Factors influencing the adoption of business intelligence for managing Jordanian SMEs during the covid-19 epidemic

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ABSTRACT

The major goal of this study is to investigate how business intelligence is used to develop business operations in SMEs, as well as the elements that influence business intelligence adoption. Following the sample verification procedure, 232 samples were collected. The SEM software was used to process all of the data acquired in the research investigation. The study's findings show that TOE has a significant effect on SMEs' adoption of business intelligence solutions. According to the study's results, the researcher believes that leaders and decision-makers in firms would use business intelligence systems to define all activities, responsibilities, and work procedures in order to increase organizational ambidexterity and performance.

Keywords: *Business Intelligence BI, Artificial Intelligence AI, TOE, Adoption, SMEs*

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1. Introduction

Covid-19, which has been labelled a pandemic by the World Health Organization and has put the whole world on lockdown, has wreaked havoc on global manufacturing and commercial operations since it is a contagious virus that demands social distance for protection until a vaccine is developed. Small and medium businesses are finding it more difficult to keep up with their global company operations and rivals; while all business units rely on human labour to run their operations, business intelligence (BI) and technology can help them do it more efficiently. In the rapidly evolving technology industry, BI is viewed as a crucial instrument for enhancing operational capabilities (Trieu, 2017; Yiu et al., 2020; Ahmada & Hajij, 2022).BI systems make use of relevant data assets to allow for more faster and informed choices, considerably improving an organization's performance and efficiency (Lin & Kunnathur, 2019). "Analytical software and solutions for gathering, aggregating, analysing, and giving access to information in a way that is expected to help an enterprise's users make better business choices," according to the definition of BI systems (Yiu et al., 2020; Gangadharan & Swami, 2004). Nevertheless, deploying a BI system successfully is typically challenging and necessitates a significant amount of resources, management commitment, and experience(Agarwal & Dhar, 2014; Mikalef et al., 2020; Popovic et al., 2019). It's a complicated process that necessitates management's long-term commitment as well as a significant amount of time and effort in creating proper organisational infrastructures, offering extensive training, and involving stakeholders (Yiu et al., 2020; Mikalef et al., 2020; Li et al., 2013). For instance, Kmart's efforts to completely adopt business analytics systems are hampered by a lack of organisational leadership, resulting in operational inefficiencies and market loss (Han et al., 2018). As a result, there is a lot of discussion over how BI systems work in practise.In general, both researchers and practitioners in SMEs use these two prominent IS theoretical foundations, namely the Diffusion of Innovation (DOI) theory and the Technology, Organization, and Environment (TOE) framework, to begin understanding the factors that may influence user adoption of BI systems.DOI identifies three types of elements that determine an organization's IT adoption intent: CEO qualities, internal characteristics, and external organisational features. The TOE framework, on the other hand, includes the external task environment, organisation, and technology. The technological support infrastructure, industrial features and market structure, and government regulation are all part of the environmental context. The official and informal connecting structures, cooperation, resource availability, and the organization's management are all part of the organisational context. The technological context is made up of technical breakthroughs and preparedness. To define their contextual factors in the adoption model, various writers employ different taxonomies.The study will extract the relevant elements from a variety of these current adoption models, reduce duplicate variables, and develop the BI adoption model for SMEs to better understand the contextual aspects that assist the BI technologies' adoption.Considering the significance of a firm's information management capability and the significance of timely and effective data handling, surprisingly little study has been done on the impact of BI adoption on a firm's overall operating competence, particularly in the dynamic, rapidly changing high-tech industry(Trieu, 2017; Lin & Kunnathur, 2019; Park et al., 2017). The goal of this study paper is to stimulate the adoption of BI by SMEs so that they can compete, generate, and match the global standards of business operations. The authors will investigate the use of BI to enhance business operations and address issues posed by the covid-19 epidemic for SMEs in this study. Furthermore, the researchers will look for a practical answer to SMEs' challenges in the form of BI adoption. We'll go over the literature review, research methods, research findings, and make some recommendations for future study in the parts that follow.

2. Theoretical Background

The Technology Organizational and Environment (TOE) framework was created by Tornatzky and Fleischer (1990).This theory claims that three elements influence the process of organisational implementation and adoption of technical innovations: TOE aspects (Frederico et al., 2019). The technological context defines important internal and external technologies to the organization, comprising those existing within the organisation as well as those that are accessible for possible implementation and adoption by the organisation, i.e., those accessible outside but not yet adopted (Junior et al., 2018; Frederico et al., 2019). It is important to note that technology in this context might have both material (e.g., equipment) and immaterial (e.g., data and procedures in use) implications. The technical background is split to emphasise how the qualities of a particular technology may influence the decision to adopt it. The organisational context refers to the resources and assets of the corporation, including its procedures, human resources, administrative structure, work-related relationships, hierarchy, size, and additional resources. The organisational framework includes, among other things, the number of employees, sales, business operations, hierarchical structure, and resources. Finally, the environmental context includes an organization's "arena," which comprises its industry, competitors, suppliers, and government connections. Several studies have used the TOE paradigm to evaluate the acceptability of technical advances such as hospital information systems, green IT, e-business, and electronic data exchange (EDI)

(Ahmadi et al., 2017; Martins et al., 2016; Popovic et al., 2019).

3. Literature review

3.1 Business IntelligenceSystem Adoption

The BI approach has emerged as a creative method for extracting new values that can enable organisations to be unique and different (Bordeleau et al., 2020). BI systems have become critical in modern business because they provide companies with information and new knowledge that, when applied at the right time and to the right problem, can have a significant positive impact on business outcomes (Fatorachian & Kazemi, 2018; Ahmada & Hajij, 2022). BI systems are a collection of tools, processes, and applications for storing, analysing, and visualising corporate data that is important for making good decisions (Park et al., 2017). However, BI systems are one of the most difficult technological innovations to implement in a business, especially because they require employee training and additional time to learn how to use the information obtained, and thus how to analyse business data (Popovic et al., 2019). Numerous papers examine the TOE framework's application to the BI system adoption process in various businesses around the world. Different writers focused on different stages of BIS implementation in business in their research. For example, used TOE determinants to analyse the BI system implementation success factors within Taiwanese firms that participated in the BI system implementation process (Popovic et al., 2019). In their research, they found that BI system implementation has two key implications on user happiness and total system efficacy.

3.2Relative advantage

The perceived benefit of BI adoption at the company level is called relative advantage. Perceived BI advantages refers to the extent to which BI outperforms other competing technologies in the context of this study (Li et al., 2013). According toRogers, (1995), an organization's desire to embrace an innovative technology is strongly influenced by the perceived advantage of the innovation. Prior studies (Yang et al., 2015; Kumar et al., 2016; Popovic et al., 2019)demonstrated a positive association between the relative benefit of new technology and innovation uptake. BI enables a company to gain a competitive edge, lower cost, expand into new markets, increase top-line earnings, improve efficiency, and enhance human intelligence (Curran et al., 2017; Ransbotham et al., 2017)

3.3 Compatibility

Numerous studies have shown a link between compatibility and the willingness to adopt new technologies (Ransbotham et al., 2017; Popovic et al., 2019). The term "compatibility" relates to the scope of the innovation and its capacity to give value and experience while meeting the demands of the anticipated adopters (Rogers, 1995). According to Yang et al., (2015), successful BI conversions require a strong business case that is aligned with existing strategy. A better fit between the adoption process and the dissemination of technological innovation makes adoption simpler, as suggested by Ifinedo (2005).

3.4 Complexities

A number of studies have found a link between complexity and the desire to embrace a new technology. The difficulty of comprehending and utilising the invention is referred to as complexity (Ifinedo, 2005; Mikalef et al., 2020). However, complexity cannot be regarded a favourable factor for adoption because artificial intelligence adoption is now exceedingly difficult and complex. The level of technical and financial assistance required is quite high (Fatorachian & Kazemi, 2018).

3.5 Top management support

According to Ifinedo, (2005) Top Management Support (TMS) refers to the involvement of a senior executive in IS/IT deployments. TMS is emphasised as a moderating factor in resource-based theory, with the notion that a lack of support not only fails to enhance a firm's competitive position(Wade & Hulland, 2004), but also increases its failure to embrace innovation. TMS may have a positive influence on the acceptance of new technologies when it comes to developing a vision, allocating resources and providing capital funds (Idris, 2015; Sulaiman et al., 2018). In IS/IT research, senior management support, for example, has been shown to increase cloud computing and e-business adoption. Using business intelligence to support company transformation is a strategic decision in general (Idris, 2015; Sulaiman et al., 2018; Gartner, 2017).

3.6 Organization size

According to Rogers (1995), the size of the organisation has a direct impact on the acceptance of innovation. According to the findings of a number of studies, the size of an organisation has a positive influence on the rate at which it adopts new technologies (Sulaiman et al., 2018; Ifinedo, 2005; Aboelmaged, 2014). Large organizations have a stronger ability to absorb technology (Duan et al., 2010). Similarly, Aboelmaged, (2014)stated that large enterprises are under more competitive pressure, while Gartner, (2017)stated that company size has a favourable influence since larger organisations have more financial and technological resources.

3.7 Competitive pressure

The prospect of losing a competitive advantage encourages an organisation to accept a new invention, which is referred to as competitive pressure (Aboelmaged, 2014). Competitive pressure has been identified as a role in the dissemination of innovative innovations by extensive empirical study (Fast & Horvitz, 2017). Sulaiman et al., (2018)identified business activities that are influenced by external variables including socioeconomic issues. As shown in a recently Gartner research (2017), building a business intelligence plan is the most important approach for technological advancement in 2018. For both people and organisations, BI has the capacity to inspire creativity and provide new possibilities(Yang et al., 2015). The capacity to utilize BI to enhance customer experience and decision-making has an impact on BI adoption (Garten, 2017).

3.8 Government regulatory issues

Government policy has been identified as one of the issues that enterprises must consider in addition to competitive pressure (Aboelmaged, 2014; Sulaiman et al., 2018). Regulatory difficulties in this research pertain to government aid offered to facilitate the implementation of BI technologies at the organisational level. Varied governments have different policies when it comes to BI. In the United States, for example, plans are being made to adapt regulatory hurdles to 'BI-enabled' goods like self-driving vehicles in order to promote BI innovation (Ahmadi et al., 2017). The following research hypotheses are offered based on earlier studies and reviews:

H_1: *Relative advantage has a positive effect on business intelligence.*
H_2: *Compatibility has a positive effect on business intelligence.*
H_3: *Complexities has a positive effect on business intelligence.*
H_4: *Top management support has a positive effect on business intelligence.*

H_5: *Organization size has a positive effect on business intelligence.*
H_6: *Competitive pressure has a positive effect on business intelligence.*
H_7: *Government regulatory issues has a positive effect on business intelligence.*

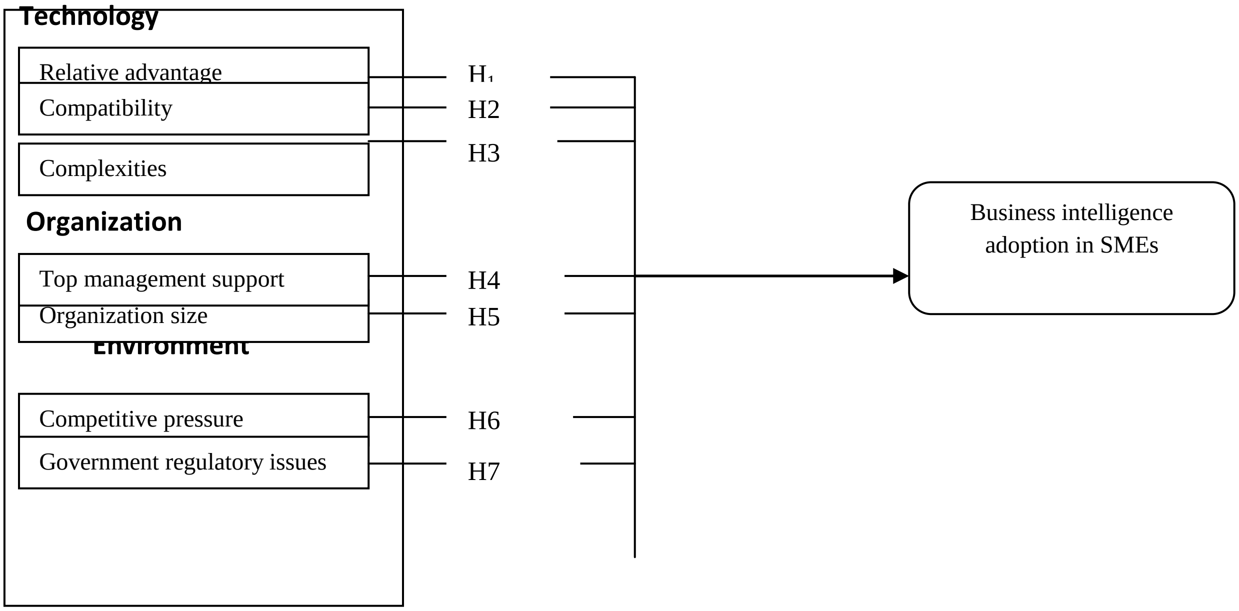

Fig. 1. Proposed Research Model

Tornatzky and Fleischer (1990) introduced the TOE framework for technology adoption. As illustrated in Fig 1, this framework categorises the factors into organisational, technological, and environmental categories. The categorization variables aid in the fitting of prior theories' components into TOE theory. The technological framework's components can be adapted from the diffusion of innovation theory.

4. Researchmethodology

4.1 Population and sample selection

For data collection and sample selection, this study employed a qualitative technique based on a questionnaire. The study's main goal was to look at how SMEs are using business intelligence to grow their businesses and what variables are driving that adoption. The majority of the data was collected using self-reported surveys developed with Google Forms and distributed through email to a select set of managers at various levels. In all, 249 responses were received, with 17 of them deemed inappropriate for statistical analysis due to missing or incorrect data. As a result, the final sample comprised (232) answers appropriate for analysis, which proved to be sufficient to the degree that was foreseeable and allowed for a data saturation presumption (Sekaran & Bougie, 2016).

4.2 Measurement instrument

The measuring variable was a self-reported questionnaire with two major parts and a section for controlling factors. Gender, age group, educational level, and experience were used as categorical measures for the control variables. A five-point Likert scale was employed to measure the two primary factors. The first portion had (32) questions that were used to assess the TOE model (Frederico et al., 2019). The following are the dimensions in which these questions were distributed: 5 items are dedicated to determining relative advantage, 4 items are dedicated to determining compatibility, 4 items are dedicated to determining complexities, 6 items are dedicated to determining top management support, 5 items are dedicated to determining organisation size, 3 items are dedicated to determining competitive pressure, and 4 items are dedicated to determining government regulatory issues. The second segment featured seven items devised to assess BI in accordance with what was mentioned in the first section (Ahmada & Hajij, 2022; Bordeleau et al., 2020).

5. Findings

5.1 Model assessment for measurement

This research evaluated hypotheses using structural equation modelling (SEM), a sophisticated statistical method for examining and quantifying the connection between variables and factors (Wang & Rhemtulla, 2021). As a consequence, the components' validity and reliability were examined using the statistical tool AMOSv21 and confirmatory factor analysis (CFA). The findings of discriminant validity and convergent, as well as the reliability indices, are summarised in Table 1.The results shown in Table 1 demonstrate that the standard loading values of the different items fell within the domain (0.624-0.881), which indicates that these values were higher than the elements' minimum retention as determined by standard loads(Sung et al., 2019). The average variance extracted (AVE), which must be more than 0.50, is a summary indicator of concept convergent validity (Sekaran & Bougie, 2016). The AVE values for all constructs were more than 0.50, indicating that the measurement methods used had sufficient convergent validity. Wang & Rhemtulla, (2021)Introduced the comparison method as a means of assessing discriminant validity in covariance-based SEM. Maximum shared variance (MSV) values are compared to AVE values, and square root of AVE values are compared to how well the remaining structures fit together. The MSV values were lower than the AVE values, and the AVE values were higher than the correlation values among the other constructs, according to the findings. As a result, the measurement model used includes discriminative validity.McDonald's Omega coefficient and Cronbach's Alpha coefficient were used to evaluate the measurement model's internal consistency and compound reliability. As indicated in Table 1, Both Cronbach's Alpha and McDonald's Omega were higher than 0.70,which is the lowest limit for assessing measurement reliability (Sekaran & Bougie, 2016).

Table 1

Results of validity and reliability tests

Constructs	1	2	3	4	5	6	7	8
1. RA	**0.765**							
2. CPL	0.710	0.786						
3. CTA	0.674	0.760	0.771					
4. TMS	0.612	0.692	0.658	0.758				
5. OS	0.614	0.687	0.647	0.741	0.717			
6. CP	0.589	0.667	0.682	0.661	0.757	0.714		
7. GRI	0.593	0.578	0.635	0.658	0.688	0.711	7.19	

8. BI	0.578	0.559	0.624	0.621	0.666	0.599	0.598	**0.744**
VIF	2.746	2.012	2.117	1.891	1.952	1.899	1.885	
Loadings range	0.686-0.868	0.771-0.881	0.654-0.842	0.692-0.815	0.658-0.749	0.661-0.766	0.626-0.728	0.624-0.742
AVE	0.565	0.577	0.581	0.587	0.559	0.512	0.521	0.557
MSV	0.427	0.486	0.456	0.437	0.547	0.585	0.566	0.541
Internal consistency	0.867	0.845	0.854	0.809	0.807	0.879	0.881	0.874
Composite reliability	0.791	0911	0.922	0.884	0.868	0.881	0.789	0.931

4.2 Structural model

Due to the fact that the Variance Inflation Factor (VIF) values are lower than the cutoff value of 5, the structural model did not uncover any multicollinearity problems among the predictor constructs, which is shown in Table 2(Hair et al., 2017). The values of model fit indices reported in Fig. 2 confirm this conclusion.

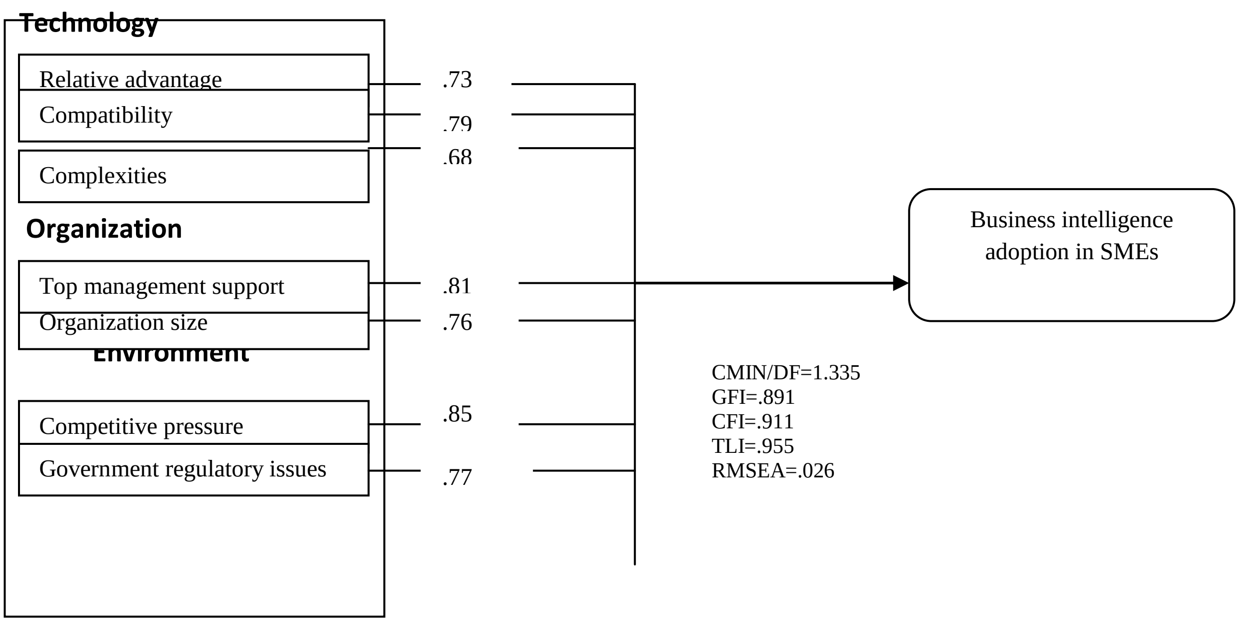

Fig. 2. Research Bootstrapping Results

As seen in Fig. 2, the ratio of chi-square to degrees of freedom (CMIN/DF) was 1.335%, which is below the maximum value of three for this indicator.The goodness of fit index (GFI), comparative fit index (CFI), and Tucker-Lewis index (TLI) were all greater than the 0.90 minimum acceptable criterion. Furthermore, the root mean square error of approximation (RMSEA) resulted in a value of 0.026, which is a tolerable approximation error because it is less than the upper limit of 0.08. As a result, the Table 2 below clearly illustrates that the model of this study based on the evaluation is good enough to move on to addressing the research hypotheses. SEM was employed to confirm the results of testing the hypotheses of the research.

Table 2

Path Coefficient Test Results

Hypothesis	Relation	Standard Beta	*t* value	*p* value	Results
H1	RA ⟶ BI	0.531***	26.52	0.000	Supported
H2	CPL ⟶ BI	0.543***	22.66	0.000	Supported
H3	CTA ⟶ BI	0.621***	25.32	0.000	Supported
H4	TMS ⟶ BI	0.609***	20.95	0.000	Supported
H5	OS ⟶ BI	0.582***	19.98	0.000	Supported
H6	CP ⟶ BI	0.523***	27.59	0.000	Supported
H7	GRI ⟶ BI	0.645***	25.35	0.000	Supported

The direct influence and linkages between the study variables have been thoroughly acknowledged, as have all of the search hypotheses.

6. Conclusion and implications

The influence of the TOE model on BI adoption systems among Jordanian SMEs is investigated in this study. According to the report, BI system adoption leads to increased operational business, which is especially true for SMEs operating in high-intensity environments. Furthermore, the findings of the study suggest that TOE has a direct and beneficial influence on SMEs' adoption of BI systems. This outcome is consistent with the findings of earlier investigations. The intensity and TOE model are crucial contextual elements for businesses to enjoy the advantages of BI adoption systems, and we contribute to the literature by giving empirical evidence that the adoption of BI systems may increase firms' operational competence.We contribute to our understanding of the contexts in which businesses are more likely to receive additional benefits from their BI adoption platforms. Based on the findings, it can be stated that BI adoption may benefit SMEs in all areas. It has the potential to improve the conditions of SMEs, particularly in the aftermath of the COVID-19 epidemic, but adoption is difficult. At the firm level, top management must make efforts to promote technology use. BI systems vary from information systems in that they use analytical approaches to find and evaluate hidden patterns in vast volumes of data on a multidimensional level. While knowledge is valuable in and of itself, having relevant and meaningful informative insights adds to the value of a company.Valueful business insights are developed by BI tools to enhance decision-making, boosting the information value of data stored in the database.Much of the literature highlights the importance of data, knowledge, and operational insights as a strategic resource that imparts company competitiveness. Business intelligence and information is a critical resource for enhancing organisational capabilities. Today's businesses must handle huge volumes of business data from a variety of internal and external sources. Firms must improve their business competence by using BI systems to support a broader range of operations. BI solutions, for example, allow operations managers to effortlessly track and collect more data from supply chains. To summarise, successful adoption of BI systems is critical for businesses to get value from their data, especially in the Internet era, when important insights may be gained by correctly analysing and sharing massive volumes of data.In addition, little is known about the contextual factors that influence the adoption of BI systems in SMEs. According to the findings of an event research on the adoption of BI technologies, the use of BI systems leads to increased business capabilities. Our research shows that high-tech companies may gain a competitive edge by implementing business intelligence solutions. Researchers can examine the advantages of BI systems in evaluating structured vs unstructured data in future studies.

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