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Innovation Capabilities as a Mediator between Business Analytics and Firm Performance

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Abstract: Although business analytics (BA) play an important role in improving firm performance, various firms struggle to deliver their full benefits. Many researchers have investigated the capabilities required to achieve better value through BA, but none have addressed the impact of innovation capabilities as a contextual variable mediating the effects on firm performance. By adopting the Technology-Organization-Environment (TOE) framework, this study suggests a model to evaluate the impact of BA capabilities on firm performance and addresses the mediating role of innovation capabilities. A quantitative approach was adopted for data collection and analysis. Based on 386 surveys of BA experts at Saudi Arabian firms and the use of PLS-SEM to test and validate the model. The results show that organizational factors have a highly significant impact on firm performance. While IT infrastructure and information quality as technological factors showed no significant and positive effect. Furthermore, the findings revealed that innovation capabilities positively mediate the link between IT infrastructure and information quality and firm performance as it affects directly and indirectly firm performance. The findings of this study contribute to the literature by addressing the research gap in BA in the Saudi Arabia context. Moreover, the study result stressing about the role of innovation capabilities on the BA capabilities and the importance of considering the interaction between TOE factors. However, research was carried out within one developing country (Saudi Arabia), which might restrict the findings' generalizability of the study, and the results must be generalized with care to avoid issues such as structural and cultural variances between developed and developing countries.

Keywords: innovation capabilities; business analytics; partial least squares structural equation modeling; Saudi context

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1. Introduction

Currently, the BA field is seen as interesting by both academics and practitioners [1,2]. Moreover, Almazmomi et al. [3] show the importance of BA in terms of how it helps firms to gain competitive advantage. Trkman et al. [4] observe that BA is a major research topic because it helps decision-makers by offering an approach to detect and utilize large volumes of data concerning organizations, both internal and external. In 2025, the amount of available data is expected to reach 180 zettabytes, which gives data a critical position in a new digital universe [5,6]. In addition, Shi et al. [7] mentioned that 95% of projects related to analytics-driven innovation fail due to technical and cultural difficulties.

BA has been defined as a set of activities that include collecting, transforming, analyzing, and interpreting data to empower organizations and help decision-makers understand market changes and gain competitive advantages [8,9]. Furthermore, the BA concept is used interchangeably with Business Intelligence (BI) and Big Data (BD) concepts [10,11]. However, many projects within analytics scope, such as BI projects, fail to deliver the benefits of use in terms of helping in the decision-making process as firms deal with a large amount of information [12].

Furthermore, Nam et al. [13] argue that the effect of using BA is extensively different from firm to firm and should be comprised in the essential process of the firm as it helps decision makers in their decision. Therefore, a respectable use of BA takes a long time after this technology is launched. However, while most of the current BA research exists for BA adoption, neither focuses on BA impact on firm performance and the role of innovation capabilities despite the importance of understanding this phase. In addition, Duan et al. [10] emphasize that there is a lack of theory relating BA to innovation despite the high use of BA in firms.

Therefore, precise BA studies addressing the innovation capability's role on firm performance and their impact on BA aspects should be highlighted to increase the firm performance by using BA to provide the firms with trending information on past or current events and with predictive and prescriptive analytics. However, studies such as Ylijoki et al. [14] used innovation capabilities as a mediator between big data and business models due to the critical role that they play in firms. Ylijoki et al. [14] say "*focusing on the organizational aspects of innovation capabilities is an important factor for a successful business transformation*".

In addition, Ashrafi et al. [2] mention that the innovation practices in BA projects that are applied by a firm are critical to be at the highest level and its equal importance to the information quality. They further argue that innovation ability is critical as the main concern of firms about capability is to sense and respond to external pressure to maximize opportunities and avoid threats before they happen. Moreover, Alaskar et al. [6] discuss that the environmental changes in Saudi Arabia based on the Kingdom Vision 2030 and the COVID-19 pandemic led firms to increase their ability to meet unforeseen events by adopting new technologies such as Big Data Analytics (BDA).

However, while it has been shown above that innovation capability plays a critical role, there are few studies considering the impact of this aspect on BA, and as far as we are aware, no previously published study has investigated the enablers of BA while considering the mediator role of innovation capabilities. Therefore, this study integrates a TOE proposed by Tornatzky and Fleischer [15] as it is considered a vital multi-view that explains the implementation of innovations based on a diversity of aspects that impact firm performance within technological, organizational, and environmental contexts [16] to help to explain the mediating role of innovation in capability on the firm performance. This paper investigates the technological (IT infrastructure and Information quality), organizational (Analytics Capability–Business Strategy Alignment and innovation capability), and environmental (competition intensity) aspects as predictors of BA firm performance within the Saudi Arabia context and the role of innovation capability as a mediator to address the research gap by understanding the BA usage of firms located in Saudi Arabia. Based on data collected from a sample of 386 Saudi Arabian firms, the partial least squares (PLS) analysis was used to test the hypotheses of this study.

2. Literature Review

2.1. Innovation Diffusion Theory (IDT)

Verma and Chaurasia [17] argue that the theory of innovation diffusion [18] is considered part of the TOE framework that is based on five technological aspects: Compatibility, relative advantage, observability, complexity, and trialability. They further argue that current empirical studies on Information System (IS) field used the TOE framework as a base to explain technological innovation adaption. However, Nam et al. [19] argue that integrating the TOE framework with other theories allows for a better understanding of IT adaption. As an example, consideration of innovation diffusion theory in addition to the TOE framework gives a better description of technology acceptance by including innovation attributes as an example included in Chong et al. [20] study, or such as relative advantage, as shown in Wang et al. [21] study.

In addition, Maduku et al. [22] mentioned that the TOE framework is chosen to be used as a theoretical base due to the focus on environmental context, which is not supported by Innovation Diffusion theory. He further argues that the TOE framework is more empirical support and has a stronger theoretical basis than the Innovation Diffusion theory. However, employing TOE framework showed significant explanation in each of the technological, organizational, and environmental contexts, and can be valuable in clarifying the complexity of technology by including innovation characteristics [19,23]. Next part will discuss the TOE framework.

2.2. TOE Framework and BA

TOE is a theoretical framework that includes three main contexts: Technology, organization, and environment [15,24]. In addition, the TOE has been defined as the explanation from the technological, organizational, and environmental perceptions that are used to determine the organization aspects that impact the process of practicing the innovations of technologies [15]. Verma and Chaurasia [17] mentioned that the determination of interior and exterior technologies that relate to the firm refers to the technological context in the TOE framework, while aspects that relate to firms, such as skills of human resources, would be related to the organizational context. Furthermore, they add that the environmental context in the TOE framework relates to aspects such as rivalry and government rules.

Furthermore, Nam et al. [19] and Maduku et al. [22] mentioned that several prior studies used the TOE framework as a base of their studies to confirm the usefulness of information technology adoption, including E-business area [24], knowledge management systems area [25], electronic supply chain management systems in Taiwan [26], enterprise systems in northwest England [27], cloud computing adoption in England [28], and the adoption of Information and Communication Technology (ICT) innovations such as green innovation in China [19,22] study.

In addition, the TOE framework is used as a theoretical base in different topics related to analytics in different contexts, such as big data analytics and supply chains for firms based in Saudi Arabia [6] and business intelligence (BI) usage [29] in the context of small and medium enterprises (SMEs). Furthermore, Nam et al. [19] discuss the importance of the TOE framework within BA studies and how it has been used as a theoretical base by many scholars [19,26,29,30] to address the main enablers of BA within technological, organizational, and environmental contexts. Furthermore, Nam et al. [19] applied the TOE framework as a theoretical background for BA study with innovation diffusion process to enable technological, organizational, and environmental as independent variables within BA initiation, adoption, and assimilation stages as dependent variables to compare their different impacts on each stage.

In addition, the TOE framework has been used as a theoretical base in Kumar and Krishnamoorthy [31] study, which focuses on BA use in Indian firms. However, Kumar and Krishnamoorthy [31] argue that the TOE framework is used widely as a theoretical base in many studies for different reasons. First, it is considered a practical framework for IT acceptance that is extensively accepted in the technology management field, as mentioned by Hsu et al. [32]. Second, it is employed in numerous advanced and developed countries' firms with extensive use. Third, different IT subject studies can be related to the different technological, environmental, and organizational aspects. Finally, the TOE framework can be applied to examine technology use in addition to technology adaption [19,30].

However, based on the discussion above, this study uses the TOE framework as a theoretical base to understand the contextual factors regarding BA usage and to address the above-stated research gap by understanding the BA usage of Saudi Arabia firms and to examine the technological, organizational, and environmental roles as the main capabilities that enable for BA use that impact firm performance. Moreover, the study focuses on innovation capabilities as a mediator to address the impact on firms within the Saudi context by including three broad perspectives. First, the impact of technological context, which includes information quality and IT infrastructure as technological aspects. Second, organizational context considers Analytics Capability–Business Strategy Alignment

(ACBSA) factor in addition to innovation capabilities as organizational aspects. Finally, considering competition intensity as an environmental aspect.

3. Research Model and Hypotheses

3.1. The Effects of Technology Factors

The technology aspect in the TOE framework has been used in many BA studies that relate to IT competence as it helps to explain the required IT competencies [33]. In this part, we propose IT infrastructure and information quality that help to empower the BA on firm performance.

3.1.1. IT Infrastructure

Technology is a wide concept that includes many aspects such as integration of different operational systems with BA systems, managing data aspect, which includes metadata management and master data management, data visualization aspect, that includes manipulation of firms' data, and innovation of technology aspect to discover new perceptions of less structured problems [34]. Furthermore, the IT infrastructures concept refers to the capabilities such as technical platforms, databases, and applications that allow for storing, transforming, and processing [6].

Furthermore, Mao et al. [35] describe IT infrastructure as capabilities to manage integrated and standardized data. They further argue that a highly mature IT infrastructure would help to improve decision-making and agility in firms [35] as a platform can help to build accurate and comprehensive information. In addition, Alaskar et al. [6] mention that the IT infrastructures as a technological aspect play a critical role in adapting big data as an analytic system. However, appropriate IT infrastructure is considered a critical technological aspect for BA to be used efficiently, as mentioned by Lai et al. [30]. Therefore, to complete the collecting and integrating phases of data processing, a solid IT infrastructure is required [36].

In addition, Nam et al. [13] argue that the lack of required IT infrastructure leads to an obstacle in the innovation adaption phase [33,37] and that confirm information systems studies, which show a strong IT infrastructure is required to improve the chances of implementation of information systems [22,38,39]. They further argue that the BA, as well as big data usage, depend mainly on IT infrastructure as those systems are required to deal with a large amount of data [40,41]. Therefore, IT infrastructure is considered a critical capability, and it is important to investigate its role as a possible enabler of BA. Hence, we hypothesize the following:

Hypothesis 1 (H1). *IT infrastructure capabilities of BA are positively related to firm performance.*

3.1.2. Information Quality

Based on DeLone and McLean [42], the level of quality of information produced by the system refers to the information quality concept. Torres and Sidorova [43] argue that while the information quality concept is used interchangeably with data quality in BI and analytics studies [9,44,45], other studies show the differentiation between the two concepts [46,47]. Moreover, the information aspect and tools that are used to analyze the data make a difference between the quality of the data concept and the quality of the analytical tool [48]. However, most studies show the importance of data quality and information quality for analytics system success [9,43,48].

In addition, the data aspect considers the most important aspect of IT infrastructure in BA and operational intelligence systems to enhance business operations and support decision-makers with helpful reports [13,49–51]. Nam et al. [13] and Ashrafi et al. [2] argue that to attain reliable perceptions from using the BA system, high-quality data based on well IT infrastructure is required. Moreover, Popovič et al. [52] mentioned that the use of information to make an accurate decision could be affected if information quality is not at a high level.

Furthermore, Peters et al. [53] argue that the accuracy and reliability of the data are the main issues of BI as an analytic system, which may lead to not using the system due to the dissatisfaction that may occur among users. However, while Shen et al. [54] show that using high information quality in BA leads to high-quality decisions, Corte-Real et al. [55] mentioned that the agility of firms requires the ability to handle a large amount of information in BA.

Nevertheless, to enhance firms' innovative capability, IT capabilities, which include information quality resources within the organization, are important [56]. Therefore, we argue that information quality is considered a critical capability that impacts BA use as it helps decision-makers. Hence, we hypothesize the following:

Hypothesis 2 (H2). *Information quality capabilities of BA are positively related to firm performance.*

3.2. The Effects of Organizational Factors

The organizational aspect is considered the second aspect of the TOE framework, which focuses on the characteristics that relate to the firms' resources and structure [57]. In this study, the ACBSA and innovation capabilities aspect as a mediator has been proposed to represent the required organizational competencies in BA.

3.2.1. Analytics Capability–Business Strategy Alignment (ACBSA)

ACBSA has been defined as the alignment between analytics strategies and the organization's business strategy [58,59]. Based on Davenport et al. [60,61], pioneer organizations are required to adopt new capabilities quickly in alignment with continual changes in the world and data, and this is the key principle of big data. Akter et al. [62] also mention the importance of ACBSA in accordance with previous studies highlighting this aspect. He further argues that the volatility of big data projects leads to a greater focus on strategic alignment by addressing firm resources and aligning them with the outside environment [62].

However, in recent years, managers have paid more attention to the alignment between business strategy and areas of IT strategy [63,64]. Furthermore, Shanks et al. [65] argue that while IT and business alignment are considered important topics for management, BA is considered an important and strategic investment based on fit alignment. In addition, there are many capabilities related to strategic alignment, such as communication and trust between IT and business staff, flexible planning to adapt changes in innovations, and hiring required staff [65–67].

Bronzo et al. [68] show that managers can increase performance by focusing on the alignment of business processes with BA applications. The authors further emphasize the importance of changing business processes to concentrate on the use of analytics within firms. Hence, we argue that the existence of ACBSA will help the firm in BA use to make superior decisions, therefore, we hypothesize the following:

Hypothesis 3 (H3). *ACBSA capabilities of BA are positively related to firm performance.*

3.2.2. Innovation Capability (IC)

The term innovation has been defined as the ability of the firm to react to challenges in the industry [69]. Furthermore, innovation capability (IC) has been defined by Yang (2012) [70] as the new approach of firms to produce value by using their vital capabilities. Ashrafi et al. [2] argue that while earlier studies show the importance of innovation to get advantages from using information systems [44]. It also shows that the innovation capabilities help to increase organizations' performance through the use of IT capabilities in an appropriate way [60,70].

Furthermore, Ashrafi et al. [2] mentioned that while developing innovation capabilities is considered a high priority for most firms [71], the use of BA is considered highly as one of the most important enterprise applications that impact the creation of new ideas and knowledge and produce insights for businesses [72,73]. The authors argue further that the high innovation capabilities of such a firm can help to attain more knowledge about the industry, and the use of BA helps to increase innovation capabilities [74,75]. Işık et al. [9] emphasize the BA capabilities importance for the detection of new market opportunities. Thus, it is possible to suggest the following hypothesis:

Hypothesis 4 (H4). *Innovation capabilities of BA are positively related to firm performance.*

3.3. The Effects of Environmental Factors on Firm Performance

In this study, competition intensity is included as an environmental aspect that addresses the third dimension of the TOE. Competition intensity refers to the impact from competitors within the industry that faced firms with adapting and using technology to sustain competitiveness [32,76–78]. Wu and Chuang [79] mentioned that competitive pressure plays a vital role in the implementation and use of technology, therefore, it is considered an important external driver of Porter's five-force model. In addition, Lai et al. [30] argue that the main reason for firms to adapt and use BA technology is due to the competition pressure to maintain competitiveness. However, while the latest studies confirm the positive impact of using BA, it also shows the important role of competition intensity from business competitors to use BA due to their impact on firm performance [45,78].

In addition, Verma and Chaurasia (2019) [17] argue that the competition intensity plays a critical role in innovation by forcing firms to adopt new analytics systems, such as BDA, which help to achieve a better understanding of markets and improve decision-making. Moreover, Alaskar et al. [6] discuss that while Porter and Millar [80] address the role of competitive pressure on IT innovations in terms of creating new value to businesses, the firms of the industry will use new technological innovation as a result of competitive pressure to protect competitive position as mentioned by Petersen and Nguyen [81].

Furthermore, Nam et al. [13] argue that as organizations usually attempt to change the market structure and rules of competition, innovation diffusion is enabled because of competition intensity and make the adoption of innovation rapidly. Furthermore, the authors argue further that competition intensity can encourage to use of BA as innovative technology. However, as previous studies positively relate the competition intensity to the use of technology such as BA [13,30,45], therefore, we argue that the competition intensity influences BA usage, and we hypothesize the following:

Hypothesis 5 (H5). *Competition intensity is positively related to firm performance.*

3.4. The Mediating Effects of Innovation Capabilities

In addition to the innovation capabilities importance within BA context, studies specifically recognize that technological and organizational innovations play a critical role in using new technology. As an example, Mao et al. [35] study shows the importance of IT innovation as it is important to exploit the current IT resources to create business opportunities and allows firms to improve the value of IT businesses [82,83]. Thus, it is critical for firms to adapt IT innovation capabilities to align with market changes by renewing internal business processes in a quick manner [35,84,85]. In addition, Ashrafi et al. [2] see a positive relationship between high-agility firms in terms of detecting and responding to market changes quickly with the information quality capabilities in BA.

In addition, Ylijoki et al. [14] study use the innovation capabilities aspect as a mediator between big data and business models and mention that there are two approaches to innovation capabilities within the big data context, human-driven and data-driven approaches. While the human-driven approach focuses mainly on people, and it requires certain skills to generate new ideas from innovative people, the data-driven approach focuses on technological capabilities, which are needed to renew and are highly required if more data exist [14].

Furthermore, Akter et al. [62] argue that the alignment between technology, management, and talent capabilities is critical for big data analytics projects and required for innovation, as discussed by Manyika et al. [86]. In addition, Shi et al. [7] argue that the top-down, technology-enhanced mechanism plays a critical role by direct customer involvement in digital innovation that is consistent with the company's goal [87].

However, while earlier studies show the importance of innovation capabilities, as mentioned above, few studies have used innovation capabilities as a mediator, thus, this study presents innovation capabilities as a mediating variable as the BA usage requires additional support from different BA capabilities as mentioned above. Hence, we hypothesize the following:

Hypothesis 6 (H6a). *Innovation capabilities mediate the relationship between IT infrastructure and firm performance.*

Hypothesis 6 (H6b). *Innovation capabilities mediate the relationship between information quality and firm performance.*

Hypothesis 6 (H6c). *Innovation capabilities mediate the relationship between ACBSA and firm performance.*

However, the proposed conceptual research model related to our hypotheses is graphically displayed in Figure 1 below.

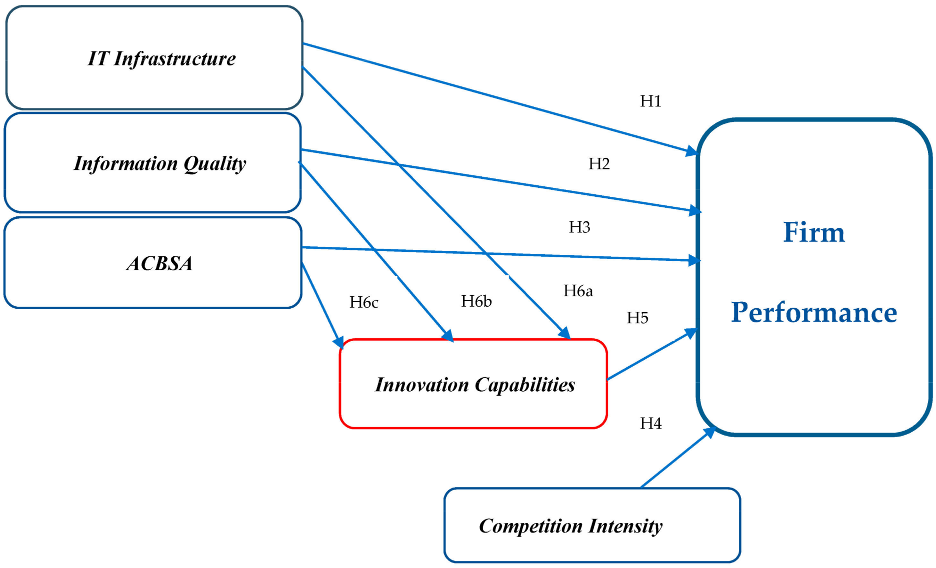

Figure 1. Research model.

4. Research Methodology

4.1. Data and Sample

The survey was adopted on the constructs identified from previous studies. A five-point Likert scale was used for all items and ranging from 1 ('strongly disagree') to 5 ('strongly agree') to measure items. The pre-test version of the survey was sent to three academicians for face validity. Then face validity was completed by five professionals to test the suitability of the research items and to gather suggestions for improvement in relation to the developed instrument. Furthermore, the survey was distributed to those who agreed to participate, and a total of 386 responses were collected. The survey was sent directly to participants or mailed to firms centered in Riyadh, the capital city of Saudi Arabia. Saudi Arabia has advanced digital information and technology use and considered one of 20G members [88]. Moreover, the sample includes BA workers and managers at a mid-high level in Saudi Arabia firms. Table 1 below shows the characteristics of the sample.

Table 1. Characteristics of the sample.

Sector	No	%	Employees	No	%
Telecommunication and IT	135	34.97%	<100	76	19.68%
Financial services	55	14.24%	100–999	98	25.38%
Retail	35	9.06%	1000–4999	94	24.35%
Manufacturing and Utilities	80	20.72%	>5000	118	30.56%
			Respondent's position		
Insurance and tourism	27	6.99%	Executive level	43	11.13%
			Middle management level	152	39.37%
Others	54	13.98%	Operational level	191	49.48%
Total			386		

4.2. Measurement

Based on current measures and measurement, items were created. The measurement model's constructs, corresponding indicators, and related literature are all listed in Table 2. However, based on the theoretical justifications stated earlier, five independent variables were employed: IT infrastructure, information quality, ACBSA, innovation capabilities, and competition intensity. Furthermore, firm performance was used as the dependent variable to gather applicable knowledge about the impact of BA capabilities and innovation and evaluate any potential benefits.

Table 2. Variables, items, and related studies.

Variables	Items
Firm Performance Adapted: [2]	We have experienced higher market share during the last 2 or 3 years.
	We have experienced higher return on investment during the last 2 or 3 years.
	We have experienced higher sales growth during the last 2 or 3 years.
	We have experienced higher profitability during the last 2 or 3 years.
Innovation Capabilities Adapted: [2]	To innovate on business and managerial processes
	To make continuous improvement in product and service quality
	To develop and adopt new technologies that enhance market offerings
	To develop new products and services with cutting-edge technology
Information Quality Developed: [2,42]	The output information is timely.
	The output information is accurate
	The output information is complete.
	The output information is reliable.
IT Infrastructure Adapted: [13,35]	IT facilities' operations/services (e.g., servers, large-scale processors, performance monitors, etc.) are superior.
	The network communication is sufficient with good connectivity, reliability, and availability in our organization
	The quality of IT applications and services (e.g., ERP, ASP, software modules/components, emerging technologies, etc.) can meet our organization's needs.

Table 2. *Cont.*

Variables	Items
Analytics Capability Business Strategy Alignment (ACBSA) Developed: [62]	The business analytics plan aligns with the company's mission, goals, objectives, and strategies.
	The business analytics plan contains quantified goals and objectives.
	The business analytics plan contains detailed action plans/strategies that support company direction.
	We prioritize major business analytics investments by the expected impact on business performance.
Competition Intensity (CI) Adapted: [13]	The rivalry among companies in the industry our company is operating in is very intense.
	There are many products/services in the market which are different from ours but perform the same function.
	Price competition in our business is severe.

4.3. Structural Equation Modelling Approach

The partial least squares–structural equation modeling (PLS-SEM) technique was used to evaluate the proposed model, while Smart-PLS Version 3.3.3 has been used to test the model and get results to complete the estimation process of the measurement model and structural model (SEM-PLS).

In contrast to traditional statistical methods, such as regression, factor analysis, and path analysis, PLS evaluates the measurement model within the context of the structural model by addressing the loadings of the indicators on constructs followed by estimations of causal relationships among constructs [89–91].

Moreover, many researchers in the BA field, such as Nam et al. [13], Ashrafi et al. [2], and Wang et al. [91], have used PLS to test the impact of BA capabilities. However, while SEM is used for both predictive and theoretical testing [92], PLS-SEM is recommended for use with complicated models that include a large number of constructs, variables, and relationships [93–95]. Therefore, since the model contains a large number of constructs and indicators that represent BA capabilities and aim to assess mediation effects, the PLS-SEM was used to achieve a high level of accuracy.

5. Results

The measurement model in this study was used to assess the degree of interrelations between the indicator variables and latent variables. Second, the structural model was used to represent the causal relationships between latent variables.

5.1. Measurement Model

The measurement model shows information about the reliability of the latent variables and observed variables [96,97]. In addition, the composite reliability indicator, which was developed by Fornell and Larcker [98], was used to examine internal consistency and reliability. The results in Table 2 show a satisfactory value for the composite reliability index as determined by Hair et al. [99], where it should be above 0.7. Moreover, for internal consistency, the result in Table 2 shows a satisfactory value for Cronbach's alpha which is above 0.6 as determined by Griethuijsen et al. [100] and 0.65, as determined by DeVellis [101].

Additionally, the average variance extracted (AVE) index was used to test discriminant validity, as suggested by Hair et al. [99], where the minimum satisfactory value for the AVE index should exceed 0.5. However, as shown in Table 3, the constructs in the model show a satisfactory AVE value, with the lowest being 0.553 for the Competition Intensity construct and the highest at 0.744 for the IT infrastructure construct.

Table 3. Constructs, Items, Loading, Cronbach's alpha, rho_A, composite reliability, and average variance extracted (AVE).

Constructs	Items	Loadings	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
ACBSA	BAAC1	0.826	0.826	0.834	0.884	0.656
	BAAC2	0.831				
	BAAC3	0.814				
	BAAC4	0.767				
Competition Intensity	BACI1	0.671	0.634	0.837	0.784	0.553
	BACI2	0.631				
	BACI3	0.901				
Firm Performance	BAF1	0.828	0.819	0.822	0.880	0.646
	BAF2	0.789				
	BAF3	0.803				
	BAF4	0.796				
IT Infrastructure	BAIT1	0.870	0.828	0.831	0.897	0.744
	BAIT2	0.860				
	BAIT3	0.857				
Information Quality	BAIQ1	0.780	0.811	0.813	0.876	0.638
	BAIQ2	0.772				
	BAIQ3	0.822				
	BAIQ4	0.820				
Innovation Capabilities	BAIC1	0.825	0.838	0.843	0.892	0.673
	BAIC2	0.861				
	BAIC3	0.831				
	BAIC4	0.762				

In addition, to test the level of discriminant validity for the used items, the latent variables must have greater values for their relevant indicators than with the other constructs, as mentioned by Alexandre et al. [92]. The result in Table 4 shows a good convergent and discriminant validity as all indicators presented higher loadings for their relevant constructs than with other constructs.

5.2. Structural Model

The structural model addresses the relationships in a framework of dependent and independent variables to theoretically test the hypotheses [97–99,102]. To validate and complete the estimation of the structural model, the PLS-SEM is appropriate to be used [103].

Moreover, to address the level of strength of the structural path, the R^2 is considered the most important indicator of the goodness of fit [104]. The statistical analyses demonstrated in Table 5 that the R^2 value of the dependent variable (Firm performance, Innovation capabilities) met the satisfactory value of the R^2, as the minimum index for endogenous variables should exceed 0.1, as mentioned by Falk and Miller [105]. This shows that the dependent variables were well explained by the independent variables.

Table 4. Correlation matrix.

	ACBSA	Competition Intensity	Firm Performance	IT Infrastructure	Information Quality	Innovation Capabilities
ACBSA	0.810					
Competition Intensity	0.368	0.744				
Firm Performance	0.416	0.147	0.804			
IT infrastructure	0.604	0.521	0.247	0.862		
Information Quality	0.455	0.540	0.231	0.513	0.799	
Innovation Capabilities	0.538	0.551	0.331	0.668	0.614	0.821

Table 5. R^2 and global fit indexes.

Constructs	R^2	Average Variance Extracted (AVE)
ACBSA	–	0.656
Competition Intensity	–	0.553
Firm Performance	0.199	0.646
IT infrastructure	–	0.744
Information Quality	–	0.638
Innovation Capabilities	0.557	0.673
Average	0.378	0.651
AVE $\times$ R^2	0.246	
GoF	0.495	

In addition, Tenenhaus et al. [106] suggest using the goodness of fit (GoF) indicator to validate the PLS model. According to Esposito Vinzi et al. [107], estimation of the overall model must be shown through the GoF index, while there is no specific level to evaluate the statistical significance of GOF values. However, Lane and Lum [108] state that the satisfactory GoF value for large effect sizes is 0.36. The achieved GOF values satisfy the goodness of fit index requirement of greater than 0.36, as shown in Table 4 with a 0.495 value.

Table 6 shows that firm performance is positively and significantly related to BA capabilities that include ACBSA and innovation capabilities constructs. In addition, the analysis of the path coefficients shows that the direct effects of IT infrastructure and competition intensity are negative at −0.102 and 0.070, while information quality, IT infrastructure, and competition intensity are not significant at the 5% level.

Checking for the mediating effect, Table 6 shows that in the technological dimension, innovation capabilities construct has a significant mediation effect on the relationship between BA technological capabilities and firm performance. First, the results show a negative relationship between IT infrastructure and firm performance in the direct model (path = −0.102, t = 1.381, p = 0.168) that is significantly mediated by innovation capabilities (path = 0.095, t = 2.802, p = 0.005). Moreover, a nonsignificant relationship between information quality and firm performance (t = 0.138, p = 0.890) that is significantly moderated by innovation capabilities (p = 2.828, t = 0.005).

Table 6. Summary results of the hypothesis development.

Constructs	Hypothesis	Path Coefficients	Standard Deviation	*t* Statistics	*p* Values
IT infrastructure -> Firm Performance	H1	−0.102	0.074	1.381	0.168
Information Quality -> Firm Performance	H2	0.009	0.062	0.138	0.890
ACBSA -> Firm Performance	H3	0.375	0.063	5.979	0.000
Competition Intensity -> Firm Performance	H4	−0.070	0.068	1.022	0.307
Innovation Capabilities -> Firm Performance	H5	0.231	0.073	3.178	0.002
IT infrastructure -> IC -> Firm Performance	H6a	0.095	0.034	2.802	0.005
Information Quality -> IC -> Firm Performance	H6b	0.079	0.028	2.828	0.005
ACBSA -> IC -> Firm Performance	H6c	0.031	0.015	2.127	0.034

Second, within organizational factors, the significant and positive relationship between ACBSA and firm performance in the direct model ($t = 5.979$, $p = 0.000$) remained significant under the mediating effect from innovation capabilities ($p = 0.034$, $t = 2.127$).

Based on the findings above in Table 6, hypotheses H3, H5, H6a, H6b, and H6c are significant, while H1, H2, and H4 are not significant. See Appendix A.

6. Discussion

While earlier studies on this topic focus on a straightforward relationship between technological, organizational, and environmental factors within BA, none of them consider the innovation capabilities' impact in terms of their role on those factors and their impact on firm performance. By using the TOE framework, this study gives background on the main capabilities that are applied as enablers of the BA that impact firm performance and investigates the role of innovation capabilities.

6.1. The Effects of Technological Factors

The statistical analyses of H1 and H2 show a negative effect between IT infrastructure and information quality on firm performance. However, while previous studies supported the positive link between the IT infrastructure in BA [6,13,30,36,43,45], few other studies support the importance of specific phases of BA implementation. For example, Sabherwal and Becerra-Fernandez [33] mentioned that the importance of IT infrastructure is in the collecting and integrating phases, while it is less in other phases. In addition, some studies mentioned that the technological aspect is not considered a critical aspect for regular improvement at companies, Alaskar et al. [6] say "*the 'technical' concerns are no longer significant* for them while dealing with IT innovation adoption". However, the result could be explained as IT infrastructureand and information quality barriers no longer playing a key role in the BA use phase as it is initiating or adapting BA phases. Regarding the differentiating of requiems at each phase of BA, Nam et al. [19] say "*there are many phases in BA it is interesting to identify that the effects of factors in each dimension on each stage are different*". Therefore, it is important to identify the effects of IT infrastructure in each phase of BA implementation, and based on specific requirements.

6.2. The Effects of Organizational Factors

The statistical analyses show that innovation capabilities and ACBSA capabilities play key roles in firm performance, so organizations with a stronger innovation capability and higher ACBSA capabilities are likely to attain greater value.

The results of the tests of H3 show that there is a positive relationship between ACBSA and firm performance, which supports the importance of analytic capability alignment as a critical capability driver, as found in previous studies [58,59,61,65–68]. Furthermore, this result confirms an observation by Barton and Court [109]: "*companies grapple with such* *problems, often because of a mismatch between the organization's existing culture and capabilities and the emerging tactics to exploit analytics successfully*".

Additionally, the results support the findings of Constantiou and Kallinikos [64] findings and Akter et al. [62] regarding the importance of alignment between firm capabilities and strategy, as the latter says, "*the fit between capability and strategy can help big data organizations to perceive, assess, and act upon their micro and macro environments*". Considering this finding, organizations should address the volatile nature of a large volume of data by focusing on strategic alignment to address all related aspects, as Akter et al. [62] observe: "*Due to the unpredictable nature of big data, strategy researchers have always emphasized establishing the strategic fit or alignment, viewing the firm as a collection of resources, interlinked by a specific governance structure*".

This result also supports the importance of a business intelligence competency center (BICC), which is considered an important factor for mature BI projects [12] established for strategic alignment purposes. Moreover, the result supports the importance of having an analytical alignment factor, confirming McAfee and Brynjolfsson [58] and Duan et al. [10] claims, which refer to the importance of aligning technology capabilities and having a data-driven approach to coordinate work.

Furthermore, the results of the H4 tests confirmed the significant direct effect of innovation capabilities on firm performance. This finding is consistent with previous studies that supported the importance and the positive role of innovation capabilities on a firm that uses BA [2,14,44,71–75]. This leads us to reason that the innovation capabilities support the required capabilities and play a strategic role in firms implementing BA projects. In addition, this implies that a high level of innovation capabilities enables a firm for better performance.

6.3. The Effects of Environmental Factors on Firm Performance

In contrast to the organizational factors mentioned above, the results of this study do not support H5. The results of H5 illustrate that there is no effect of competition intensity on firm performance as not supported by the data collected. This implies that when to use BA the technological and organizational factors are important in the use phase of BA regardless of environmental pressure. However, previous studies emphasize the competition intensity's role in firm performance [13,30,30,44,45,78–80]. Moreover, this result does not support Alaskar et al. [6] study, which shows the importance of competitive pressure in the Saudi Arabia context for BDA adoption.

However, these results could be explained as leading competitors in the Saudi Arabia context would not inspire other Saudi firms to use BA to support their performance stance. Moreover, it could be argued that while there are different phases for BA as explained by Nam et al. [13], this leads to assuming that the pressure on the firm could be related to the adoption phase of BA and not using BA, which shows that the characteristics of adoption phase are different from use phase. In addition, this could be interpreted as indicating that the degree of competition intensity is critical mainly for firms that work in high-risk environments, as argued by Isik et al. [9].

Moreover, it could be argued that it is important to consider context characteristics and their competition intensity from competitors to help to maintain alignment strategically and to adapt the required innovation in a quick manner. Nam et al. [13] claim as they assert that "*Competition results in market uncertainty and fierce competition drive firms to initiate and adopt innovation to maintain a competitive advantage (Robertson and Gatignon, 1986)* [110]. *If an organization receives pressure from competitors that are using BA technology, they actively initiate and adopt BA to avoid losing their competitive edge (Lai et al., 2018)* [30]".

6.4. Innovation Capabilities and the Mediating Role

This study proposed a theoretical model including the innovation capabilities aspect as a mediator of the technological and organizational impacts on firm performance.

Moreover, the innovation capabilities show that it has a significant direct effect on firm performance and a positive impact on mediating the relationship between technological aspects and firm performance. The result of H6a and H6b confirms the importance of innovation capabilities to mediate the effects on the relationship between IT infrastructure and information quality. However, this result confirms previous studies that showed the significant role of innovation capabilities on data analytic projects [2,35,44,82–85].

In addition, the result specifically shows that innovation capabilities are vital for firms to renew the IT infrastructure as technological capabilities positively impact firm performance, and the absence of those required capabilities could lead to failure. Nam et al. [13] say "*the absence of required internal IT infrastructure could present a barrier to adopting innovation*". However, the findings add to the literature on how IT infrastructure can allow the development of BA once renewal of the capabilities. In addition, it confirms previous studies that show the high importance of leveraging information quality and working effectively to respond to changes, as mentioned by Ashrafi et al. [2]. Therefore, once a firm has the capabilities to respond to such changes, this gives the firm an advantage in using BA. Ashrafi et al. [2] say "*firms' responses to change is differentiated by their information quality. As argued by Zain et al., 2005* [71], *there is a positive relationship between the information quality and agility in the firm*".

Regarding organizational capabilities, the result of H6c shows innovation capabilities do mediate the links between ACBSA and firm performance as it is supported by the data collected, which support previous studies [14]. However, considering previous studies, organizations should consider the volatile nature of a large volume of data by focusing on strategic alignment to address all related aspects. Akter et al. [62] emphasize that "*Due to the unpredictable nature of big data, strategy researchers have always emphasized establishing the strategic fit or alignment, viewing the firm as a collection of resources, interlinked by a specific governance structure*".

This result also could be interpreted as the ACBSA is more critical in a dynamic environment that includes the volatility of data analytics projects, as argued by Akter et al. [62], which required high innovation capabilities. Nam et al. [13] claim as they assert that "*Competition results in market uncertainty and fierce competition drive firms to initiate and adopt innovation to maintain a competitive advantage (Robertson and Gatignon, 1986)* [110]*. If an organization receives pressure from competitors that are using BA technology, they actively initiate and adopt BA to avoid losing their competitive edge (Lai et al., 2018)* [30]".This conclusion also implies that the establishment of a solid alignment based on data facts through the use of BA can be helpful for decision-makers for innovations and in every context, as Aydiner et al. [50] observe "*operational efficiency is improved with the support of BA applications, and the business processes performance is increased. Likewise, managerial decision-making at all levels may be carried out based on the facts (Klatt et al., 2011)* [111]. *Optimizing the business operations, forecasting the outcomes, improving efficiency, making better decisions* . . . ". Moreover, the result support Ylijoki et al. [14] claim as alignment by the automated process is highly needed to renew the capabilities automatically. They say "*Data-driven innovation suggests that the innovation processes could and should, be automated (Shaughnessy, 2015)* [112]. *This approach puts technology and (big) data at the core of the innovation processes*".

7. Conclusions and Implications

Grounded in the TOE framework, this paper aimed to develop and validate a theoretical framework that explains the roles of BA technological, organizational, and environmental factors in firm performance in the Saudi Arabia context and the mediating role of innovation capabilities. Furthermore, this study examined the direct impact of BA technological and organizational aspects on firm performance. The results show that organizational factors (ACBSA and innovation capabilities) have a highly significant impact on firm performance, as stated in H3 and H5. While IT infrastructure and information quality as technological factors showed no significant and positive effect, as stated in H1 and H2. Moreover, the competition intensity as an environmental factor showed no positive effect on firm performance, as stated in H5.

In addition, this finding supports the importance of determining the vital innovation capabilities that drive BA use in Saudi firms to achieve success. While previous studies examined TOE with BA adoption, none of those studies used TOE to examine the mediating role of innovation capabilities as a critical organizational factor to determine the impacts of technological and organizational factors on firm performance. One of the several theoretical contributions of this study is to determine the importance of innovation capabilities as a mediating factor that can support to conform the impacts of technological and organizational factors while using BA. Furthermore, the study finding shows that the innovation capabilities aspect has a statistically significant mediation impact on the relationship of BA technological (IT infrastructure, Information quality) and organizational (ACBSA) factors with firm performance inside the Saudi Arabia context, as stated in H6a, H6b, and H6c.

From a managerial perspective, this study offers managers and BA practitioners practical advice to improve their ability to get more value from BA. Moreover, this study provides advice for practitioners within the context of a developing economy on the importance of innovation capabilities for BA use and their impact on firm performance. Firms should renew their BA capabilities for high firm performance by focusing on improvements that can be achieved on those capabilities in alignment with market needs and competition levels.

Nevertheless, there are future opportunities and limitations that need to be considered. First, to allow for higher firm performance, more BA technological and organizational aspects need to be investigated. Second, the study was conducted within one developing country (Saudi Arabia) and did not cover many geographical locations. Therefore, the generalizability of the study is somewhat limited, and the results must be generalized with care to avoid issues such as structural and cultural variances between developed and developing countries, as noted by Ashrafi et al. [2] and Zare Ravasan and Mansouri [113]. However, Saudi Arabia is among the 20G group countries and has a well-developed information technology infrastructure. Third, future academic research on BA could use a qualitative approach or mixed methodologies to obtain a better understanding and in-depth knowledge of BA and how it can add more value to firms.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

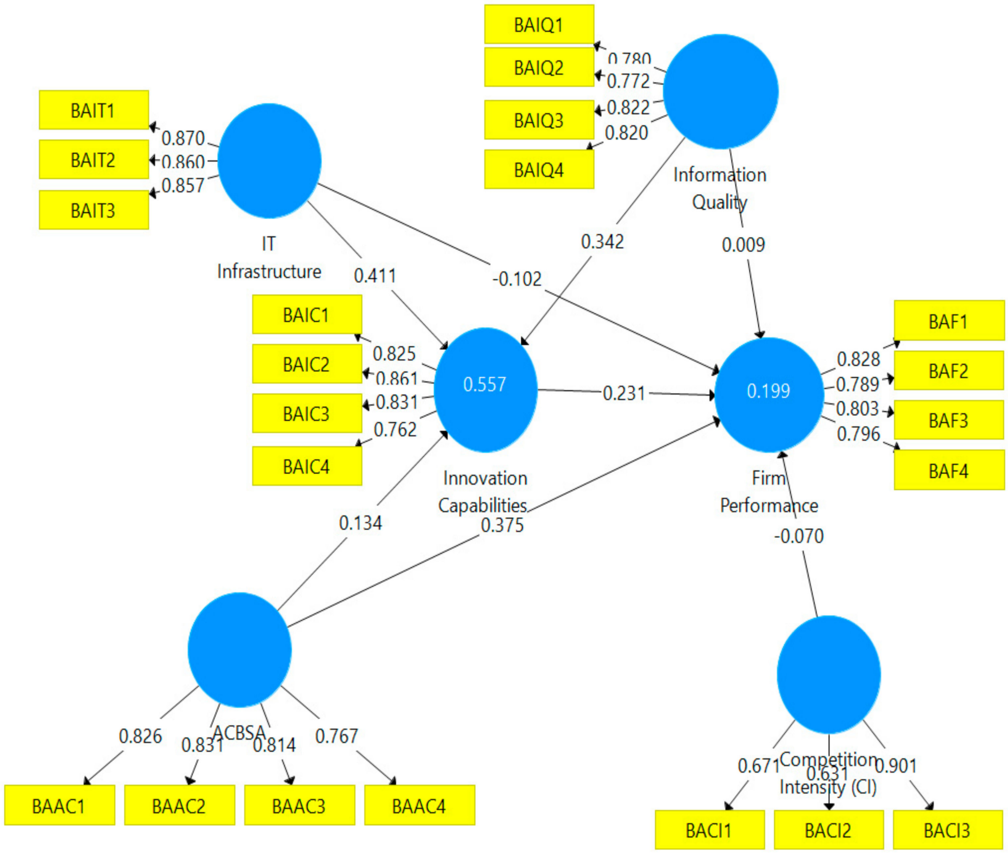

Figure A1. Fitted model.

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