirms the formation of predictive capacity. Furthermore, the Q2 value of 0.386 supports the predictive significance of the variables. A Q2 larger than "0" shows that the model is both predictive and predictively relevant.

The results in Table 4 and Figure 3 provide insight into the hypotheses testing and overall model evaluation. H1 indicates a statistically significant relationship between PU and the adoption of business intelligence, with a T statistic of 2.228 and a p-value of 0.026. As a result, H1 is supported, implying that users who find the BI system beneficial are more likely to contribute to its adoption. H2, the T-statistic of 2.321 and the p-value of 0.020, PEOU has a statistically significant but relatively smaller impact on business intelligence adoption. As a result, H2 is supported, but the magnitude of the effect may be less pronounced compared to other factors. H3, A substantial and statistically significant association between PEOU and PU is indicated by a T statistic of 4.613 and a p-value of 0.000. This supports H3, implying that users who find the BI system straightforward to use are more likely to find it beneficial. H4, the findings show a substantial and statistically significant relationship between IQ and PU, with a T statistic of 9.562 and a p-value of 0.000. This supports H4, demonstrating that the perceived utility of the BI system is influenced by the quality of its information. H5, with a T statistic of 7.813 and a p-value of 0.000, indicates that there is a highly statistically significant link between IQ and PEOU. As a result, H5 is strongly supported, which implies that higher quality of information is related to greater perceived ease of use of the BI system. H6, A statistically significant association between technological infrastructure (TI) and business intelligence adoption is indicated by a T statistic of 2.832 and a p-value of 0.005. As a result, H6 is supported, implying that a well-developed technological infrastructure influences the adoption of business intelligence by SMEs. H7, 8.234 T statistics and 0.000 p-values demonstrate a statistically significant association between organizational readiness (OR) and adoption of business intelligence. As a result, H7 is supported, implying that firms with greater preparedness, which includes elements such as leadership support, organizational culture, and IT infrastructure, are more likely to positively adopt business intelligence.

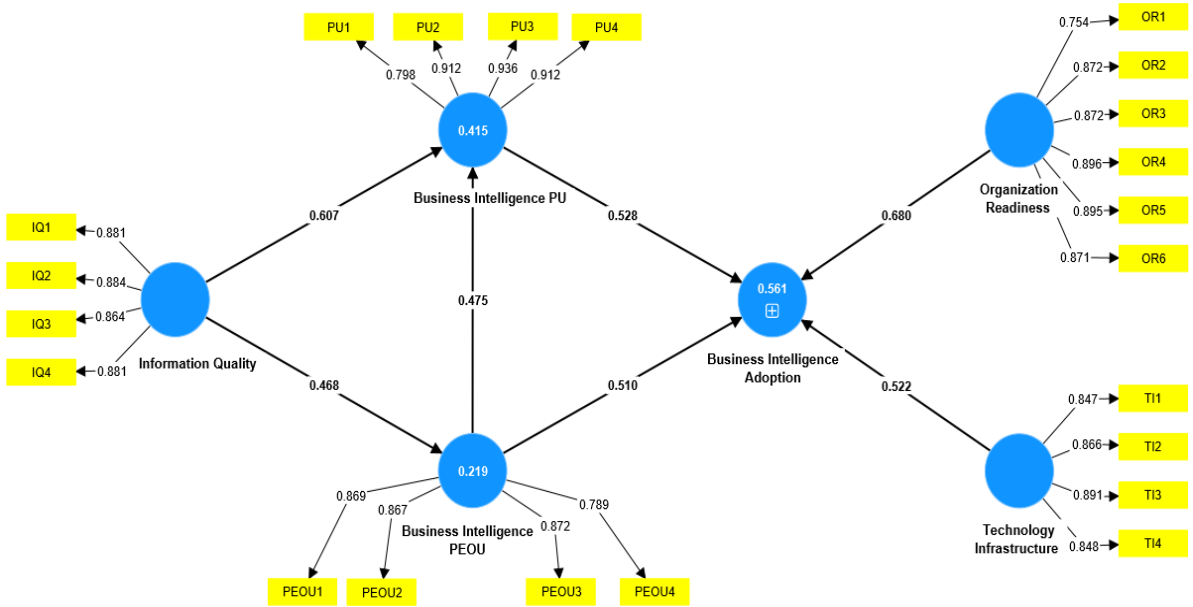

Figure 2: Measurement model

Table 4: Hypotheses Results

	Sample mean	T statistics	P values	Finding
Information Quality -> Perceived ease of use	0.469	7.813	0.000	Supported
Information Quality -> Perceived usefulness	0.492	9.562	0.000	Supported
Organization Readiness -> BI	0.474	8.234	0.000	Supported
Perceived ease of use -> BI	0.150	2.321	0.020	Supported
Perceived ease of use -> Perceived usefulness	0.243	4.613	0.000	Supported
Perceived usefulness -> BI	0.139	2.228	0.026	Supported
Technology Infrastructure -> BI	0.172	2.832	0.005	Supported

BI: Business Intelligence

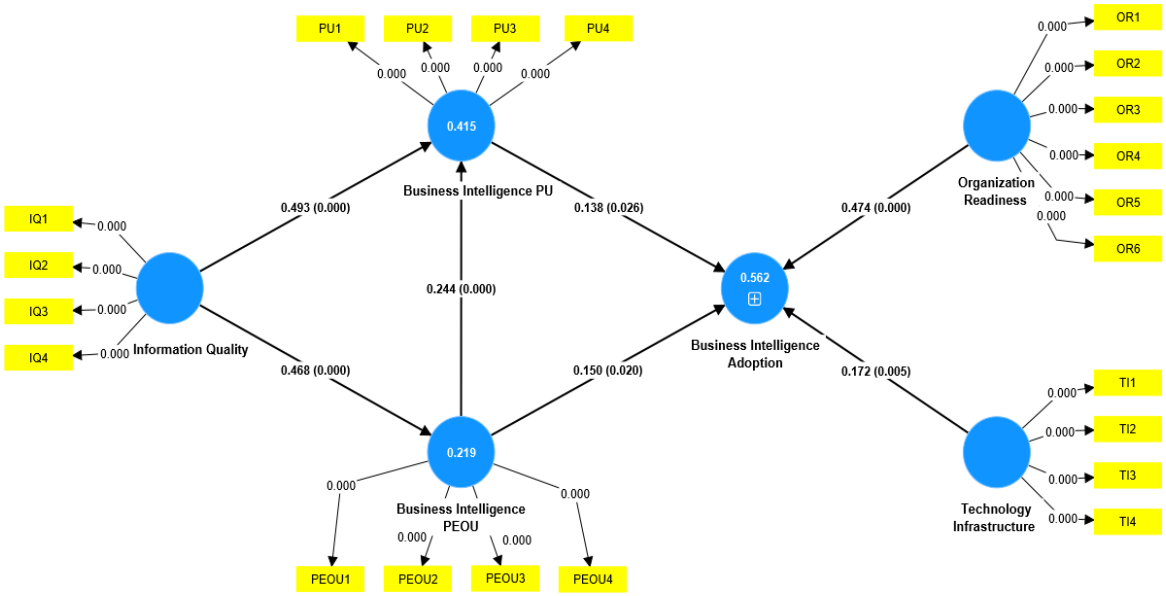

Figure 3: Structural Model

5. Discussion

Our study expands the Technology Acceptance Model (TAM) by integrating new variables such as Information Quality (IQ), Technology Infrastructure, and Organizational Readyness, providing valuable information on the factors driving the adoption of Business Intelligence (BI) among Iraqi SMEs.

5.1. Perceived Usefulness (PU) and Perceived Ease of Use (PEOU)

Consistent with previous research (Bach et al., 2022; Guo et al., 2021; Hou, 2016), our findings confirm a significant positive association between PU and BI adoption. This underscores the importance of end-user perceptions of the value of BI systems in influencing adoption decisions. Interestingly, while PEOU also showed a statistically significant impact on BI adoption, its effect was comparatively less pronounced than other factors. This suggests that while ease of use is important, other factors, such as utility and quality of information, may have a greater influence on BI adoption among Iraqi SMEs.

5.2. Relationship between PU and PEOU

Our results align with previous findings (Bach et al., 2022; Guo et al., 2021; Masa'Deh et al., 2021), indicating a significant link between PEOU and PU. This highlights the interaction between perceived ease of use and perceived usefulness, where a user-friendly interface enhances the perceived benefits of the BI system, thereby promoting its adoption.

5.3. Impact of Information Quality (IQ)

Consistent with previous research (Guo et al., 2021; Kohnke et al., 2011; Masa'Deh et al., 2021), our study reveals a significant influence of IQ on both PU and PEOU of the BI system. High-quality information, characterized by accuracy, completeness, and currency, enhances the perceived benefits and usability of the BI system. This underscores the importance of ensuring the quality of data inputted into BI systems to maximize their effectiveness.

5.4. Role of Technological Infrastructure

Our findings corroborate previous research (Bany Mohammad et al., 2022; Lateef & Keikhosrokiani, 2023), indicating a significant link between technological infrastructure and BI adoption. A well-developed technological

infrastructure is crucial in facilitating the adoption of BI among SMEs, highlighting the importance of strong IT resources and systems in enabling the deployment and use of BI technology.

5.5. Organizational Readiness (OR)

Our study identifies organizational readiness as a key driver of adoption of BI, consistent with previous research. Leadership support, corporate culture, and IT infrastructure play a pivotal role in fostering an environment conducive to BI adoption in SMEs. This emphasizes the multifaceted nature of BI adoption, where organizational factors interact with technological and user-related aspects to influence the effectiveness of the implementation.

5.6. Key Findings and Contributions

Overall, the study contributes to a better understanding of BI adoption in Iraqi SMEs by identifying critical factors such as perceived utility, ease of use, information quality, technological infrastructure, and organizational readiness. By integrating theoretical insights and empirical evidence, we highlight the complex interactions between these factors and emphasize their implications for practitioners and policymakers aiming to improve the adoption and efficacy of BI in Iraqi small businesses.

In summary, the study underscores the importance of considering a holistic approach to BI adoption, recognizing the interconnectedness of technological, organizational, and user-related aspects in shaping implementation outcomes within SMEs.

6. Conclusion and implications

In conclusion, this study offers a detailed exploration of the dynamics of business intelligence (BI) adoption within Iraqi SMEs. By extending the Technology Acceptance Model (TAM) and incorporating additional factors such as perceived usefulness (PU), perceived ease of use (PEOU), information quality (IQ), technology infrastructure and organizational readiness, we have gained a nuanced understanding of the multifaceted influences on BI adoption.

The methodological approach of the study, which includes a quantitative survey technique, selective sampling, and advanced statistical analysis using SMART PLS 4, has ensured the reliability and validity of our findings. The findings underscore the importance of perceived utility in driving the adoption of BI among Iraqi SMEs. In addition, the critical roles of information quality, organizational preparation, and technological infrastructure have been highlighted. The interplay of these factors underscores the complexities of decision-making processes and emphasizes the need for a holistic approach to the deployment of BI.

Importantly, our study reveals the relationship between perceived ease of use and perceived usefulness, highlighting the pivotal role of user experience in shaping the adoption of BI. These insights have practical implications for Iraqi SMEs, policymakers, and technology suppliers, offering actionable recommendations for fostering an environment conducive to BI adoption. Specifically, recognizing the importance of organizational preparedness, investing in robust IT infrastructure, and ensuring the availability of high-quality data are key strategies for facilitating successful BI integration within Iraqi SMEs.

In terms of contributions, our study advances the literature on the adoption of BI by providing empirical evidence and theoretical insights into the specific context of Iraqi SMEs. By addressing our research questions and elaborating on our findings within the theoretical framework, we have contributed to a deeper understanding of the factors that influence the adoption of BI and their implications for practice and policy. Overall, this study serves as a valuable resource for stakeholders seeking to improve BI adoption in Iraqi SMEs, offering practical guidance and theoretical insights to inform decision-making processes and improve organizational results.

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