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Examining the Drivers and Performance Impact of Business Intelligence Adoption in Healthcare Organizations: Evidence from Jordan

Maryam Alzawahra[1], Shihadeh Alqrainy[2]

[1] Department of Software Engineering, Hashemite University, Jordan

[2] Faculty of Artificial Intelligence, Al-Balqa Applied University, Jordan

Maryam_alz@hu.edu.jo, alqrainy@bau.edu.jo

Abstract. This study examined factors influencing business intelligence (BI) adoption and its impacts on performance in Jordanian healthcare organizations. A survey of 303 healthcare providers assessed seven hypotheses related to technological, organizational, and environmental determinants of BI adoption, grounded in the TOE framework and resource-based view theory. Structural equation modelling revealed significant positive effects of relative advantage, cost-effectiveness, organizational readiness, and competitive pressure on BI adoption. However, top management support and government regulations were non-significant. Additionally, BI adoption had a significant positive impact on healthcare providers' performance. The findings provide insights on leveraging BI strategies in healthcare, with implications for practitioners, system vendors, and policymakers in Jordan.

Keywords: business intelligence, healthcare performance, adoption, antecedents.

1. Introduction

A business intelligence (BI) system is a technology, application, or practice for collecting, integrating, analyzing, and presenting enterprise data (Olszak & Batko, 2012). It is designed to help businesses make better and faster decisions and improve business operations. Organizations must capture, understand, and harness data to support decision-making and streamline operations. Owing to the constantly evolving business world, many firms are now under increasing pressure to develop and ramp up their BI (Balachandran & Prasad, 2017). For example, Llave (2017) claimed that finding a thriving organization without BI technology is virtually impossible. The increasing importance of data use for effective decision-making is driving companies to discuss ideal ways to leverage data for better decision-making. BI provides decision-makers with information and expertise in new ways to allow them to make quality decisions and support broader business decisions throughout the organization (Nithya & Kiruthika, 2021). The escalating relevance of data in decision-making is compelling organizations across various sectors, including healthcare, to deliberate optimal strategies for leveraging data.

The healthcare sector, in particular, is facing a rising demand for BI adoption as providers aim to leverage data analytics to enhance quality and efficiency (Ramakrishnan et al., 2020). However, BI acceptance varies across countries. Adopting BI in Jordan's healthcare industry can enhance decision-making procedures and offer insightful data. However, there is a dearth of studies concentrating on the critical factors facilitating the effective implementation of business BI in developing nations, such as Jordan, and there are few studies on BI implementation in this sector (Jaradat et al., 2022; Salisu et al., 2021b). This highlights the need to examine the determinants of BI adoption, specifically in the Jordanian healthcare system.

While prior studies have applied the TOE framework and RBV theory to examine BI adoption across sectors (Kumar & Krishnamoorthy, 2020; Pillai et al., 2022; Salisu et al., 2021b), the theoretical understanding of the determinants and performance implications, specifically within healthcare, remain underexplored. Furthermore, the factors driving BI acceptance differ between developed countries, where most studies have been conducted, and developing nations, such as Jordan (Salisu et al., 2021b). This study addresses these gaps by empirically investigating the technological, organizational, and environmental predictors of BI adoption in Jordanian healthcare organizations using the TOE framework (Tornatzky & Fleischer, 1990). The performance impacts are evaluated through the RBV lens (Barney, 1991), assessing BI's role as a strategic resource for competitive advantage. The findings will provide novel theoretical insights into the factors of BI acceptance and its business value for healthcare providers in emerging economic environments.

The Jordanian healthcare sector represents an essential context for this study. Healthcare accounts for over 8% of the national GDP; however, the system faces sustainability challenges amidst population growth, increased chronic illnesses, and public spending constraints (Hammad et al., 2022). As healthcare providers aim to enhance quality while controlling costs, understanding BI's role of BI is salient. Thus, this study investigates the factors influencing BI adoption in Jordanian healthcare organizations and evaluates their impact on provider performance outcomes. The following research questions were addressed:

RQ1: How do technological, organizational, and environmental factors influence BI adoption in Jordanian healthcare?

RQ2: Does BI adoption significantly improve healthcare providers' performance in Jordan?

2. Business Intelligence Adoption

In the previous literature, BI adoption has been categorized into three main themes: its role in healthcare, its determinants of adoption, and its impact on organizational performance.

With regard to its role in the healthcare sector, healthcare is one of the domains where the adoption of BI aims to use data analytics to improve efficiency, quality, and decision-making in healthcare (Mettler & Vimarlund, 2009; Zheng et al., 2018). Despite this, the assimilation of BI has been a gradual process and has varied across different contexts (Foshay & Kuziemsky, 2014). For example, Western European countries have shown widespread implementation of the system, but developing countries like Jordan have shown a lower uptake (Jaradat et al., 2022; Salisu et al., 2021b). The disparities between BI acceptance rates in the Middle East and those in other parts of the world emphasize the need for research into BI acceptance drivers, particularly in understudied regions.

Furthermore, studies have examined the technological, organizational, and environmental factors influencing BI adoption across various sectors. For instance, some studies have advocated that cost-benefit analysis and relative advantage analysis are two of the proposed technological drivers (Llave, 2017; Puklavec et al., 2018a), while several organizational determinants contribute to an organizational adoption, including top management support, organizational readiness, and information culture (Hmoud et al., 2023). In addition to competitive pressure, economic factors also influence environmental factors (Ahmad et al., 2020). However, there is limited empirical evidence in healthcare settings due to the nuances between industries (Salisu et al., 2021b).

Lastly, regarding its impact on performance, BI has been connected to a number of healthcare improvements, including increased satisfaction among patients, efficiency, and clinical quality (Ali et al., 2018; Foshay & Kuziemsky, 2014; Lateef & Keikhosrokiani, 2022). Nevertheless, the extant literature lacks a comprehensive assessment of its business value, particularly for healthcare providers utilising reliable and data-driven approaches.

In conclusion, most prior studies have concentrated on the benefits of BI and the variables driving its adoption in developed Western nations, with limited empirical evidence available from developing countries. As such, research is needed to understand better how performance outcomes and organisational, technological, and environmental factors interact in developing countries' healthcare systems, which have not received much attention in the literature. This leads to the following research questions for this study: How do technological, organizational, and environmental factors influence BI adoption in Jordanian healthcare? Does BI adoption significantly improve healthcare providers' performance in Jordan?

3. Underpinning Theories

This study adopted two theories to build our model: the TOE framework and the RBV theory. Technology, Organization, and Environment (TOE) is a framework developed by Tornatzky et al. (1990). The theory explains the elements that influence the adoption of new technologies. Tornatzky et al. (1990) emphasize the impact of technology context, organizational context, and environmental context on how a company absorbs and implements technological breakthroughs.

In the TOE framework, three context groups are identified as potentially affecting the organizational adoption of an invention (technological, organizational, and environmental). To examine the adoption of many types of innovations, the TOE framework was first proposed in IT adoption research (Iacovou et al., 1995; Lin & Lin, 2008). Despite the varying elements found within each of the three contexts (Oliveira & Martins, 2011), The TOE framework is used in several studies in the BI field, and healthcare is one of those sectors (Kitsios & Kapetaneas, 2022; Pool et al., 2018; Salisu et al., 2021a). Moreover, TOE has been used in both developing and developed countries (Owusu, Ghanbari-Baghestan et al., 2017; Salisu et al., 2021a). Overall, the TOE framework successfully explains what determines adopting new technologies. In this study, the technological context refers to characteristics of the technology itself, like perceived benefits and complexity. Organizational context includes resources, top management support, and IT capabilities. Environmental context comprises industry competition, regulatory policies, and external organisational pressures. Prior studies have applied TOE to identify drivers of BI adoption across sectors, including healthcare (Kitsios & Kapetaneas, 2022). This highlights TOE's utility for understanding multi-level influences on BI adoption.

The resource-based view (RBV) refers to assessing the strategic resources that an organization can leverage to gain a competitive advantage and ensure commercial value (Priem & Butler, 2001). Under RBV, we explore adopting BI applications and their impact on organizational performance. Its structure is based on increasing organizational performance through improved resource utilization to generate competitive advantages (Chatterjee et al., 2021; Delen & Zolbanin, 2018). The success of an organization is determined by its ability to gather and deploy resources efficiently (Peppard & Ward, 2016). The most critical resource for improving company operations should be viewed in the context of BI adoption. As previously stated, the acquisition of data and tools are both crucial to the success of a BI solution that adds value to the business (Wamba et al., 2017). Under RBV, BI applications represent a vital capability for healthcare providers to enhance data-driven decision-making and performance (Ashaari et al., 2021). As such, investing in BI as a resource supports core competencies like data analysis, enabling healthcare organizations to extract greater value and insights from information.

Together, the TOE framework and RBV provide complementary lenses for examining drivers of BI adoption as well as its business value as a strategic resource for performance gains. The TOE framework and RBV theory are integrated in this study in a way that is not just a parallel application but rather a synergistic conjunction whereby TOE finds the contexts and conditions that are conducive to innovation adoption, and RBV assesses how these innovations, when viewed as strategic resources, can be used to obtain an advantage over competitors. This dual-theoretical approach offers a comprehensive view of BI adoption, which enables a nuanced comprehension of the internal and external variables influencing organisational decision-making and performance improvement in the healthcare industry.

Integrating the TOE framework and RBV theory provides a robust analytical framework for examining the internal and external factors that impact BI adoption of business intelligence. It offers a sophisticated grasp of how businesses can strategically match organisational resources with technological advancements to generate value and gain a competitive edge, especially in healthcare settings where well-informed decision-making is essential. This integrative method provides deep insights into the complicated relationship between resource optimization and technology adoption, highlighting the multidimensional character of organizational performance development.

4. Hypotheses Development

Research in this section develops the research model (see Figure 1) and hypotheses based on previous studies that have been conducted on the BI. The following subsections illustrate the hypothesis development process.

4.1. Technological impact on BI adoption

In this study, the technological impact on BI adoption in the healthcare sector was hypothesized to be determined by relative advantage and cost-effectiveness. Relative advantage refers to the degree of edge that a new technology has over existing tools and processes (Rogers et al., 2014). According to Ifinedo (2011), innovations that are regarded as having superior benefits will be adopted more rapidly. Many studies have discussed the perceived benefits of BI Systems, elevating their adoption and implementation to higher levels (Hočevar & Jaklič, 2010; Malladi, 2013; Owusu Ghanbari-Baghestan et al., 2017). In numerous studies, BI systems and other relevant technologies have been positively correlated with perceived relative advantage benefits (Malladi, 2013; Olexova, 2014; Puklavec et al., 2014). However, other studies have not demonstrated that relative advantage significantly affects innovation adoption (Sujitparapitaya et al., 2012; Yoon et al., 2014). In light of the above, we hypothesized

H1: A higher level of relative advantage for BI applications is positively related to BI system adoption.

Cost-effectiveness is one of the factors that receive greater attention in healthcare sectors related to the cost of adopting a technology overriding its costs when the benefits of this technology outweigh those costs (Jena & Philipson, 2008; Premkumar & Roberts, 1999; Puklavec et al., 2018b). Cost-effectiveness is vital to healthcare decision-makers, as it can help them identify the most efficient way of using resources while providing quality care (Premkumar & Roberts, 1999). Empirical evidence shows that a higher level of cost-effectiveness of BI applications is positively related to BI system adoption. Puklavec et al. (2018b) found that a higher level of cost-effectiveness is positively associated with BI system adoption. The authors found that when BI systems were more cost-effective, this was generally due to lower implementation and maintenance costs. This suggests that when BI systems can provide benefits that outweigh their costs, organizations are more likely to adopt them. Drawing from this, we propose the following hypothesis:

H2: A higher level of cost-effectiveness of BI applications is positively related to BI system adoption.

4.2. Organizational impact on BI adoption

This study hypothesizes that the organizational impact of BI in the healthcare sector is influenced by two factors: top management support and organizational readiness. Regarding top management, support refers to the "active engagement of top management with IS implementation" (Thong et al., 1996). It is important that top management supports technology adoption because they are the ones who make important decisions in any type of company (Bhatiasevi & Naglis, 2020). Top management supports the adoption of new technologies by providing a positive environment and removing any resistance from employees (Wang et al., 2016). In the BI domain, previous studies have found that BI system adoption is determined by the degree of top management support. In the BI domain, previous studies have found that BI system adoption is determined by the degree of top management support (Bhatiasevi & Naglis, 2020; Puklavec et al., 2018b; Vallurupalli & Bose, 2018). For example, Bhatiasevi and Naglis (2020) found that the level of top management support influences BI adoption in Thailand's SMEs organisations. Based on this, we argue that:

H3: A higher level of top management support for BI applications is positively related to BI system adoption.

In turn, an organisation's readiness to use IS is determined by a combination of its human resources, financial resources, and IT complexity (Côrte-Real et al., 2014). When deciding whether to adopt an innovation, organizational readiness is a crucial factor (Tsai et al., 2013). As Iacovou et al. (1995) argue, financial and technological resources are the primary motivators for firms to accept technological innovation. The ability to invest in new technologies is a measure of financial readiness, whereas the extent of technological readiness includes competence and complexity. It is not surprising to assume an association between organizational readiness and innovation adoption when considering the well-known aspects of BI, such as the requirement for thousands of dollars and a high degree of technical competency (Rouhani et al., 2018). Several studies on BI adoption have found that organizational readiness has a significant impact on its adoption (Owusu, Agbemabiasie et al., 2017; Puklavec et al., 2018b; Rouhani et al., 2018). Thus, we propose the following hypothesis:

H4: A higher level of organizational readiness for BI applications is positively related to BI system adoption.

4.3. Environmental impact on BI adoption

According to this study, BI's environmental impact on the healthcare sector is influenced by two factors: competitive pressure and government regulations. Competitive pressure refers to how much stress is experienced by the firm due to its competitors (Gu et al., 2012). According to Themistocleous et al. (2004), these competitions push firms to look for more efficient ways to produce products, ultimately leading to a competitive advantage. As Ifinedo (2011) also discusses, organizations are increasingly compelled to adopt innovations by external forces such as partners, customers, and competitors. Additionally, competition from rivals can create uncertainty in the environment that can increase innovation adoption rates in different industries (Owusu, Agbemabiasie et al., 2017). Several studies have advocated that competition intensity is an antecedent to BI system adoption (Ahmad et al., 2020; Bhatiasevi & Naglis, 2020; Owusu, Agbemabiasie, et al., 2017). For instance, a qualitative study conducted by Ahmad et al. (2020) showed that companies have an increasing tendency to adopt BI systems to increase decision-making and cost-effectiveness. Drawing on this, we hypothesis the following:

H5: Higher levels of competitive pressure are positively related to the adoption of BI systems.

In turn, government regulations and policies encourage businesses to innovate in terms of technology (Leinbach, 2008). New technologies may be affected by existing laws and regulations. Regulating governments can either stimulate or discourage new technology adoption by businesses (Amini & Bakri, 2015). Regulations are essential factors to consider when embracing cloud computing as an environmental aspect (Morgan & Conboy, 2013). Jordan's central bank, for instance, forbids Jordanian banks from storing crucial data online (core banking) (Al-Hujran et al., 2018). According to prior studies on IT adoption, regulations and policy support can encourage or deter new technology adoption (Acheampong & Moyaid, 2016; Oliveira & Martins, 2011). Based on these, we formulate the following hypothesis:

H6: Government regulations and policies significantly affect BI adoption.

4.4. Impact of BI adoption on healthcare providers' performance

One of the most significant impacts of BI adoption on healthcare providers' performance is the improvement in communication and coordination between different healthcare providers (Ashrafi et al., 2014). This is because BI allows healthcare providers to track and analyse data more comprehensively, which helps identify potential problems early and address them before they become major issues (Foshay & Kuziemsky, 2014). This is particularly important for healthcare providers' efforts to improve patient safety. By identifying potential problems early, healthcare providers can avoid potentially serious incidents (Ramakrishnan et al., 2020). Additionally, by improving communication and coordination between different healthcare providers, patients can receive better-quality care. This is because it eliminates the need for patients to repeat information or wait for responses from multiple healthcare providers (Ivan & Velicanu, 2015). Another significant impact of BI adoption on healthcare providers' performance is enabling them to track and analyse data more granularly and identify areas where they can improve their services (Tumpa et al., 2020).

Several case studies have shown that integrating BI can result in positive outcomes for healthcare providers. The study by Wamba-Taguimdje et al. (2020), which clarifies the benefits of applying BI in the healthcare industry, is one noteworthy example. This study presents a comprehensive examination of a hospital that used a BI system to improve decision-making and operational efficiency. The hospital effectively assembled and evaluated the large data sets by using BI tools. This allowed them to pinpoint areas that required improvement and make data-driven decisions. Consequently, significant improvements were noted in a number of performance parameters, such as shortened patient wait times, elevated patient contentment, and better resource distribution. The use of BI significantly influences healthcare providers by enabling them to optimise their operations through data-driven insights, as this case study demonstrates. This ultimately leads to increased efficiency and better quality of care for the patient. Drawing on these, we hypothesise that:

H7: BI adoption in the healthcare sector has a significantly positive impact on healthcare providers' performance.

Figure 1 shows the conceptual framework of the current study based on related theories and hypotheses.

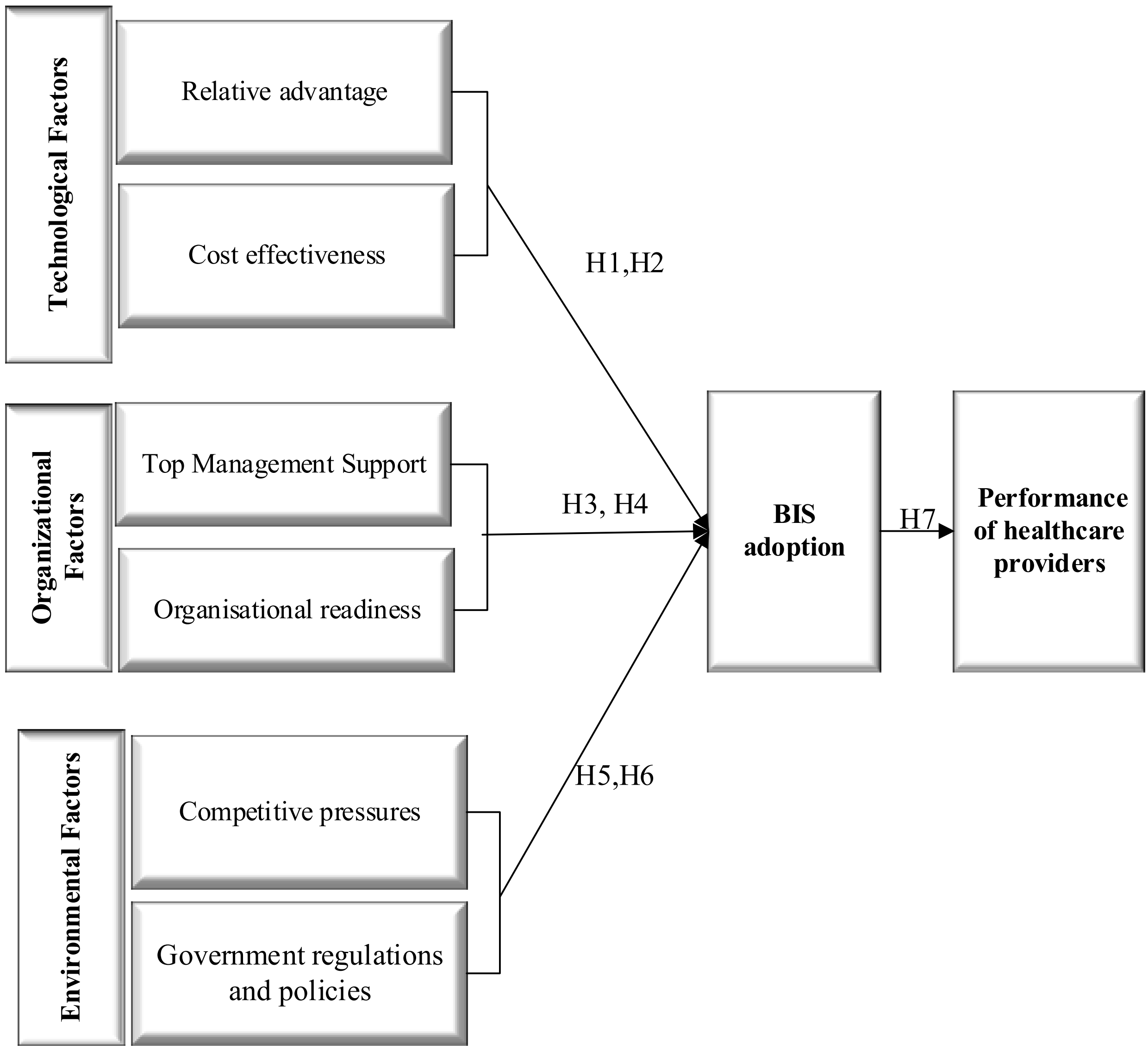

Fig.1: Conceptual Framework

Based on the proposed conceptual framework and hypotheses, the following section outlines the methodology used for data collection and analysis to empirically test the research model.

5. Methodology

5.1 Sampling and Data Collection

Jordanian healthcare workers make up the study population. According to Sekaran (2006), a sample size of 30 respondents and less than 500 will suffice for most studies. A target population is defined as a subset of a population identified as relevant to a research project (Zikmund et al., 2013). In determining the sample size, cost and time are crucial factors. A total of 106 hospitals in Jordan offer medical services. Various samples from the Jordanian healthcare sector will be used in this study. In this case, stratified random sampling was the most suitable since it involved categorizing the subjects and selecting a random sample from each stratum. The sampling frame consisted of healthcare providers working in Jordanian Ministry of Health-registered organisations from all 12 governorates. This comprised both public and private hospitals, primary care clinics, laboratories, and speciality care institutions. Based on facility type, the sample population was separated into the following strata: public hospitals, private hospitals, public primary healthcare centres, private clinics, laboratories, and speciality centres (e.g. dental, ophthalmology, oncology). Respondents were then selected using a simple random selection from each facility type. This ensured that the sample was spread across the entire Jordanian healthcare system. There were 400 questionnaires distributed, but only 303 were retrieved and suitable for analysis. Only those with sufficient knowledge of BI were selected to fill out the questionnaire to ensure the credibility of the response. The data collection process took two months to complete an adequate number of reliable questionnaires.

5.2. Measures and data analysis techniques

A structured questionnaire was developed as a survey instrument based on previously validated measures from the literature. The measurement items for each construct were adapted from previous studies on BI adoption and healthcare technology acceptance. Relative advantage, cost-effectiveness, top management support, organizational readiness, and BI adoption measures were adapted from the survey scales validated by Puklavec et al. (2018a). The competitive pressure items were adapted from Stjepić et al. (2021). Government regulation measures were adapted from Lai et al. (2018). Finally, healthcare provider performance measures were adapted from Salleh et al. (2016).

Using previously validated items enhances the content validity of the survey instrument. The adapted scales showed acceptable psychometric properties in their original studies, with composite reliability scores above 0.80 and average variance extracted exceeding 0.50 (Lai et al., 2018; Puklavec et al., 2018a; Salleh et al., 2016; Stjepić et al., 2021). All items used a 5-point Likert scale. A panel of five information systems experts and BI specialists in healthcare reviewed the initial questionnaire draft to improve validity further. Their feedback was then incorporated into the final version of the questionnaire. A pilot study with 30 healthcare providers was conducted, indicating that the survey demonstrated adequate reliability and validity for the main data collection.

SmartPLS software was used to analyse the survey data using structural equation modelling (SEM). SEM allows for simultaneously evaluating numerous independent and dependent variables (Gefen et al., 2011). Partial least squares SEM (PLS-SEM) was chosen specifically because of its capacity to handle complex models with multiple latent variables and indicators (Lowry & Gaskin, 2014). The investigation was divided into two stages: confirmatory factor analysis was used to evaluate the measurement models' reliability and validity, while the path coefficients between the constructs and their statistical significance were examined to evaluate the structural model.

The suggested conceptual framework contains many technological, organisational, and environmental elements impacting BI adoption and its influence on healthcare provider performance, and the PLS-SEM approach is well suited for analysing it.

6. Results

In this section, we shall proceed to offer the outcomes of our investigation, first with a concise summary of the descriptive statistics. These statistics serve as a fundamental basis for cultivating a more profound comprehension of upcoming sections. Subsequently, we proceed to examine the evaluation of the measurement model, wherein we offer the employed models and analyse their efficacy. Finally, we report the results of the hypothesis testing, with a primary emphasis on the main findings and excluding minor statistical details to maintain conciseness. Supplementary analyses and supplementary statistical information can be found in the Appendix.

6.1. Demographic Profile

During data collection, we collected information about the three demographic characteristics of the respondents. This information was related to the gender, age, and experience of healthcare providers in Jordan. Table 1 presents the frequency distribution of this type of information. According to the table, there were 303 total participants in this study, out of whom 187 (61.7%) were males, while 116 (38.3%)

were females. This indicates that the majority of Jordanian healthcare providers were male. These professionals fall into the age range of 20 to over 40 years.

Table 1. Demographic Characteristics

		Frequency	Percent
Gender	Male	187	61.7
	Female	116	38.3
	Total	303	100.0
Age	20 – Less than 25 Years	21	6.9
	25 – Less than 30 Years	37	12.2
	30 – Less than 35 Years	66	21.8
	35 – Less than 40 Years	102	33.7
	40 Years and Above	77	25.4
	Total	303	100.0
Experience	Less than 3 Years	85	28.1
	3 – Less than 6 Years	54	17.8
	6 – Less than 9 Years	38	12.5
	9 Years and Above	126	41.6
	Total	303	100.0

Table 1 shows that the lowest number of respondents (6.9%) fell in the age range of 20 to less than 25 years; however, the majority of the respondents (33.7%) belonged to the age range of 35 to less than 40 years. This indicates that the majority of healthcare providers in Jordan are not very old. Finally, Table 1 shows that the least number of participants had 6 to 9 years of working experience, while the majority of the participants had 9 or more than 9 years of working experience. This denotes that respondents are mostly experienced in their field, and Husband (2020) stated that experienced respondents are often in a better position to respond accurately regarding their field.

6.2. Measurement Model Assessment

First, the study evaluates the measurement models for each construct. Various statistical techniques have been used to assess the reliability and validity of these models. Cronbach's alpha, composite reliability and rho_A were used to assess reliability. All coefficient values exceed the 0.80 criterion, indicating that each scale has internal consistency (Nunnally & Bernstein, 1994).

Convergent validity is determined by analysing the extracted average variance (AVE), which should be greater than 0.50. This criterion ensures that the items effectively measure the constructs to which they are assigned (Hair et al., 2017). The Fornell-Larcker criterion was also used to measure discriminant validity. The square root of the AVE for each concept was compared to its inter-construct correlations (Appendix A) (Henseler et al., 2015). When the results are considered collectively, it is clear that the measurement scales have satisfactory reliability, convergent validity, and discriminant validity. These findings confirm the research study's overall reliability and validity.

6.3. Structural Model Assessment

The developed hypotheses were tested with the help of SmartPLS software, in which bootstrapping was performed to evaluate the impact of predictors on outcome variables. Figure 2 shows the impact of the independent variables on the predictor and dependent variables. Furthermore, this figure shows the factor loadings of all the items developed to measure the variables. Importantly, the values of R-square

are also represented in the figure, where the combined effect of all independent variables causes 80.5% of the variance in BI adoption. BI adoption's effect on healthcare providers' performance was evaluated; therefore, the R-square value was comparatively low. Here, the R-squared value shows that the positive influence of BI adoption causes 56.3% of the variance.

The detailed results are presented in Table 2. This table shows the individual effect of each independent variable on a mediator and the impact of the mediator on the dependent variable. According to Table 5, the relative advantage has an 18.7% positive and significant effect on BI adoption, with a significance value equal to 0.01. Here, the original mean value shows that for each one-point increase in relative advantage, BI adoption increases by 0.187. This relationship supports the first hypothesis.

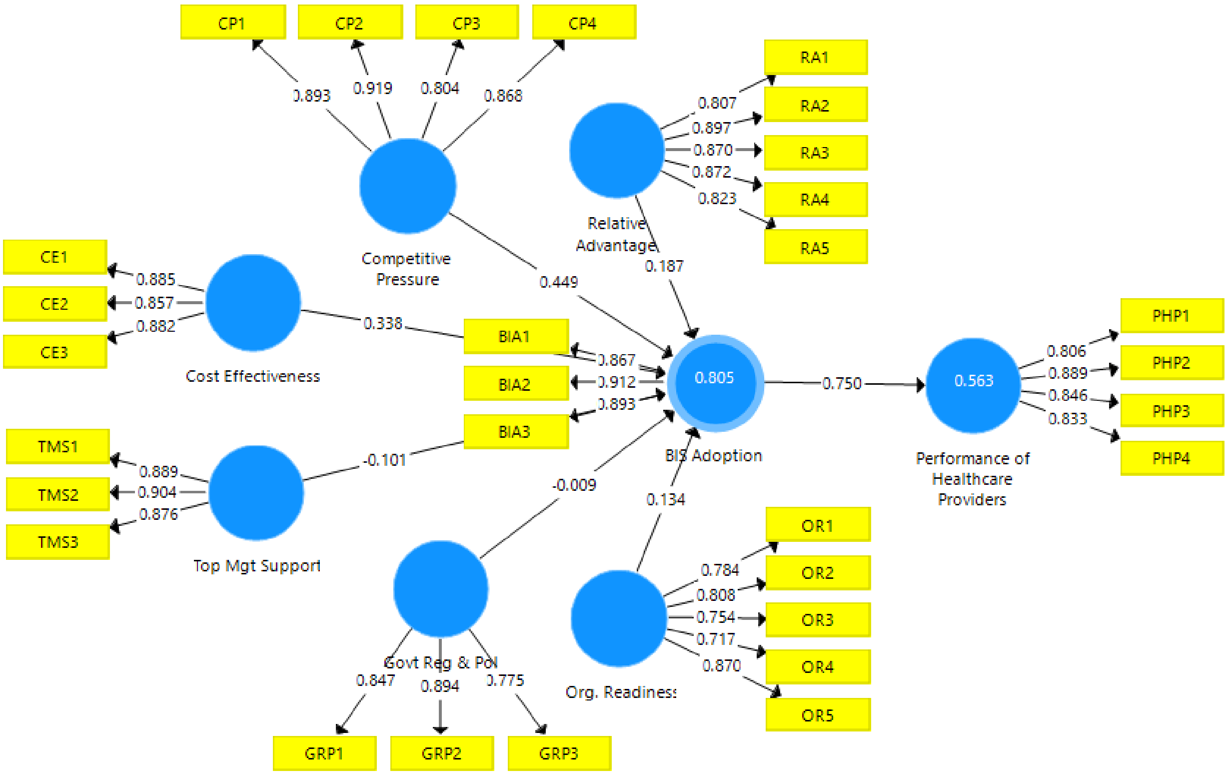

Fig.2: Measurement Model

According to Table 2, cost-effectiveness has a 33.8% positive effect on BI adoption at p<0.01. Therefore, the second hypothesis is also accepted. However, top management support had a 10.1% negative effect on BI adoption at p<0.05. The third hypothesis proposes a positive effect of top management support on BI adoption; therefore, the third hypothesis is rejected. Furthermore, Table 2 shows that organizational readiness has a 13.4% positive impact on BI adoption, with a p-value equal to 0.001; therefore, the fourth hypothesis of this study is accepted. Among the predictors, competitive pressure has the most significant positive influence on BI adoption. According to Table 2, competitive pressure has a 44.9% positive effect on BI adoption at p<0.01; therefore, the fifth hypothesis of this study is accepted. However, government regulations and policies have no significant impact on BI adoption, as p=0.761, which is greater than 0.05. Therefore, the sixth hypothesis of this study was rejected. Finally, Table 5 shows that BI adoption has a 75% positive influence on the performance of healthcare providers at p<0.01; therefore, the seventh hypothesis is accepted.

Table 2. Path Coefficients

Variable Names	Original Sample	Sample Mean	SD	t	P	Status

Relative Advantage ➔ BI Adoption	0.187	0.187	0.072	2.590	0.010	Accepted
Cost Effectiveness ➔ BI Adoption	0.338	0.340	0.052	6.443	0.000	Accepted
Top Management Support ➔ BI Adoption	-0.101	-0.095	0.047	2.163	0.031	Rejected
Organizational Readiness ➔ BI Adoption	0.134	0.139	0.039	3.422	0.001	Accepted
Competitive Pressure ➔ BI Adoption	0.449	0.439	0.068	6.655	0.000	Accepted
Government Regulations & Policies ➔ BI Adoption	-0.009	-0.008	0.030	0.305	0.761	Rejected
BI Adoption ➔ Performance of Healthcare Providers	0.750	0.753	0.026	28.448	0.000	Accepted

7. Discussion

The purpose of this study is to identify the factors influential to BI adoption and to investigate how BI adoption affects the performance of healthcare providers in Jordan. Various previous studies were also conducted to identify the factors which have directly or indirectly impacted the adoption of BI. Bhatiasevi and Naglis (2020) found that compatibility, technology readiness, top management support, and competitive pressure have a significant impact on the adoption of BI. This study, however, evaluated the impact of BI adoption on overall organizational performance. The current study, on the other hand, has identified some different and additional factors as well as examined the impact of BI on the performance of healthcare providers. Out of the six identified factors, the impact of four factors on BI proved to be significant. The difference in results might appear owing to differences in economic, social, cultural, political, and technological among various nations. These differences appeared between countries that belong to different regions, like Asian and Western countries (Malladi, 2013).

Ali et al. (2018) identified two factors, including technological capability and personnel capability, which have a significant direct impact on the adoption of BI. Similarly, Malladi (2013) identified the same factors. Some other studies also identified the factors which have a significant influence on the adoption of BI. Although researchers have identified these factors in different studies, they found them to be in a scattered form. The current study has incorporated important factors into a single study to provide a broader scope. Although these factors provide efficient and effective implications for the adoption of BI, their effectiveness may differ over the regions (Ali et al., 2018; Bhatiasevi & Naglis, 2020; Malladi, 2013). Several other studies have further elaborated on the impact of BI adoption on the performance of organizations; however, evidence is missing with respect to the Jordanian healthcare sector. Researchers have evaluated the impact of BI adoption on the performance of banks (Nithya & Kiruthika, 2021), organizational performance (Bhatiasevi & Naglis, 2020), firm performance (Popovič et al., 2018), supply chain performance (Pool et al., 2018), food manufacturing business performance (Jayakrishnan et al., 2018), and performance of retail chain (Olexova, 2014) among others. This means the adoption of BI is beneficial in almost every industry so far. Therefore, to enhance the performance of healthcare providers, the adoption of BI proved to be beneficial in this study. While for BI adoption, technological, environmental, and organizational factors have significance.

However, the impact of top management support and government regulations is not proved in the current study. In Jordanian healthcare organisations, it appears that the support and involvement of top management may not hold as much importance in driving BI initiatives. This finding suggests that it is the IT departments within these organisations that take the lead in promoting and implementing BI projects rather than executive leaders (Singh & Hess, 2020). This observation opens up avenues for further qualitative research to delve deeper into the dynamic relationship between IT departments and top management. Additionally, the non-significant effect of government regulations on fostering BI adoption within the Jordanian healthcare sector raises questions about the current optimisation of policy mechanisms. It seems that existing regulations may not effectively encourage the adoption of BI practices in these organisations (AlBar & Hoque, 2019). This finding calls for a closer examination of the current policy landscape and the identification of potential areas for improvement.

7.1. Study Implications

This study has multiple theoretical and practical implications. With respect to theory, this study has contributed by providing a holistic approach, where multiple antecedents of BI adoption are identified. Amongst these antecedents, some were identified by previous authors; however, those were utilized in a scattered form. This study has used major antecedents of BI and evaluated the impact of BI on the performance of professionals. Importantly, this study has contributed to the context of healthcare providers. Additionally, this study has particularly provided evidence with respect to Jordan. Therefore, theoretically, this study is helpful for academicians, researchers, and students.

Practically, this study offers valuable insights and practical contributions to the field of BI adoption. It identifies important factors that influence BI adoption and provides guidance for BI developers, organisations, vendors, and policymakers. First, this study highlights the significance of the factors that impact BI adoption. These factors can be used by organisations and policymakers during the planning stage to assess their capabilities and resources. To achieve successful BI adoption, organisations must have sufficient funds, support from top management, favourable government regulations, relative advantage, competitive pressure, and organizational readiness. Strengthening these factors will enhance BI adoption, leading to improved performance among healthcare providers. Second, the findings suggest that healthcare providers should focus on highlighting the tangible benefits and cost-effectiveness of BI to their staff. Additionally, software solutions should be designed with ease of use, considering the limited specialised IT skills among users. Last, at the national level, policies could be implemented to incentivise BI adoption, particularly when tied to quality and efficiency goals.

7.2. Limitations and Future Recommendations

Although this study provides useful information, numerous limitations suggest areas for future investigation. First, the sample was limited to Jordanian healthcare providers. The model's generalizability can be improved by testing it across different sectors and nations (Lee & Baskerville, 2003). Second, the cross-sectional approach merely provides a glimpse of BI effects rather than a long-term picture. Longitudinal studies could provide a more accurate picture of the effects across time (Andreev et al., 2009). Third, only direct relationships were examined. Evaluating mediating effects may help explain more complex interactions among drivers, adoption, and performance (Baron & Kenny, 1986). Fourth, including more technological, organizational, and environmental predictors could uncover additional adoption reasons and provide a more complete picture. Finally, to highlight nuances around BI implementation challenges and impacts on Jordanian healthcare, this quantitative analysis could be supplemented with qualitative data. In conclusion, while tackling these constraints through multi-context, longitudinal, and mixed-methods techniques is an important first step, it represents a promising field for future research.

8. Conclusion

This study examines how BI is adopted in Jordan's healthcare sector and how it affects provider performance. The research addresses two main questions: RQ1: How do technological, organisational, and environmental factors affect Jordanian healthcare BI adoption? Q2: Does BI improve Jordanian healthcare providers' performance?

The study analyzed survey data from 303 Jordanian healthcare providers using the Technology-Organization-Environment (TOE) framework and Resource-Based View (RBV) theory. This investigation revealed some intriguing results. As in earlier studies, relative advantage, cost-effectiveness, organizational preparation, and competitive pressure positively affect BI adoption. Contrary to expectations, top management assistance and government laws had little influence. The study concluded that BI adoption enhanced healthcare providers' communication, coordination, safety, and efficiency. This finding supports the international evidence of BI's healthcare advantages. In practice, the study helps Jordanian healthcare providers maximize BI usage. The proposals emphasize BI's practical benefits, user-friendly design, and supportive policies.

The study provides significant information, but its limits suggest future research on long-term studies and BI uptake in different nations. This study advances the theoretical and empirical understanding of BI integration in healthcare and offers Jordanian healthcare providers meaningful guidance. It also lays a framework for future studies on how BI helps enhance global healthcare delivery through data.

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Appendix A

Table 1. Construct Reliability & Validity

Variable Names	Items	Factor Loadings	VIF	Cronbach's Alpha	Rho_A	CR	AVE
Relative Advantage	RA1	0.807	2.253	0.907	0.910	0.931	0.730
	RA2	0.897	3.508				
	RA3	0.870	3.239				
	RA4	0.872	4.376				
	RA5	0.823	4.420				
Cost Effectiveness	CE1	0.885	2.262	0.847	0.852	0.907	0.765
	CE2	0.857	1.944				
	CE3	0.882	2.005				
Top Management Support	TMS1	0.889	2.190	0.869	0.871	0.919	0.792
	TMS2	0.904	2.628				
	TMS3	0.876	2.184				
Organizational Readiness	OR1	0.784	1.760	0.848	0.868	0.891	0.621
	OR2	0.808	2.074				
	OR3	0.754	1.890				
	OR4	0.717	1.599				
	OR5	0.870	2.283				
Competitive Pressure	CP1	0.893	2.833	0.894	0.897	0.927	0.760
	CP2	0.919	3.546				
	CP3	0.804	1.843				
	CP4	0.868	2.636				
Government Regulations & Policies	GRP1	0.847	2.101	0.790	0.795	0.878	0.706
	GRP2	0.894	2.306				

	GRP3	0.775	1.372				
Business Intelligence Adoption	BIA1	0.867	2.106	0.870	0.874	0.920	0.794
	BIA2	0.912	2.617				
	BIA3	0.893	2.333				
Performance of Healthcare Providers	PHP1	0.806	1.885	0.866	0.879	0.908	0.712
	PHP2	0.889	3.918				
	PHP3	0.846	3.266				
	PHP4	0.833	1.766				

Table 2. Discriminant Validity

Variables	1	2	3	4	5	6	7	8
Business Intelligence Adoption	**0.891**							
Competitive Pressure	0.830	**0.872**						
Cost Effectiveness	0.800	0.692	**0.875**					
Govt Regulations & Policies	0.514	0.471	0.541	**0.840**				
Organizational Readiness	0.658	0.563	0.648	0.478	**0.788**			
Performance of Healthcare Providers	0.750	0.678	0.739	0.429	0.643	**0.844**		
Relative Advantage	0.727	0.705	0.680	0.606	0.615	0.636	**0.854**	
Top Management Support	0.569	0.556	0.571	0.483	0.580	0.496	0.822	**0.890**