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An Empirical Investigation of Business Intelligence Adoption in Jordanian Healthcare Organizations Using the TOE Framework

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Abstract

In response to the rising prominence of data-driven decision-making in healthcare, this study explores the critical determinants shaping the adoption of Business Intelligence (BI) systems within Jordanian healthcare organizations. Grounded in the Technology-Organization-Environment (TOE) framework, the research systematically investigates the interplay of technological, organizational, and environmental factors influencing BI adoption. Employing a quantitative approach, data were gathered from 256 IT professionals across public and private healthcare institutions in Jordan. The hypotheses were tested using partial least squares structural equation modeling (PLS-SEM), revealing that perceived usefulness, compatibility, relative advantage, top management support, and competitive pressure significantly drive BI adoption. In contrast, government support and organizational readiness exhibited no notable impact. The results underscore the pivotal role of internal capabilities and leadership commitment, while underscoring the limited influence of external institutional support in Jordan's healthcare context. By contextualizing BI adoption within a developing nation's healthcare sector, this study enriches the literature and offers actionable

recommendations for stakeholders aiming to optimize BI implementation strategies. Ultimately, these insights pave the way for enhancing healthcare delivery through robust, data-informed decision-making processes.

Keywords: Business Intelligence, Healthcare, TOE Framework, BI Adoption

Introduction

The contemporary healthcare sector stands at the intersection of rapid technological evolution and increasing demands for high-quality, efficient care delivery (Kesavan & Dy, 2020). As global health systems face mounting pressure to optimize resource allocation, improve service delivery, and enhance patient outcomes, the role of data-driven technologies has never been more critical (Miranda et al., 2024). Among these innovations, Business Intelligence (BI) has emerged as a vital enabler of evidence-based decision-making, offering healthcare institutions the tools necessary to transform complex datasets into actionable insights. The importance of this topic is underscored by the global shift toward digital transformation, where BI systems support strategic planning, operational efficiency, and clinical performance improvements (Qatawneh, 2024). Healthcare organizations generate vast amounts of data through clinical, administrative, and financial activities (Dash et al., 2019; Lv & Qiao, 2020). However, without effective tools to interpret and utilize this data, much of its value remains untapped. BI systems bridge this gap by integrating, analyzing, and visualizing disparate data sources to support real-time decision-making and long-term planning (Delen et al., 2018). Consequently, the adoption of BI in healthcare is not merely a technological upgrade; it is a strategic imperative to enhance institutional effectiveness, reduce costs, and elevate the quality of patient care (Alkhwaldi, 2024).

Contemporary healthcare presents an expanding arena for innovative technological advancements. The integration of new devices, methodologies, data analysis strategies, and other pioneering developments has bolstered sophisticated information technology and information systems (IT/IS), including technologies like Blockchain and Artificial Intelligence (AI). These advancements have significantly enhanced the provision of superior services essential to the well-being of individuals (Ali et al., 2023; Chatterjee et al., 2021; Javaid et al., 2021). Leveraging IT within the healthcare sector Possesses the capacity to improve operational effectiveness, leading to reduced costs and organizational transformation. This, in turn, may Enable the provision of cost-effective healthcare services to the community (Sutarno & Anam, 2022). In recent years, BI has emerged as the leading area for global business investment in IT (Bany Mohammad et al., 2022). In 1989, Howard Dresner, who would later become an analyst at Gartner Group, introduced the term "business intelligence" to describe concepts and methodologies aimed at improving business decision-making by leveraging evidence-based support systems. However, it was not until the late 1990s that this term gained widespread adoption (Elena, 2011; Hassan, 2019; Watson & Wixom, 2007). It is widely acknowledged that BI represents a modern decision support system that leverages sophisticated information technologies and methodologies (Qatawneh, 2024), It encompasses a robust, methodical capacity to acquire and analyze data, translating it into meaningful insights or understanding concerning possible opportunities and challenges, thereby delivering strategic approaches for optimizing business functions (Chen & Lin, 2021).

Despite the acknowledged potential of BI, its implementation in healthcare—especially in developing countries like Jordan—remains limited and under-explored (Alkhwaldi, 2024). This presents a significant research gap. Many healthcare institutions in Jordan struggle with resource constraints, fragmented IT infrastructure, and a lack of sector-specific frameworks to guide BI integration (Al-Dwairi et al., 2024; Jalghoum et al., 2021). Thus, the need to study BI adoption in this context is both timely and essential. It is crucial to understand the specific technological, organizational, and environmental factors that influence adoption decisions in Jordan's healthcare sector, where contextual variables differ significantly from those in developed nations.

Jaradat et al. (2022) argues that in the contemporary economic landscape, technological advancements and their practical implementation have the potential to consistently enhance and refine business processes. Nevertheless, earlier research suggests that only a select group of organizations successfully increase their profitability following the integration of cutting-edge information technologies and methodologies, like BI (Mikalef et al., 2018; Torres et al., 2018). In operational terms, BI integrates business analytics, graphical representation, data management tools and infrastructure, along with established best practices, to enable organizations to formulate decisions grounded in data-driven insights (Hosen et al., 2024). Debates between scholars and professionals regarding the strategic and operational methods for achieving effective uptake and utilization of BI systems have become a key driver of recent developments in BI research endeavors. However, relatively few published works have sought to examine these systems within the context of a particular field, such as healthcare. In the healthcare domain, BI can be defined by the employment of information and customized diagnostic instruments to enhance evidence-based decision-making procedures (Basile et al., 2023; Ramalingam et al., 2024). These systems consolidate data aggregated from various internal systems and external entities, providing stakeholders in the healthcare sector with essential informational platforms (Ramakrishnan et al., 2020). BI also supports the development of predictive models, improves communication between care teams and patients, and enables more accurate assessments of clinical and administrative performance (Huang et al., 2024).

This study is particularly beneficial for multiple stakeholders. Healthcare administrators and IT professionals can leverage the findings to guide investment decisions, prioritize integration strategies, and mitigate adoption challenges. Policymakers can also benefit by formulating supportive regulations and infrastructure investments that facilitate digital transformation in the health sector. Moreover, the academic community gains insights into how the TOE (Technology-Organization-Environment) framework can be applied and validated in the under-studied healthcare context of a developing country.

The healthcare sector is facing increasing pressure to strengthen its performance and continuously seek effective approaches for the efficient allocation and utilization of resources, while upholding a high standard of patient care (Ritika Goel et al., 2024). To achieve this, the role of IT and IS is vital in transforming data into valuable insights, which can then be applied to optimize process management, strengthen healthcare infrastructure, and enhance patient care (Klecun, 2016). A key characteristic of BI systems is their capacity to consolidate data aggregated from various internal systems and external entities, thereby providing stakeholders in the healthcare sector with essential informational platforms (Ramakrishnan et al., 2020). Moreover, these systems also support the development of prediction models for medication adherence, which can be integrated into clinical practice to enhance patient management and communication between care managers and patients (Huang et al., 2024). The implementation of BI in healthcare faces several challenges. A significant number of healthcare organizations have not yet adopted BI systems, primarily due to the absence of frameworks tailored specifically to the healthcare sector to facilitate the implementation process (Foshay & Kuziemsky, 2014).

BI is expanding rapidly on a global scale. Technological innovations, particularly in the realm of BI, have become essential for organizations to enhance their managerial approaches, outcomes, offerings, and service delivery due to the increasing competition from both traditional and digital industries (Hmoud et al., 2023). Recently, there has been growing interest among executives and decision-makers in BI systems, as they can improve the decision-making process by providing more insightful and data-driven information (Salisu et al., 2021)A report by Fortune Business Insights (2024)) forecasts that the global BI market will expand from USD 31.98 billion in 2024 to USD 63.76 billion by 2032, reflecting a compound annual growth rate of 9.0% throughout the projected period . Healthcare is a sector where BI holds significant potential, as it is one of the primary industries where technology can greatly influence decision-making processes and improve outcomes.

Although there has been a rise in investments, market growth, and notable advantages associated with the adoption of BI, research has highlighted that BI systems continue to face high failure incidences (S. Ahmad et al., 2021; Williams et al., 2024). Over 70% of BI projects fail to achieve the anticipated results or deliver only limited benefits to organizations (García & Pinzón, 2017). One major reason is the lack of understanding surrounding the factors that influence the acceptance and utilization of BI systems (Kašparová, 2023). Furthermore, organizations encounter challenges such as security concerns, lack of user readiness, and the absence of implementation frameworks tailored to the healthcare environment (Foshay et al., 2014; Marshall & De la Harpe, 2009; Papachristodoulou et al., 2017).

Therefore, this study aims to explore the determinants affecting the adoption of BI in Jordanian healthcare organizations using the TOE framework. By investigating how internal technological capabilities, organizational readiness, and external pressures shape BI implementation, the research contributes valuable evidence for theory and practice in the fields of healthcare informatics and technology adoption.

Literature Review

Business Intelligence Adoption

A BI system is typically regarded as a collection of technological tools (Bhatiasevi & Naglis, 2020) that enable organisations to collect, consolidate, and analyse large-scale data to gain insights into their opportunities, strengths, and areas for improvement (Nithya & Kiruthika, 2021). BI as an IS that enhances decision-making processes by i) facilitating the comprehensive collection, seamless integration, and efficient handling of both structured and unstructured data, ii) handling vast datasets (such as “Big Data”), iii) equipping end-users with advanced processing tools to uncover new insights (Wieder & Ossimitz, 2015), and iv) delivering analytical solutions, on-demand queries, comprehensive reporting, and predictive forecasting (Ain et al., 2019). BI is increasingly recognized as a strategic necessity for modern enterprises, offering critical insights and fresh perspectives that, when utilized quickly and effectively, can greatly improve business performance. BI can be defined as a comprehensive approach involving an integrated set of functions, procedures, and tools designed to collect, store, and examine, and disseminating data to support improved decision-making within an organization (Qatawneh, 2024). Therefore, employees within the organization are empowered to make informed decisions that are promptly executed and backed by a high degree of reliability (Alzghoul et al., 2024). Owing to its capacity to improve operational efficiency across a wide spectrum of organizations, BI has become a significant area of interest for academic researchers exploring its diverse applications. Additionally, leading companies across various industries have made substantial investments in BI (Djerdjouri, 2020).

Information Systems Adoption Theories, Models, and Frameworks

A review of previous studies clearly demonstrates that adoption models are being utilized from various perspectives to examine the factors that affect the intention to use technology (Gangwar & Date, 2016). Numerous theoretical frameworks and models have been developed to explore successful technology adoption pathways in businesses, with the specific focus of the research varying between an emphasis on the organization as a whole or the individual stakeholders involved. As a result, various researchers have investigated the adoption of technological innovations within organizations using the Technology-Organization-Environment (TOE) framework (e.g., Ahmad et al., 2021; Hmoud et al., 2023), Technology acceptance model (TAM) (i.e., Jalil et al., 2019; Kester & Preko, 2015), DOI (i.e., A. Ahmad et al., 2016; Zoubi et al., 2023), UTAUT (i.e., ARNET ZITHA, 2023), Theory of planned behavior (i.e., Yoon et al., 2014). Additionally, Almusallam et al. (2021)integrated the TOE and DOI frameworks to investigate the adoption of BI systems within Saudi's SMEs. The study revealed that complexity, relative advantage, observability, knowledge of IT, resource availability, personal innovativeness, and external support significantly influence the adoption of BI. In contrast, competitive pressure and compatibility were found to be insignificant factors in BI adoption. By using the TOE framework as the foundational theory, Bhatiasevi & Naglis, (2020) investigated the adoption of BI in small and medium enterprises (SMEs) in Thailand. Their study employed a mixed-methods approach, integrating a quantitative survey with expert interviews. The study found that top management support was the most influential factor in BI adoption among Thai SMEs, with compatibility, technological readiness, and competitive pressure also positively affecting adoption. BI adoption improved internal processes, learning, and growth, but had no significant impact on customer or financial performance. The adoption of BI has garnered significant attention across various sectors, including education (Hmoud et al., 2023; A. F. Yusof et al., 2015), finance (Jaradat et al., 2024; Nithya & Kiruthika, 2021), manufacturing (S. Ahmad et al., 2021; E. M. M. Yusof et al., 2019), and SMEs (Kalema & Carol, 2019; Owusu, 2020). Overall, the Diffusion of Innovation (DOI) theory (Rogers, 1995), the Technology Acceptance Model (TAM) (Davis, 1989), and the Technology-Organization-Environment (TOE) framework (Tornatzky & Fleischer, 1990), are primary theoretical perspectives that have been widely applied in prior information systems adoption research (Ain et al., 2019). To accomplish our objective, we draw upon theoretical concepts from one of these frameworks, which guide our understanding and influence the direction of the research. Based on this theory, we suggest that internal and external organizational factors, accessible technologies, and environmental influences are critical drivers of successful BI adoption in healthcare organizations in Jordan. In this context, we aim to comprehensively review and examine the factors that may obstruct the successful adoption of BI in healthcare organizations in Jordan. To achieve this, we utilize the Technology, Organization, and Environment (TOE) framework developed by Tornatzky and Fleischer (1990). The TOE framework was chosen because of its foundational philosophical principles. Additionally, this framework has been widely used to study the acceptance of various IT innovations, particularly at the organizational level. It offers a solid theoretical foundation, consistent empirical support, and potential applicability to IS innovation, despite the fact that specific factors within the three contexts may differ across studies.

Theoretical Background and Hypothesis Development

The TOE model addresses the issue of IT adoption through three distinct dimensions: technology, organization, and environment, as shown in **Figure 1**. A significant number of academic studies have been dedicated to exploring the influence of this framework and have provided validation for its role in shaping IT adoption. **Table 1** presents a selection of studies that have applied the TOE framework across various contexts of IT adoption.

Table 1
Studies utilizing the TOE framework in various fields of IT adoption

Authors	**context**
(Awa & Ojiabo, 2016)	ERP system
(Kumar & Krishnamoorthy, 2020)	Business Analytics (BA)
(Umam et al., 2020)	Mobile-based Smart Regency
(wael AL-khatib, 2023; J. Yang et al., 2024)	Artificial intelligence (AI)
(Aligarh et al., 2023; Skafi et al., 2020)	Cloud computing (CC)
(Bag et al., 2023; Chittipaka et al., 2023)	Blockchain (BC)
(Maroufkhani et al., 2023; Park & Kim, 2021)	Big data (BD)

Tornatzky and Fleischer (1990) suggest that the technological dimension encompasses both internal and external technologies relevant to the organization. Similarly, Tornatzky and Klein (1982) emphasized that the purpose of research on innovation characteristics is to examine the connections between the attributes of an innovation and the decision to adopt it.

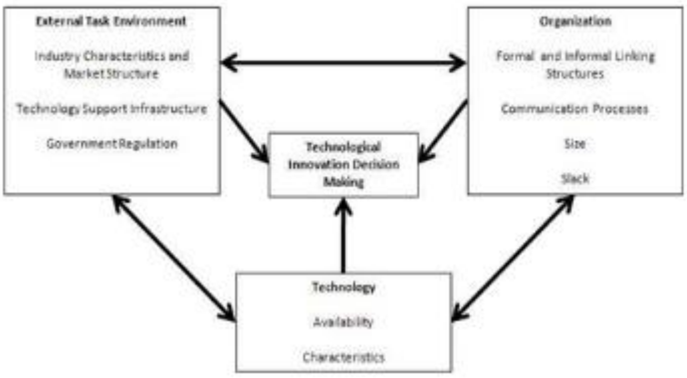

Figure 1. TOE framework (Tornatzky & Fleischer, 1990)

The technological context highlights the significance of technology availability in relation to the perceived benefits for the firm. Similarly, the organizational context addresses factors such as the firm's type, size, scope, managerial levels, and other relevant issues. Meanwhile, the environmental context refers to the external factors influencing the firm's operations, such as government agencies, industry regulations, and business competition (Mahakittikun et al., 2021; Skafi et al., 2020). Chatterjee et al. (2021) highlighted that the TOE framework offers a robust empirical and theoretical foundation, which has been validated by prior researchers for predicting and explaining technology adoption at the firm level. Additionally, Qatawneh et al. (2024) affirmed the framework's appropriateness for evaluating technological innovation. Tornatzky and Fleischer (1990) suggest that the technology dimension encompasses both the technologies and tools that are currently in use or accessible to the organization. The following sections outline the factors associated with each of the three primary constructs, along with the development of the hypotheses. **Figure 2** illustrates the suggested framework, which is composed of 7 distinct dimensions, outlined as follows:

Technological Context

Previous studies on IT adoption that applied the TOE framework in various contexts have shown that an organization's technological characteristics often explain the attributes of IT innovations that influence the adoption process (Ahmad Khan et al., 2024; Aligarh et al., 2023; Alkhalil et al., 2017; Cruz-Jesus et al., 2019).This study focuses on three innovation characteristics in the context of BI adoption by healthcare organizations: compatibility, perceived usefulness, and relative advantage.

Compatibility

Compatibility plays a crucial role in the adoption of BI systems, referring to how well the BI system aligns with an organization’s existing infrastructure, technologies, tools, and business practices (D Macredie & Mijinyawa, 2011). It involves the smooth integration of the BI system into the organization's current technological setup (Bhatiasevi & Naglis, 2020). The significance of compatibility in BI adoption is substantial, as it directly affects the likelihood of an organization adopting a BI system (Stjepić et al., 2021). A higher degree of compatibility with the organization's infrastructure, technologies, tools, values, and procedures enhances the chances of successful adoption. In contrast, perceived incompatibility may result in the rejection of the BI system (Stjepić et al., 2021). Many studies highlight the importance of compatibility as a key factor in the adoption of BI (S. Ahmad et al., 2021; Hmoud et al., 2023; Stjepić et al., 2021). Organizations are more likely to adopt BI when it aligns with their existing technological infrastructure, capabilities, values, organizational culture, and work practices (S. Ahmad et al., 2021). Conversely, incompatibility can act as a barrier to adoption (Bhatiasevi & Naglis, 2020). Thus, this study suggests:
***H1**: Compatibility positively influences the adoption of BI.*

Perceived Usefulness

Perceived usefulness (PU) is the personal conviction of prospective users that implementing a particular system or application will enhance their efficiency within the organization’s environment (Davis, 1989). Ajzen (1991) argued that users are more likely to develop an intention to use a particular technology when they perceive it as beneficial and valuable. PU includes subjective norms, image, work relevance, output quality, and outcome demonstrability (Venkatesh & Bala, 2008). Individuals assess a system's utility by comparing its features to their job tasks (Venkatesh & Davis, 2000), meaning a perceived sense of usefulness fosters the intention to adopt new technology. Thus, this study suggests:
***H2**: Perceived usefulness has a significant positive impact on the intention to adopt BI.*

Relative Advantage

According to Rogers (2003), certain attributes of an innovation can impact the likelihood of its adoption. One such attribute is relative advantage, which reflects the extent to which an innovation is perceived as superior to existing alternatives, particularly in terms of benefits such as economic gains and social status (Gangwar et al., 2015). Within the TOE framework, relative advantage plays a pivotal role in analyzing how new technologies or innovations are adopted (Awa & Ojiabo, 2016). Thus, this study suggests:

H3: *Relative advantage positively influences the adoption of BI.*

Organisational Context

In the TOE framework, the Organizational Context is a key factor in understanding how a company's internal characteristics affect its adoption of technological innovations. This includes elements such as organizational size and structure, which influence resource allocation and decision-making approaches (Nguyen et al., 2022).

Top Management Support

Top management support refers to the extent to which senior executives advocate for and facilitate the integration of new technologies for business operations (Grover & Goslar, 1993). In the context of BI adoption, it specifically relates to how actively senior leadership recognizes the significance of IS and the extent of their engagement in IS-related initiatives (Salisu et al., 2021). The support of senior leadership is crucial for maintaining and enhancing the necessary tools for adopting new technologies. Since the successful implementation of innovation depends on resource allocation and the restructuring of business processes, top management plays a pivotal role in driving these changes (Abdallah Moflih et al., 2020). Thus, we suggest:

H4*: Top management support positively influences the adoption of BI.*

Organizational readiness

Organizational readiness, as a unique characteristic of a business, plays a crucial role in determining whether a new innovation will be adopted. Additionally, successful adoption depends on the organization's proficiency in information technology, including the necessary knowledge and skills (Xie et al., 2023). Iacovou et al. (1995) stated that a business's willingness to embrace technological innovation is primarily influenced by its level of preparedness, which encompasses both financial capacity and technological infrastructure. Based on the proceeding discussion, this study suggests:

H5*: Organizational readiness has a significant positive impact on the intention to adopt BI.*

Environmental Context

Competitive Pressure

Competitive pressure refers to the extent to which an organization responds to challenges posed by its competitors (ELDALABEEH et al., 2021). To sustain a strategic advantage in the market, businesses must adopt emerging technologies. Essentially, competitive pressure reflects how a company reacts to industry demands and the influence exerted by its rivals (George et al., 2020). Therefore, this study suggests:

H6: Competitive pressure *has a significant positive impact on the intention to adopt BI.*

Government Support

Government support serves as both an initiative and an opportunity aimed at promoting adoption (R. Yang et al., 2021). Research suggests that policymakers can facilitate the adoption of BI by establishing favorable corporate tax policies and financial incentives (Asongu & Biekpe, 2017). Additionally, it can be inferred that government funding acts as a strategic tool that influences businesses' willingness to embrace innovation (Chaveesuk & Horkondee, 2015). Thus, we suggest:

***H7**: Government support has a significant positive impact on the intention to adopt BI.*

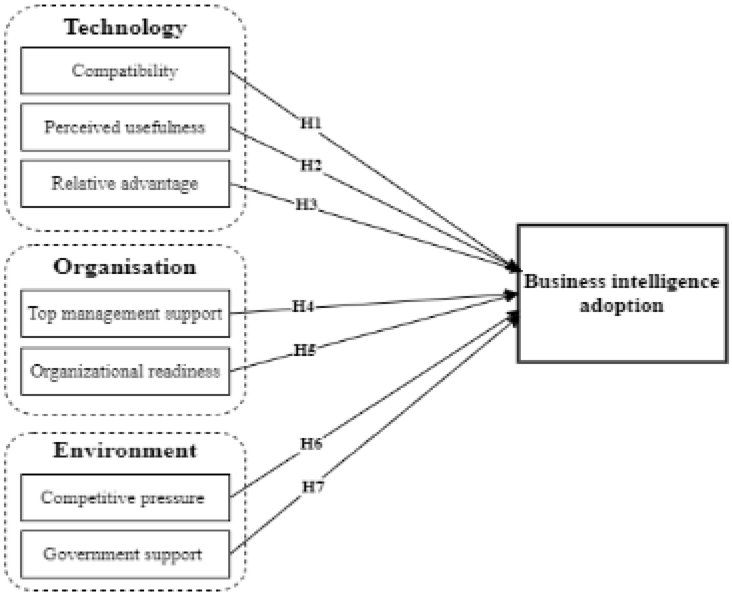

Figure 2. The research proposed model

Methodology

This research adopts a quantitative approach to evaluate the hypotheses established during the initial stage. By applying statistical analysis, the study seeks to explore the relationships among the variables (Sekaran & Bougie, 2016). The data was collected through an online survey created with Google Forms and circulated across multiple social media channels to connect with participants, targeting IT professionals in the healthcare organizations in Jordan who actively engage with BI systems. Lacking a complete directory of healthcare organizations in Jordan, the study relied on convenience sampling to meet its research objectives. The process of gathering and refining the data took place from January 15 to March 16, 2025. While 270 responses were initially received, only 256 were considered suitable for analysis after review. This study's constructs were derived from the extended TOE framework, which encompasses three key dimensions: technology, organization, and environment. To measure each construct, multiple indicators were adapted from established literature, as shown in **Table 3**. These items were then tailored to fit the healthcare sector in Jordan, with translations conducted between English and Arabic to ensure linguistic accuracy and contextual relevance. SPSS is employed to verify the authenticity and reliability of the data while also generating a profile of respondents. The data is categorized based on various demographic factors, including participants' gender, age, education level, organizational role, and years of experience. Meanwhile, SmartPLS is utilized to examine the relationships between hypotheses concerning healthcare BI adoption in Jordan. At this stage, an internal model analysis is conducted, incorporating a path coefficient test, determinant coefficient (R^2), t-test, effect size (f^2), and predictive relevance (Q^2) through the blindfolding technique.

Table 2
Demographic information

Demographic Variables		**Frequency**	**%**
Gender	Male	172	67.2
	Female	84	32.8
Age	18-29	68	26.6
	30-39	104	40.6
	40-49	60	23.4
	> 50	24	9.4
Type of healthcare institution	Public	154	60.2
	Private	102	39.8
Job title	Staff Member	106	41.4
	Team Leader	64	25
	Manager	54	21.1
	IT director	32	12.5
Experience	< 5 years	72	28.1
	5-9 years	96	37.5
	10-15 years	58	22.7
	> 15 years	30	11.7

Table 3
Measurement Items

Measurement dimension	**Code**	**Items**	**References**
Compatibility	CO1	The BI system aligns effectively with the established practices within our organization.	(Qatawneh, 2024; Stjepić et al., 2021)
	CO2	The BI system integrates smoothly with our current IT infrastructure	
	CO3	The BI system can be incorporated with minimal adjustments to our existing systems.	
	CO4	The BI system aligns closely with our organization's existing values and strategic objectives.	
Perceived usefulness	PU1	Employing BI facilitates improved handling and examination of data, leading to more informed decision-making processes.	(Chatterjee et al., 2021; Davis & Venkatesh, 1996)
	PU2	BI facilitates improved teamwork and synchronization when overseeing geographically dispersed activities within our organization.	
	PU3	Implementing BI solutions enhances the effectiveness and efficiency of organisational processes.	
	PU4	Implementing BI has helped our organization lower operational costs.	
Relative advantage	RA1	The BI system has the potential to enhance operational effectiveness.	(Jaradat et al., 2024; Njenga et al., 2019)
	RA2	The implementation of the BI system enables organisations to discover novel pathways for innovation and organizational development.	

	RA3	The BI system could improve the overall performance of our organization.	
	RA4	The BI system equips our organization with prompt and insightful data, enabling informed decision-making processes.	
Top management support	TMS1	Senior management plays a key role in developing the organizational vision and crafting strategies regarding the implementation of BI systems.	(Alharbi et al., 2016; Gangwar et al., 2015)
	TMS2	The leadership team within our organization actively promotes the integration of BI, aligning it with our long-term strategic objectives.	
	TMS3	Senior management is responsible for allocating essential resources to facilitate the implementation of BI.	
	TMS4	Senior management plays a significant role in making decisions regarding IT and IS projects.	
Organizational readiness	OR1	Insufficient funding will hinder our organization's capacity to integrate BI systems.	(Njenga et al., 2019; Popovič et al., 2019)
	OR2	A lack of essential technological infrastructure limits our ability to adopt BI solutions.	
	OR3	The shortage of skilled personnel poses a significant barrier to implementing BI systems within our institution.	
	OR4	Our organization's mission, vision, and core values are strongly aligned with adopting BI technologies into our operational practices.	
Competitive pressure	CP1	Adopting a BI system is crucial for maintaining competitiveness within the industry.	(Gangwar et al., 2015; Gutierrez et al., 2015)
	CP2	Our decision to implement BI solutions is highly influenced by observing our competitors' actions.	
	CP3	We are aware that our competitors have already integrated BI systems into their operations.	
	CP4	We clearly recognize the competitive advantages associated with implementing BI in our organization.	
Government support	GS1	Government initiatives actively promote the integration of BI technologies.	(Ali & Osmanaj, 2020)
	GS2	Existing legislation by the government adequately safeguards the utilization of BI systems.	
	GS3	Clear governmental guidelines outline responsibilities concerning data ownership and privacy issues related to BI.	
	GS4	Improved regulatory measures from the government can facilitate smoother adoption processes for BI solutions.	

Data Analysis and Results

PLS-SEM 4 was utilized to analyze the relationships within the conceptual model. This method is distinct in assessing the connections between exogenous and endogenous variables, as well as forecasting the correlation strength between exogenous and endogenous variables, thus allowing for the testing of research hypotheses (Qatawneh, 2024). The evaluation of PLS-SEM generally follows a two-step approach, which includes distinct assessments of the measurement models and the structural model. For the reflective measurement model, it is important to assess indicator reliability, internal consistency reliability, convergent validity, and discriminant validity during the evaluation process (Hair et al., 2019). The first stage involves estimating the associations between reflective latent constructs and their respective indicators, commonly referred to as outer loadings. A threshold value above 0.700 is generally advised to ensure acceptable indicator reliability (Hair et al., 2019), indicating that the construct explains over half of the variance in the indicators. As presented in **Figure 3**, all outer loadings exceed 0.700, except for three indicators (RA1, RA2, and GR2). In accordance with the recommendations outlined in prior research (Liang et al., 2021), removing these indicators is unnecessary, as the deletion would reduce the average variance extracted (AVE), and composite reliability (CR), And could compromise the content validity of the construct. Hence, the indicators are considered to exhibit acceptable reliability.

The assessment of internal consistency was conducted through Cronbach's alpha (CA) and CR metrics, with their values reported in **demonstrates** that all AVE values surpass the 0.5 threshold, thereby confirming strong convergent validity.

Table 4, both CA and CR values for all constructs exceed the threshold of 0.700, indicating excellent reliability of the measurement (Hair et al., 2020).
Convergent validity, which refers to how well a construct converges to explain the variance of its items (Katebi et al., 2022), is assessed using the average variance extracted (AVE) (Fornell & Larcker, 1981). An AVE value greater than 0.5 is recommended as it Offers empirical support for convergent validity, indicating that the construct accounts for a minimum of 50% of the variance in its associated indicators. **demonstrates** that all AVE values surpass the 0.5 threshold, thereby confirming strong convergent validity.

Table 4 demonstrates that all AVE values surpass the 0.5 threshold, thereby confirming strong convergent validity.

Table 4
Reliability and Convergent Validity

Construct	Cronbach's alpha	CR	AVE
Business Intelligence Adoption	0.871	0.914	0.727
Compatibility	0.930	0.950	0.825
Competitive Pressure	0.932	0.951	0.829
Government Regulations	0.799	0.868	0.624
Organizational Readiness	0.911	0.937	0.788
Perceived Usefulness	0.933	0.951	0.831
Relative Advantage	0.741	0.821	0.547
Top Management support	0.933	0.952	0.833

Discriminant validity reflects the extent to which a construct is empirically distinguishable from other related constructs. To evaluate discriminant validity, the Fornell–Larcker criterion is employed, stipulating that the square root of each construct's Average Variance Extracted (AVE) must exceed its correlations with other constructs (Hair et al., 2020). As displayed in

Table 5, the discriminant validity for all constructs is verified.

Table 5
Discriminant Validity (Fornell-Larcker Criteria)

Construct	**BIA**	**CO**	**CP**	**GS**	**OR**	**PU**	**RA**	**TMS**
BIA	**0.853**							
CO	0.563	**0.908**						
CP	0.617	0.684	**0.910**					
GS	0.656	0.536	0.467	**0.790**				
OR	0.557	0.497	0.606	0.475	**0.887**			
PU	0.559	0.143	0.177	0.356	0.345	**0.911**		
RA	0.421	0.157	0.234	0.510	0.175	0.236	**0.739**	
TMS	0.751	0.332	0.436	0.545	0.428	0.527	0.305	**0.913**

Once the measurement model is confirmed, the subsequent phase involves evaluating the structural model. This assessment is substantiated by analyzing the coefficient of determination (R^2), predictive relevance (Stone–Geisser's Q^2) (Stone–Geisser's Q^2) (Sarstedt et al., 2014), the statistical significance and magnitude of the path coefficients, and the effect sizes (f^2). During this stage, the hypotheses are examined to determine their consistency with the relationships posited in the proposed framework.

The path coefficients in the structural model, which reflect the associations among the constructs, are obtained through the estimation of multiple regression equations. Before evaluating structural relationships, multicollinearity must be checked to ensure it does not distort the regression results. Multicollinearity is assessed using the variance inflation factor (VIF). As shown in **Table 6**, all VIF values are less than the recommended value of 3, indicating that multicollinearity is not a concern.

Table 6
Multicollinearity Test

Construct	VIF Value
BIA	--
Compatibility	2.232
Competitive Pressure	2.465
Government Regulations	2.327
Organizational Readiness	1.845
Perceived Usefulness	1.487
Relative Advantage	1.424
Top Management support	1.881

The statistical significance of the parameter estimates was evaluated using a bootstrapping technique involving 5,000 resamples. The structural model results, depicted in **Figure 3**, display the explained variance for the endogenous constructs (R^2) alongside the standardized path coefficients (β).

As shown in **Figure 3**, compatibility (β= 0.184, p <0.01), perceived usefulness (β= 0.0.217, p <0.01), relative advantage (β= 0.121, p <0.01), top management support (β= 0.384, p <0.01), competitive pressure (β= 0.180, p <0.01) have significant effect on BIA in health organizations in Jordan. Thus, hypotheses (H1, H2, H3, H4, H7) are supported. In contrast, the results indicated that organizational readiness (β= 0.047, p > 0.05) and government support (β= 0.103, p > 0.05) indicating that hypotheses H5 and H6 are not supported. **Presents an** overview of the hypothesis testing outcomes.

Table 7 Presents an overview of the hypothesis testing outcomes.

Table 7
Path coefficient and t-statistics

Hypothesis	Path	β	T value	P value	Result
H1	Compatibility -> BIA	0.184	3.973	0.000	Supported
H2	Perceived Usefulness -> BIA	0.217	5.647	0.000	Supported
H3	Relative Advantage -> BIA	0.121	2.613	0.009	Supported
H4	Top Management support -> BIA	0.384	6.139	0.000	Supported
H5	Organizational Readiness -> BIA	0.047	1.150	0.250	Not supported
H6	Government Support -> BIA	0.103	1.775	0.076	Not supported
H7	Competitive Pressure -> BIA	0.180	3.230	0.001	Supported

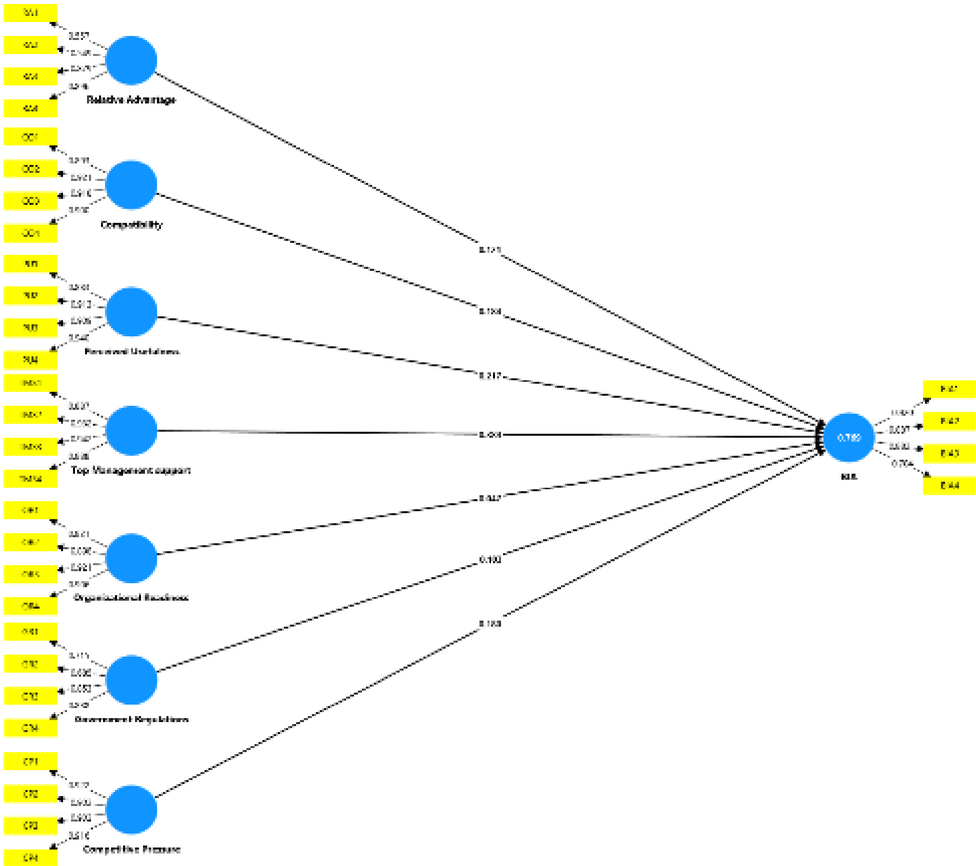

Figure 3. Estimated relationships of the structural model

The R^2 value is the most used criterion to evaluate the structural model, as it assesses the goodness of fit in regression analysis. The coefficient of determination (R^2) is commonly used to assess the explanatory capability of a model and is indicative of its in-sample predictive strength. According to established benchmarks, R^2 values of 0.75, 0.50, and 0.25 are interpreted as substantial, moderate, and weak levels of explanation, respectively. As illustrated in **Figure 3**, the proposed model accounts for 76.9% of the variance in Business Intelligence adoption, reflecting a high level of explanatory power.

Beyond examining the R^2 values of all endogenous constructs, the model's evaluation also includes the effect size (f^2). This metric assesses the extent to which excluding a particular predictor variable alters the R^2 of a dependent construct, thereby indicating the influence of an exogenous variable on the explained variance of the endogenous construct. According to guidelines, f^2 values higher than 0.02, 0.15, and 0.35 indicate small, medium, and large effect sizes, respectively (Mikalef et al., 2020). The f^2 effect sizes for the exogenous constructs are presented in **Table 8**. Compatibility (0.066), competitive pressure (0.057), government support (0.020), perceived usefulness (0.137), and relative advantage (0.045) demonstrate a small effect size, while top management support (0.34) shows a medium effect on BI adoption. Organizational readiness (0.005) has no effect on BI adoption. addition to relying on R^2 values to evaluate predictive accuracy, it is also essential to examine the structural model's predictive relevance. This is assessed using the Q^2 statistic, which estimates the model's out-of-sample predictive capability through the blindfolding technique—a resampling method. According to established guidelines, Q^2 values above 0, 0.25, and 0.50 reflect small, medium, and large levels of predictive relevance, respectively. As indicated in

Table 8, the Q^2 value for Business Intelligence (BI) adoption is 0.550, suggesting that the exogenous constructs demonstrate a moderate level of predictive relevance for the dependent construct.

Table 8
Predictive relevance results for endogenous constructs

Construct	**R^2**	**f^2**	**Explanatory power**	**Q^2**
Compatibility		0.066	Small	
Competitive Pressure		0.057	Small	
Government Support		0.020	Small	
Organizational Readiness		0.005	No Effect	
Perceived Usefulness		0.137	Small	
Relative Advantage		0.045	Small	
Top Management support		0.340	Medium	
BI Adoption	0.769			0.550

Discussion

This study focused on identifying the factors inspiring the adoption of business intelligence systems in healthcare organizations in Jordan based on the TOE framework. The findings have also been able to unearth significant and worthwhile relationships that make meaning in the emerging basket of knowledge regarding BI adoption, especially in an under-explored healthcare context, particularly in developing countries.

Technological Context

Among the technological factors, perceived usefulness, compatibility, and relative advantage were found to significantly influence BI adoption. The strong support for perceived usefulness aligns with prior studies (e.g., Chatterjee et al., 2021; Davis, 1989), confirming that healthcare professionals are more likely to adopt BI systems when they perceive clear benefits in terms of operational efficiency, cost reduction, and improved decision-making. This reflects the practical utility of BI tools in managing large volumes of healthcare data and supporting evidence-based practices. Similarly, the significance of compatibility echoes findings by Bhatiasevi and Naglis (2020)and Stjepić et al. (2021), which highlight the importance of alignment between existing infrastructure and new technologies. In a healthcare setting where legacy systems and data security are critical concerns, seamless integration is vital. Relative advantage, although statistically significant with a smaller effect size, still underscores the importance of perceived benefits over current methods as a driver of innovation acceptance (Rogers, 2003).

Organizational Context

The most influential factor in the study was top management support, reinforcing its central role as identified in earlier literature (e.g., Gangwar et al., 2015; Salisu et al., 2021). Senior leadership's commitment to BI adoption, resource allocation, and strategic alignment is a strong predictor of successful implementation. This finding is particularly pertinent in hierarchical healthcare organizations, where decision-making often cascades from the top. Contrary to expectations, organizational readiness did not have a significant influence on BI adoption. While earlier research (e.g., Iacovou et al., 1995; Xie et al., 2023) emphasized the role of financial and technical preparedness, its insignificance in this study may suggest that many Jordanian healthcare institutions either overestimate their preparedness or lack awareness of the resources truly required for BI implementation. Alternatively, this result may reflect a broader organizational inertia or limited technical capacity that is not captured adequately through self-reporting.

Environmental Context
Competitive pressure emerged as a significant driver, consistent with findings from Gangwar et al. (2015) and Gutierrez et al. (2015). The growing demand for digital transformation and improved patient services appears to push organizations to adopt BI as a competitive necessity, particularly in the private healthcare sector. Surprisingly, government support did not have a statistically significant impact on BI adoption. This diverges from prior studies (e.g., Ali and Osmanaj, 2020; Asongu and Biekpe, 2017), which emphasized the importance of regulatory frameworks, funding, and policy incentives. In the Jordanian context, this may reflect a gap between governmental intentions and their practical implementation, or possibly a lack of tailored support mechanisms for BI acceptance in the healthcare sector.

Theoretical and Practical Implications
Theoretically, the study contributes by extending the TOE framework by empirically testing its constructs in a new and highly pertinent setting—healthcare in an emerging nation. This demonstrates the framework's strength and flexibility, while also revealing context-specific nuances, particularly regarding organizational readiness and external support. Practically, the findings suggest that healthcare organizations aiming to adopt BI should prioritize enhancing leadership engagement, improving system compatibility, and clearly communicating the benefits of BI to potential users. Policymakers and stakeholders should also recognize the critical role of strategic alignment and the need for a more supportive governmental role in facilitating digital transformation in healthcare.

Summary
In conclusion, the research validates that BI adoption in Jordanian healthcare organizations is strongly driven by internal technological and organizational forces, and external environmental forces have mixed impacts. The results provide a clearer image of facilitators and inhibitors of BI adoption in healthcare and can be used as a strategic guidebook for stakeholders seeking to harness the power of BI to enhance healthcare delivery.

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