Uncertain Supply Chain Management 11 (2023) 1257–1264

Contents lists available at GrowingScience

Uncertain Supply Chain Management

homepage: www.GrowingScience.com/uscm

Critical success factors for business intelligence and bank performance

Khaled ALzoubi[a], Khaled Bataineh[a], Mohammad Al Matalka[b], Osama Al-Rawashdeh[c], Ahmed Malkawi[d], Yahya AlGhasawneh[a], Mohammad Alghadi[a], Mohammad M. Alibraheem[a] and Mohammad ALzoubi[a*]

[a]*Irbid National University, Jordan*
[b]*Rabdan Academy, United Arab Emirates*
[c]*Aqaba University College, Al-Balqa Applied University, Salt, Jordan*
[d]*Jerash University, Jordan*

A B S T R A C T

Article history:
Received November 1, 2022
Received in revised format December 10, 2022
Accepted March 30 2023
Available online March 30 2023

Keywords:
Bank performance
Business intelligence
Jordan
TOE
Information technology

This research attempts to investigate the technological, organizational, and environmental aspects that impact the banking industry's use of business intelligence (BI). In addition, the present research aims to quantify the effect of business intelligence adoption on bank performance to contribute to the current understanding of business intelligence adoption. Upon the completion of the sample verification procedure, 232 samples are collected. Throughout the research investigation, the SEM software is used to process all the acquired data. The study's findings indicate that TOE had a direct and beneficial effect on the adoption of BI systems by banks. Based on the results of the study, the researchers believe that decision-maker and managers would define all activities, responsibilities, and work processes using business intelligence platforms in order to increase their organization's versatility and performance.

1. Introduction

Business intelligence (BI) is regarded as being among the most essential technologies, systems, practices, and applications that assist organisations increase their competitiveness by gaining a deeper understanding of business data, developing strategies and products, and enhancing consumer connections (Nithya & Kiruthika, 2021). BI plays an even greater role in the banking industry by empowering specialists and leaders to make more precise, informed, relevant, and timely choices to boost the bank's productivity and profitability and comply with the many environmental aspects and regulatory requirements of this industry (Owusu, 2017). In today's business world, BI is a trending topic and a necessity for developing an amazing corporate image, which is consistent with achieving a successful strategy that includes the wide use of technology. Hence, this helps companies make choices and achieve a significant advantage in today's dynamic economy, which necessitates attempts to allocate enormous expenditures to improvement and research (Mohammad et al., 2022). Data is a fundamental concern and is regarded as the future fuel because it is possible to be handled quickly and utilised effectively to support dangerous occurrences and choices that may have a significant impact on bank performance (Al-Okaily et al., Teoh). Recent advancements in areas such as voice recognition, robotics, deep learning, machine learning, natural language processing, and expert systems are having the most important effect on artificial intelligence and business, as stated by Purdy and Daugherty (2016). In this context, artificial intelligence has arisen as a tool for enhancing the re-creation, ecosystems, and decision making of the consumer experience (Al-Okaily & Al-Okaily, 2022). The study of artificial intelligence is currently an active field of study in many different industries and fields, such as science, engineering, education, medicine, business, and law (Cartwright, 1997; Ramesh et al., 2004; Nithya & Kiruthika, 2021). It is currently being used in a variety of fields, including healthcare, new media, and self-driving cars, among others (Bollier, 2020). There have been several reports of artificial

* Corresponding author
E-mail address Mzoubi@inu.edu.jo (M. ALzoubi)

doi: 10.5267/j.uscm.2023.3.022

intelligence in the literature (Purdy & Daugherty, 2016; Aghion et al., 2017); nevertheless, this has not been the issue for artificial intelligence adoption decisions or preparing organisations to implement artificial intelligence. Particularly, artificial intelligence will contribute significantly to the economic prosperity of nations including the United States, China, and Jordan (Vempati, 2016; Makridakis, 2017; Mohammad et al., 2022). An investigation that was recently conducted by PwC found that the potential contribution of artificial intelligence to the world's economy will increase by 14% (15.7 trillion USD) by the year 2030. China and the United States are anticipated to realise the greatest economic benefits from artificial intelligence, with their GDPs increasing by 14.4% and 26.1%, respectively (AlSheibani et al., 2018). It is currently having enormous economic effects, particularly in the financial services, healthcare, and information and communications technology sectors (Purdy & Daugherty, 2016). Leading artificial intelligence sector rivals, including Apple, Amazon, Google, and Facebook (Infosys, 2016), are thus striving to acquire market and competitive advantage dominance through advancing artificial intelligence (AlSheibani et al., 2018). Numerous studies on BI have been conducted on topics such as comparative examination of hybridization methodologies, the critical success of BI deployment, BI adaptation, cloud computing, and big data. The emphasis on BI has increased in significance owing to the considerable beneficial impact it has had on the business in achieving the intended objective. The banking industry is a significant sector with extensive consumer engagement and a substantial impact on business and the economy. All business actions revolve around it, regardless of whether they are business-to-customer, customer-to-customer, or business-to-business. The fact that bank employees are required to complete many transactions across all counters on a daily basis adds another layer of complexity to the banking process. In this context, data analytics may make a contribution to the fixing and evolving of banking issues as well as achieving the best possible outcomes for decision making. Since the number of data points is always expanding, managers are unable to discern the link between various factors in organisational data. It's because the amount of data is increasing. In addition, leaders require additional effort in order to arrive at a conclusion on the behavioural pattern as well as the desires and requirements of clients. Furthermore, a large amount of additional work is required to understand and keep the appropriate customers while also acquiring new ones. As a result, BI through data analysis assists product managers and managers in identifying different customer categories, developing services or products that are associated with customer requirements, defining pricing strategy and competition, improving revenue management, increasing sales, and expanding the customer segment (Al-Okaily et al., 2022). Studies have described BI as the capacity of businesses to plan, think, predict, comprehend, solve problems, devise novel methods for enhancing business and decision-making processes adequately, ensure greater action, and assist in the creation and achievement of business objectives (Aws et al., 2021). Similarly, applications, dashboards, procedures, technologies, data, online analytical processing, and scorecards are considered to play a part in providing BI capabilities. BI processes and technologies are considered crucial facilitators for data driven decision-making because they offer the foundation and assistance banks need to make correct, fact-based choices and conduct business effectively and differently (Airinei & Berta, 2012; Wells, 2022). Although the field of study of the use of BI in the banking industry is growing, it's impossible to assert that the field has significantly expanded. In addition to inconsistent outcomes, the present research does not give sufficient evidence of the elements that influence the use of BI. Despite this, banks continue to rely heavily on BI, particularly given the availability of vast consumer data sets that may aid in decision-making in this regard. Understanding the impact of technological elements on boosting the performance of banks has been the subject of little research. To add value to the current perspectives on BI adoption, the study sought to provide a conceptual framework for measuring the influence of TOE on BI adoption as well as the link between BI and bank performance.

The following section describes the theoretical foundation. In section 3, a synopsis of the key relevant literature is provided. Part 4 describes data gathering and methodologies, while Section 5 offers the study's results. Section 6 contains the scientific contributions, as well as a conclusion, limits, and future research potential.

2. Theoretical Foundation

At the organisational level, the TOE framework is used to describe the elements that impact adoption choices. Tornatzky and Fleischer (1990) discovered that the decision to accept an innovation at the business level is impacted by organisational and environmental circumstances in addition to technical variables. The model investigates an organization from three separate perspectives: technology, organisation, and environment. The technical component encompasses all essential technologies inside and outside the organisation. The organisational element highlights corporate features and resources that may impact the adoption process, including firm size, management structure, decision-making, and communication. The environmental factor has to do with the industry's competitors, suppliers, customers, and rules and regulations (Tornatzky & Fleischman, 1990). The TOE model has been studied extensively in information communication technology and other fields, including e-marketing, e-commerce, e-business, e-maintenance, and business resource planning (Idris, 2015; Nithya & Kiruthika, 2021; Al-Okaily & Al-Okaily, 2022; Mohammad et al., 2022). The TOE framework has also been evaluated in several other sectors (Idris, 2015). However, TOE has rarely been used in research on the incorporation of BI at the level of the enterprise. The results of previous studies indicate that the model is an appropriate tool for analysing the process of innovation adoption at the level of an organisation (Aboelmaged, 2014). Because of this, the study was able to apply the TOE model to BI adoption with a few adjustments. BI stands for business intelligence. For instance, when adopting BI, personnel problems and IT infrastructure resources are both necessary considerations because of the considerable correlations that exist between these factors and BI technology and ideas (AlSheibani et al., 2018). Due to this, the authors of the study believe that the performance of the bank, as well as its human, organizational, and technological resources, are crucial criteria for the adoption of BI.

3. Literature review

3.1 Business Intelligence

Information is now a vital competitive factor for contemporary organisations. Contemporary businesses generate large quantities of data. It is essential to support strategic, operational, and tactical decision-making by supplying the appropriate individuals with information that is complete, accurate, timely, and relevant (Popovi et al., 2012; Mirjana et al., 2017). Hence, the transformation of usable information into knowledge enhances a company's competitive advantage. BI is a collection of analytical techniques, including data mining, for extracting information from data (Mohammad et al., 2022). By analysing an organization's performance, BI enables businesses to increase their competitiveness and income, make wise decisions, and develop new strategies. The word "Bis" refers to a data driven decision making support system that integrates information technology utilised for analysis, data collection, and storage in order to give business-driven and results-oriented information. BI is a group of tools for translating data into actionable intelligence (Aruldoss et al., 2014; Aws et al., 2021).

3.2 Technology competence

Technological Competence (TC) describes the technical resources of an organisation, including its IT infrastructure, which comprises technologies, applications, and systems (Mata et al., 1995). IT professionals are those inside an organisation with the knowledge to adopt information solutions (Martins et al., 2016). According to Ritter and Gemunden (2004), the TC enables organizations to exploit technology internally, use it, and understand it. TC is a way of assisting in the preparation of a technology infrastructure, such as the implementation of a fundamental degree of knowledge about accessible technology (San-Martn et al., 2016). Hence, as organisations appreciate the benefits generated by a particular technology, including BI solutions, TC plays a significant role in the organization's environment (Cruz-Jesus et al., 2019). As shown by Martins et al. (2016), a high degree of TC positively influences a propensity to adopt a behaviour that will enhance the administration of customer and employee data. Furthermore, to create a technique or product that obtains a larger profit from the advancement of technology Consequently, we may argue that technological proficiency is essential for understanding BI systems' advantages. This notion has been offered in previous research, including in the electronic commerce environment (Cruz-Jesus et al., 2019; San-Martn et al., 2016). Remember that BI involves a variety of hardware and software applications. To maximise its potential, it also expects its employees to have technical expertise. During the BI implementation process, organisations need not just technology but also skilled and experienced human resources. Therefore, businesses with more technical proficiency are more likely to achieve success at each level of the BI implementation process. Thus, we developed the following hypothesis:

H$_1$: *The technology competence has a positive impact on the adoption of business intelligence in the Jordanian Bank.*

3.3 Data quality and integration

AlSheibani et al. (2018) stated that Business Intelligence (BI) and Data Quality and Integration (DQI) use the same language for all relevant tasks. Consequently, the importance of DQI processes, which include BI applications, all transactions, interactions, and networked touchpoints, has made them one of the key obstacles to successfully analysing BI performance. Moreover, various administrative, operational, and strategic considerations exist behind DQI challenges. Thus, the organisational system and BI infrastructure jeopardise a successful strategy, such as the organisation's revenue and profitability.

H$_2$: *The data quality and data integration have a positive impact on the adoption of business intelligence in the Jordanian Bank.*

3.4 Top management support

When referring to IS/IT implementations, the term *Top Management Support (TMS)* refers to the involvement of high-level managers. According to Wade and Hulland (2004), the resource-based hypothesis highlights support from TMS as a moderating element and asserts that a lack of cooperation not only fails to enhance a company's competitiveness position but moreover raises the likelihood that the company will not embrace innovation. The commitment of TMS is another factor that can have a strong positive impact on the acceptance of new technology (Yang et al., 2015). This commitment may be useful in terms of outlining a vision, contributing capital, and distributing resources and finances (Hung, 2016). For instance, according to the findings of a study into the adoption of IS/IT, support from TMS was demonstrated to increase acceptance of cloud computing and e-business (Yang et al., 2015; AlSheibani et al., 2018). In general, using BI to support organisational change is, in most cases, a strategic option that should be made. The following hypothesis is consequently put out for consideration:

H$_3$: *The top management support has a positive impact on the adoption of business intelligence in the Jordanian Bank.*

3.5 Organization size

According to Rogers (2003), the size of the organisation has a direct effect on how quickly it adopts new innovations. Based on the findings of several research (Aboelmaged, 2014), the size of an organisation has a beneficial impact on the rate at which it adopts new technologies. Given the findings of Aruldoss et al. (2014), big organisations have a stronger capacity to absorb new technologies. In a similar vein, some people said that bigger companies are subjected to a higher amount of competitive pressure, while Aboelmaged (2014) mentioned that the reason why larger organisations have a beneficial influence on the market is because they have more financial and technological resources. The following hypothesis is therefore postulated because of this research:

H_4: *The organizational size has a positive impact on the adoption of business intelligence in the Jordanian Bank.*

3.6 Resources

In addition to organisational variables, enterprise resources (Iacovou et al. 1995), human resources, and information technology resources are all essential components of successful innovation adoption at the business level. The terms data, networking, and computer hardware are all examples of technology resources, all of which are necessary to implement new innovations (Aboelmaged, 2014). Standard machine learning algorithms provide the basis for many existing BI tools, which acquire intelligence via training (Ransbotham et al. 2017). According to a recent Narrative Science (2016) survey, 59% of big data-savvy businesses use BI Technology as well. Chiang and Hung (2014) divided the available means into human workers and technological tools. Based on a recently published report, most organisations fail to deploy BI and smart devices because they prioritise technology over proper implementation skills and procedures. Many empirical IS studies have shown that organisations with human, enterprise, and technology resources are more likely to embrace innovations, including websites, e-maintenance, and e-business. (Aboelmaged, 2014). Therefore, this study hypotheses that resources impact BI adoption favourably.

H_5: *The* resources *have a positive impact on the adoption of business intelligence in the Jordanian Bank.*

3.7 Competitive pressure

The prospect of losing a competitive advantage pushes a business to embrace an invention in response to competitive pressure (Aboelmaged, 2014). Substantial empirical study has investigated rival pressure as a role in the spread of innovative innovations (Yang et al., 2015). AlSheibani et al. (2018) identified company operations that are influenced by external conditions, including socioeconomic issues. In accordance with a recent analysis by Fast & Horvitz (2017), the top technological advancement plan for 2018 is the development of an BI strategy. BI has the potential to stimulate innovation and provide new possibilities for both people and businesses (Fast & Horvitz, 2017). BI adoption is influenced by the capacity to apply BI to enhance decision-making and customer experience (Fast & Horvitz, 2017). This research thus suggests the hypothesis:

H_6: *The competitive pressure has a positive impact on the adoption of business intelligence in the Jordanian Bank.*

3.8 External Market Influence

When it comes to competition, new goods and services and demanding customers are always putting pressure on the banking industry from the outside. As a result, banks depend on novel technologies, including BIA, as part of their strategic and data warehouse efforts to combat these problems (Ahani et al., 2017). According to Cruz-Jesus et al. (2019), banks confronting environmental uncertainty "invest in higher advisory and research operations" to better comprehend their market and internal activities. Furthermore, Mohammed et al. (2022) underlined that banks make greater utilization of information technology, including BI, which may have a significant effect on their efforts to handle external market impacts (Aboelmaged, 2014). This research thus suggests the hypothesis:

H_7: *The competitive pressure has a positive impact on the adoption of business intelligence in the Jordanian Bank.*

3.9 Bank Performance

Even though several research studies have been conducted on bank performance, the incorporation of environmental and technological elements has been observed to be uncommon. Bearing this in mind, the current study focuses on studies of bank performance in relation to a variety of banking industry variables. In a limited number of reviews conducted in the United States and New Zealand, the necessity of determining the bank's efficiency was based on indicators such as mergers and acquisitions, alternative profit efficiency in comparison to other banks, institutional efficiency in resolving challenges associated with government policies and managerial practices, etc. In addition, it was stated that innovative theoretical perspectives are required to further knowledge of the development process (Dobbs & Hamilton, 2006; Nithya & Kiruthika, 2021). This was demonstrated even further by an empirical study that was carried out by Rumler and Waschiczek (2010) among 1042 employees of an Austrian bank. The researchers came to the conclusion that the banks had successfully overcome the significant challenges posed by the restructuring of the financial market. Profits were not affected by the liberalisation and integration of the Austrian banking market or the economic policy modifications. As such, it is evident that the integration of the banking industry would raise profitability and strengthen its ability to face obstacles. Implementing BI adoption in banks makes this integration very feasible. To examine the performance of banks, the current research has identified variables such as bank growth, internal processes, client responsiveness, and the bank's financial status. This demonstrates that bank performance is an essential criterion for evaluating the existence of a bank and the quality of its customer service. Among the several determinants of bank performance, the majority of research has focused on client requirements, low debt, increased NPA, etc. Understanding the impact of technological elements in boosting the performance of banks has been the subject of little research. Hence, the effect of BI on monitoring banks performance would contribute to a more reasonable evaluation of the current situation.

H_8: *The bank's performance has a positive relationship with the adoption of business intelligence in the Jordanian Bank.*

3. Method

3.1 Population and sample selection

In order to assess the hypotheses of the research, a questionnaire-survey methodology was used. Its dimensions and components are dependent on the study's theoretical framework as well as past research on the topic of the investigation. The research population is comprised of banks in Jordan that make extensive use of organisational information and analytics. As such, the research population includes essentially all Jordanian bank workers in the sales department, compliance department, risk management department, branches, and information technology department. Because of the challenges of including the whole research population at each of the Jordanian Bank's 818 branches, the population was sampled at random. In December 2022, surveys were sent to businesses with over 35 employees. With the use of deliberate sampling, banks that had implemented BIS to a certain extent were singled out. The questionnaire has 49 questions divided into three sections. The survey questions were evaluated on a five-point scale ranging from strongly disagree to strongly agree, and Google Form was used to distribute online surveys. 421 out of the total number of disseminated online surveys were recovered, deemed legitimate, and confirmed. Two procedures were used to validate the questionnaire. The questionnaire was revised by academic specialists as a first step. Then, the findings of the revised questionnaire were evaluated using a pertest. Hence, the research ensured that the parts were logical and that the language was accurately comprehended. Furthermore, participant feedback was incorporated into the final product.

3.2 Measurement instrument

The item was a self-reported survey that was divided into two core parts and one component that focused on the experimental control variables. For the objective of regulating the factors, it was determined to employ gender, age group, educational level, and experience as categorical measurements on the aspects that affected the experiment. Using a five-point Likert scale (from 1 to 5 = strongly disagree), the TOE framework and performance were evaluated. To measure the researcher's components, a self-assessed rating questionnaire was designed. After reviewing the literature and having discussions with a number of BI experts and practitioners, we developed a set of TOE and bank performance measurement measures. While constructing this questionnaire, the following evaluation-related procedures must be implemented: The ten-item assessment of technological settings was based on Aboelmaged, (2014), Makridakis, (2017), and Aws et al., (2021) Organisational contexts, as measured by nine questions, were based on Bollier (2020) and Al-Okaily and Al-Okaily (2022) and Yang et al. (2015) served as the foundation for the 11-item environmental contexts measure; BI adoption, as measured by seven items, was based on Nithya and Kiruthika (2021) and Aboelmaged (2014); bank performance, as measured by twelve items, was In accordance with the literature analysis, all advancements were operationalized as reflective. Thus, BI adoption was examined using dichotomous questions.

4. Findings

4.1 Measurement model evaluation

This research was carried out to investigate research issues utilizing the technique of structural equation modelling (SEM), a modern statistical technique for assessing and quantifying the connection between variables and factors. As a consequence, the factors' dependability and validity were evaluated utilizing confirmatory factor analysis (CFA) using the statistical programme AMOS. Table 1 provides a summary of convergent, discriminant, and reliability validity tests. As demonstrated in Table 1, the standard loading values of all elements fell beyond the domains' permissible range (0.633–0.853), which exceeded the components' minimum retention based on their standard loads. If the extracted average variance (AVE) is greater than 0.50, the concept is convergent. Hair (2017) revealed that all constructs had AVE values greater than 0.50, suggesting that the measurement procedures had excellent convergent validity. Hair et al. (2010) developed the covariance-based SEM comparison method for assessing discriminant validity. Maximum shared variance (MSV) and square root of AVE (AVE) values are used to compare the relationship between the remaining components. The MSV values were less than the AVE values, and the AVE values were larger than the correlation values across other components. Hence, the adopted assessment model has discriminative validity. Internal consistency (as assessed by Cronbach's alpha) and compound reliability (as defined by McDonald's omega) were used to evaluate the measurement model. Both Cronbach's alpha and McDonald's omega exceeded 0.70, the minimal level for gauging measurement reliability, as seen in Table 1 (Ramirez et al., 2013).

Table 1
Results of validity and reliability tests

Constructs	1	2	3	4	5	6	7	8	9
1. TC	0.689								
2. DQI	0.758	0.796							
3. TMS	0.775	0.788	0.740						
4. OS	0.720	0.728	0.735	0.750					
5. KS	0.798	0.679	0.769	0.753	0.721				
6. Re	0.639	0.678	0.675	0.777	0.710	0.723			
7. CP	0.667	0.671	0.647	0.717	0.762	0.759	0.629		
8. EMI	0.698	0.687	0.783	0.745	0.682	0.748	0.765		
9. BP	0.752	0.768	0.670	0.674	0.633	0.625	0.692		
VIF	2.574	2.911	2.852	2.677	2.498	2.488	2.353	2.907	2.575
Loadings range	0.762- 0.768	0.709- 0.832	0.734- 0.852	0.633- 0.792	0.771- 0.801	0.802- 0.822	0.821-0.788	0.741-0.697	0.755-0.749
AVE	0.565	0.543	0.522	0.537	0.590	0.509	0.510	0.572	0.578
MSV	0.481	0.469	0.447	0.404	0.582	0.513	0.525	0.591	0.550
Internal consistency	0.856	0.835	0.851	0.855	0.858	0.801	0.856	0.873	0.845
Composite reliability	0.889	0.908	0.911	0.890	0.880	0.901	0.807	0.869	0.854

4.2 Structural model

We were prompted to analyse the structure of the conceptual model because of the high degree of congruence with the model (Fig. 2). As a consequence of this, the purpose of the research is to determine whether or not the hypothesised theoretical correlations are verified in a given study situation. Over the course of the route analysis, we take into account (i) the signs of the parameters, (ii) the statistical significance of the parameters (as determined by the t-value), and (iii) the variance of the endogenous constructs (measured by the squared multiple correlation coefficient, $-R^2$). As can be seen in Table 2, there was no multicollinearity among the predictor components in the structural model since the values of the variance inflation factor (VIF) were fewer than 5. This was due to the fact that the values were less than 5. According to Hair et al. (2017), the results of the model fit index that are reported in Fig. 1 corroborate this conclusion.

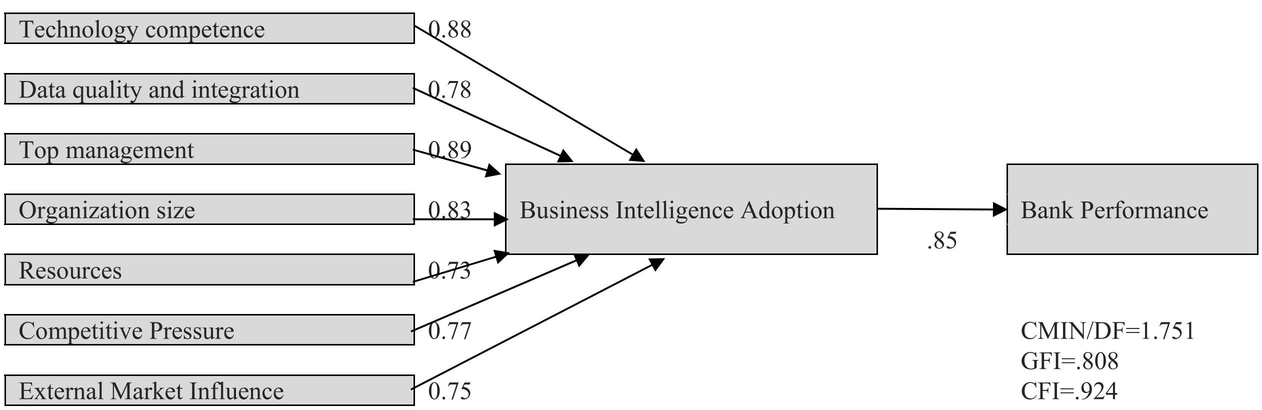

Fig. 1. Research Bootstrapping Results

As shown in Fig. 1, the ratio of chi-square to degrees of freedom (CMIN/DF) was 1.751%, which is less than the maximum value of 3, which is the top limit for this indicator. All the scores for the Tucker-Lewis index (TLI), the goodness of fit index (GFI), and the comparative fit index (CFI) were higher than 0.90, which is the lowest possible score. In addition, the root mean square error of approximation (RMSEA) was estimated to be 0.029, which is regarded as a fair approximation error since it is less than the 0.08 criterion that was established as the upper limit.

Table 2
Path Coefficient Test Results

Hypothesis	**Relation**	**Standard Beta**	***t* value**	***p* value**	**Results**
H1	TC → BI	0.524***	24.88	0.000	Supported
H2	DQI → BI	0.755***	29.51	0.000	Supported
H3	TMS → BI	0.678***	29.41	0.000	Supported
H4	OS → BI	0.733***	20.25	0.000	Supported
H5	KS → BI	0.696***	28.43	0.000	Supported
H6	Re → BI	0.656***	21.78	0.000	Supported
H7	CP → BI	0.687***	28.83	0.000	Supported
H8	EMI → BI	0.715***	27.96	0.000	Supported
H9	BP → BI	0.711***	22.74	0.000	Supported

As a result, the information shown in Table 2 demonstrates quite clearly that the assessment-based research model is sufficient to proceed to the analysis of the study's hypotheses. The findings from evaluating the hypotheses of the research were validated using the structural equation model (SEM). Based on the TOE model, the elements investigated in this research were categorised along three dimensions, namely technical, organisational, and environmental settings. All the search hypotheses and the direct effects and relationships among the research variables have been clearly recognised. In conclusion, the route model confirmed the goodness of fit of the hypothetical model. Analysing the route model to verify the conceptual foundation. All research hypotheses were validated, indicating the following relationships: BI adoption is significantly and positively linked to the technology competence, data quality, and integration of BIS; top management, organisation size, and resources have a significant impact on the BI; competitive pressure and external market influence have a significant impact on the BI; and BI adoption is significantly related to bank performance. Finally, the findings demonstrate the relationship between regulatory compliance and BIA use, such that the greater the rate of regulatory compliance, the higher the BIA usage rate. In reality, BIA is an essential instrument for banks to comply not only with local and internal legislation but also with worldwide norms and regulations.

5. Conclusions and implications

BI is a key tool that interacts with huge amounts of different types of data, whether they are structured or not. This gives banks a huge value in the form of better operations and significant competitive advantages. To keep up with the rapid pace of technology in today's dynamic world, every bank must emphasise the importance of developing a massive BI system. In this research, we investigated the variables that affect the adoption of BI in the banking industry. Many elements, including the technological, organisational, and environmental dimensions as well as the relationship between BI adoption and performance, have been investigated. The findings of the investigation revealed not just the significance of these variables on BI acceptance and usage but also the immense value that such technology can bring to the banking industry. In fact, it is crucial to understand the dynamics of these aspects not only to improve BI use but also to better design and deploy such technologies in the banking industry. The findings of this research indicate that in order to improve fact-based decision making, business intelligence technologies need the availability of quality-level data-related infrastructure capabilities, strong backing from senior management, and heightened knowledge of the "market environment." To completely grasp the crucial success element of BI use and utilisation, the studies claim that other aspects involving bigger and more thorough populations must be explored. In other words, more study may test the suggested model in diverse situations, such as Jordanian public-shareholding enterprises that substantially invest in BI systems, in order to generate more generalizable findings. In addition, future studies might apply the model to industrialised nations in order to compare their outcomes with those of emerging nations. Finally, the authors have considered the influence of BI on firm performance and innovation capacities; however, further study is required to analyse the adoption of BI in terms of organisational effectiveness from a holistic perspective. In conclusion, the findings of this study are of the utmost importance to the literature in this study and may inspire the conduct of other vital investigations to throw more light on their positions.

References

Aboelmaged, M. G. (2014). Predicting e-readiness at firm-level: An analysis of technological, organizational and environmental (TOE) effects on e-maintenance readiness in manufacturing firms. *International Journal of Information Management*, *34*(5), 639-651.

Aghion, P., Jones, B. F., & Jones, C. I. (2018). Artificial intelligence and economic growth. In *The economics of artificial intelligence: An agenda* (pp. 237-282). University of Chicago Press.

Ahani, A., Rahim, N. Z. A., & Nilashi, M. (2017). Forecasting social CRM adoption in SMEs: A combined SEM-neural network method. *Computers in Human Behavior*, *75*, 560-578.

Airinei, D., & Berta, D. (2012). Semantic business intelligence – a new generation of business intelligence. Informatica Economica [Online]. 16(2/2012).

Al-Okaily, A., Al-Okaily, M., & Teoh, A. P. (2021). Evaluating ERP systems success: Evidence from Jordanian firms in the age of the digital business. *VINE Journal of Information and Knowledge Management Systems*, (ahead-of-print).

Al-Okaily, M., & Al-Okaily, A. (2022). An empirical assessment of enterprise information systems success in a developing country: the Jordanian experience. *The TQM Journal*, *34*(6), 1958-1975.

AlSheibani, S., Cheung, Y., & Messom, C. (2018). Artificial Intelligence Adoption: AI-readiness at Firm-Level. *Conference on Information Systems*, 15, pp. 25-36. Twenty-Second Pacific Asia Japan.

Aruldoss, M., Lakshmi Travis, M., & Prasanna Venkatesan, V. (2014). A survey on recent research in business intelligence. *Journal of Enterprise Information Management*, *27*(6), 831-866.

Aws, A. L., Ping, T. A., & Al-Okaily, M. (2021). Towards business intelligence success measurement in an organization: A conceptual study. *Journal of Systems Management Science*, *11*, 155-170.

Bollier, T. (2020). Artificial Intelligence Comes of Age. The Promise and Challenge of Integrating AI into Cars, Healthcare and Journalism. Washington, DC: The Aspen Institute.

Cartwright, M. (1997). Applications of Artificial Intelligence Chem Oxcp 11. Oxford University Press,Inn.

Chiang, Y. H., & Hung, K. P. (2014). Team control mode, workers' creativity, and new product innovativeness. *R&D Management*, *44*(2), 124-136.

Cruz-Jesus, F., Pinheiro, A., & Oliveira, T. (2019). Understanding CRM Adoption Stages: Empirical Analysis Building on the TOE Framework. *Computers in Industry, 25*(10), 1-13. doi:https://doi.org/10.1016/j.compind.2019.03.007

Dobbs, M., & Hamilton, R. T. (2007). Small business growth: recent evidence and new directions. *International journal of entrepreneurial behavior & research*, *13*(5), 296-322.

Fast, E., & Horvitz, E. (2017, February). Long-term trends in the public perception of artificial intelligence. In *Proceedings of the AAAI conference on artificial intelligence* (Vol. 31, No. 1).

Hair, J. F., Anderson, R. E., Tatham, R. L., & Black, W. C. (2010). *Multivariate data analysis*. Englewood Cliffs, New Jersey: Prentice Hall.

Hair. (2017). A primer on partial least squares structural equation modeling (PLS-SEM). Thousand Oaks: Sage. https://doi.org/10.1016/j.lrp.2013.01.002.
http://dx.doi.org/10.1016/j.chb.2017.05.032.

Iacovou, C. L., Benbasat, I., & Dexter, A. S. (1995). Electronic data interchange and small organizations: Adoption and impact of technology. *MIS quarterly*, *19*(4), 465-485.

Idris, A. O. (2015). Assessing a Theoretically-Derived E-Readiness Framework for E-Commerce in a Nigerian SME. *Evidence Based Information Systems Journal*, *1*(1), 1-20.

Infosys, S. (2016). *Towards Purposeful Artificial Intelligence*, pp. 4-8.

Makridakis, S. (2017). The forthcoming Artificial Intelligence (AI) revolution: Its impact on society and firms. *Futures*, *90*, 46-60.

Martins, R., Oliveira, T., & Thomas, M. A. (2016). An empirical analysis to assess the determinants of SaaS diffusion in firms. *Computers in Human Behavior*, *62*, 19-33.

Mata, F. J., Fuerst, W. L., & Barney, J. B. (1995). Information technology and sustained competitive advantage: A resource-based analysis. *MIS quarterly*, *19*(4), 487-505.

Mohammad, A., Al-Okaily, M., Al-Majali, M., & Masa'deh, R. (2022). Business Intelligence and Analytics (BIA) Usage in the Banking Industry Sector: An Application of the TOE Framework. *Journal of Open Innovation: Technology, Market, and Complexity, 24*(2), 1-17. doi:https://doi.org/10.3390/joitmc8040189

Nithya, N., & Kiruthika, R. (2021). Impact of Business Intelligence Adoption on performance of banks:a conceptual framework. *Journal of Ambient Intelligence and Humanized Computing, 24*(2), 1-12.

Owusu, A. (2017). Business intelligence systems and bank performance in Ghana: The balanced scorecard approach. *Cogent Business & Management*, *4*(1), 1364056.

Purdy, M., & Daugherty, P. (2016). Why artificial intelligence is the future of growth. *Remarks at AI now: the social and economic implications of artificial intelligence technologies in the near term*, 1-72.

Ramesh, A. N., Kambhampati, C., Monson, J. R., & Drew, P. J. (2004). Artificial intelligence in medicine. *Annals of the Royal College of Surgeons of England*, *86*(5), 334.

Ramirez, E., David, M. E., & Brusco, M. J. (2013). Marketing's SEM based nomological network: Constructs and research streams in 1987–1997 and in 1998–2008. *Journal of Business Research*, *66*(9), 1255-1260.

Ritter, T., & Gemünden, H. G. (2004). The impact of a company's business strategy on its technological competence, network competence and innovation success. *Journal of business research*, *57*(5), 548-556.

Rogers, M. E. (2003). Attributes of Innovations and Their Rate of Adoption. Library of Congress Cataloging-in-Publication Dat.

Rumler, F., & Waschiczek, W. (2010). The impact of economic factors on bank profits. *Monetary Policy & the Economy*, *4*(10), 49-67.

San-Martín, S., Jiménez, N. H., & López-Catalán, B. (2016). The firms benefits of mobile CRM from the relationship marketing approach and the TOE model. *Spanish journal of marketing-ESIC*, *20*(1), 18-29.

Tornatzky, L. G., & Klein, K. J. (1982). Innovation characteristics and innovation adoption-implementation: A meta-analysis of findings. *IEEE Transactions on engineering management*, *29*(1), 28-45.

Vempati, S. (2016). *The Artificial Intelligence Revolution. Carnegie Endowment for International Peace*.

Wade, M., & Hulland, J. (2004). The Resource-Based View and Information Systems Research: Review, Extension, and Suggestions for Future Research. *MIS quarterly, 28*(1), 107-142.

Wells, D. (2022). Business Analytics—Getting the Point. BeyeNetwork. 2008. Available online: http://www.b-eyenetwork.com/view/7133 (accessed on 5 January 2022).

Yang, Z., Sun, J., Zhang, Y., & Wang, Y. (2015). Understanding SaaS Adoption from the Perspective of Organizational Users: A Tripod Readiness Model, Computers in Human Behavior (45), pp.

Zhai, I. (2010). Research on Post-Adoption Behavior of B2B E-Marketplace in China, Management and Service Science (MASS), *2010 International Conference on: IEEE,* pp. 1-5.