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Moderating the Synergies between Business Intelligence and Strategic Foresight: Navigating Uncertainty for Future Success through Knowledge Management

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Abstract: The role of business intelligence in driving strategic planning in organizations have received considerable attention from many scholars. Nonetheless, there remains a promising area for further research, especially when considering moderating variables on effects such as knowledge management, which has contributed to businesses' appreciation of the importance of business intelligence. To this end, in this study, the researchers constructed a conceptual model based on existing literature by incorporating relevant research variables. A questionnaire survey was conducted among a random sample of 307 employees selected from three telecom companies in Jordan. The researchers then utilized structural equation modeling with AMOS 21.0 to validate and test the model. The findings of the study revealed that business intelligence has a significant positive influence on strategic foresight. Furthermore, the analysis indicated that knowledge management mediates the relationship between business intelligence and strategic foresight. The implications and recommendations of academic research are also discussed.

Keywords: business intelligence; strategic foresight; knowledge management; telecom companies

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1. Introduction

The telecom sector in Jordan holds a pivotal role in driving national economic development and fostering technological innovation and entrepreneurship [1]. Accounting for 14% of the country's GDP in 2014, this sector presents Jordan with a valuable opportunity to establish a competitive advantage over neighboring Arab nations [2]. The performance enhancement and capability development of telecom companies in Jordan significantly impact the country's overall economic growth [3]. Nevertheless, the telecom industry is not immune to the influences of its surrounding environments [4]. The recent COVID-19 pandemic, in particular, has imposed significant challenges on businesses, including small and large firms alike [5–7]. The telecom sector has felt the adverse effects, ranging from funding and resource issues to inadequate networking capabilities [8]. To address these survival and growth challenges, it is imperative to conduct further research that offers practical solutions. Additionally, fostering collaborative efforts among national telecommunications firms can enhance their competitiveness on a global scale and contribute to the advancement of the economy.

Strategic foresight (S.F.) has long been a powerful tool for decision-making in the face of competition and uncertainty, utilized by government planners, corporate managers, and military analysts [9,10]. S.F. enables companies to envision future scenarios and develop new capabilities to navigate challenges successfully [11]. The advantages of S.F. are manifold, including anticipating future trends, improving decision-making, managing risks, gaining competitive advantage, fostering innovation and adaptability, and ensuring long-term sustainability [9,12,13]. In dynamic and competitive environments, S.F. plays a crucial role in shaping the competitiveness, growth, and sustainability of organizations [14].

While the origin of S.F. remains ambiguous, it offers the opportunity to develop diverse scenarios that can be explored, manipulated, or experienced by future users to support future planning and decrease uncertainty [13,15–17]. In this era of data proliferation, tools are required to efficiently organize the increasing volume of data [18]. Business intelligence (B.I.) solutions, encompassing appropriate technologies and tools for data collection, integration, storage, editing, and analysis, have gained immense importance in recent years [13]. The effective implementation of B.I. systems can streamline workflows and enhance organizational performance [19]. According to the theory of effective use (TEU), B.I. effectively supports decision-making processes, enabling companies to align their technological capabilities [20]. A study by Cammarano et al. [21] indicated that B.I. knowledge enhances decision-making processes, enabling companies to align their technological capabilities with customer expectations and market demands.

In the context of globalization and technological advancements, organizations must differentiate themselves and effectively utilize their resources to create value and gain a competitive advantage [13,16,22,23]. Sustaining competitive advantage requires the development of value-creating strategies based on organizational resources [13,24]. The link between S.F. and scenario building is also closely tied to knowledge management (K.M.) and the utilization of modern technology for market positioning [25]. In the Jordanian telecom sector, strategies that enhance performance and embrace digital technologies are crucial for maintaining competitiveness [2,13,26]. K.M. facilitates knowledge sharing within organizations, supporting the assimilation, organization, and dissemination of knowledge [26,27]. Studies have also shown a positive correlation between K.M. and new technology adoption [28].

By examining the interplay between S.F., B.I., and K.M., this research aims to contribute to the performance enhancement and capability development of telecom companies in Jordan. It addresses the challenges posed by the COVID-19 pandemic and the imperative need for future planning. This research recognizes the significance of S.F. in envisioning future scenarios, the role of B.I. in managing data and supporting decision-making, and the importance of K.M. in knowledge sharing and new technology adoption. Through an integrated approach, this research seeks to offer insights and recommendations that can assist Jordanian telecom companies in navigating the competitive landscape.

Research Problem

In today's highly competitive landscape, organizations are increasingly recognizing the vital role of B.I. in their success, especially in the face of challenges such as the COVID-19 pandemic [7,29,30]. The pandemic has underscored the urgency of exploring the strategic impact of B.I. on S.F. [7,18,29,30]. While there is a growing interest in understanding how B.I. drives S.F., a notable gap exists in comprehensively examining the interplay between K.M., S.F., and emerging technologies [11,25,29,31,32]. Furthermore, to gain a deeper understanding of the relationship between B.I. and S.F., it is essential to consider the moderating role of K.M. While some studies have explored these individual relationships [28,30,33], a comprehensive examination that integrates these dimensions is limited. For instance, Nascimento et al. [34] suggest studying the influence of B.I. on S.F., while other researchers [35] focus on the role of K.M. as a moderating variable as a structured approach for capturing, sharing, and utilizing knowledge to improve future planning scenarios [26,36]. Importantly, the significance of these relationships becomes particularly pronounced when examining emerging economies such as Jordan, where empirical evidence on this topic is limited [35].

In this context, the research gap that this study aims to address is twofold: first, to comprehensively examine the impact of B.I. on S.F., and second, to investigate the role of K.M. in moderating the relationship between B.I. and S.F. Accordingly, this study could insightfully contribute to the body of literature by showing the significance of K.M. as a moderating factor on the effect of B.I. and S.F. This becomes more important when being tested in an important sector, such as the telecom sector, in a developing country like Jordan. The findings and recommendations derived from this research will provide valuable guidance to Jordanian telecom companies, enabling them to navigate the competitive landscape, make better informed decisions, and achieve long-term sustainability and success.

2. Theoretical Foundation and Hypothesis Development

2.1. Business Intelligence

The term B.I. made its debut in the mid-1990s when Howard Dresner, an analyst at Gartner Group, introduced it as a concept and set of methods facilitating decision-making through information analysis and delivery [36,37]. In a historical context, Hans Peter, an investigator at IBM, coined 'business intelligence' in 1958 to describe an automated method for sharing information within a company [38,39]. Broadly, B.I. encompasses a collection of applications and tools designed to gather, store, retrieve, and analyze data, all with the aim of enhancing decision-making processes [36]. Organizations relying on B.I. must consider factors such as strategic vision, sponsorship level, resource requirements, and impacts on personnel and procedures. The scope of B.I. extends to various applications and the underlying information technology infrastructure, encompassing servers, operating systems, integration platforms, and networks. This diversity leads to variations in functionality, sophistication, and complexity, and these aspects can be elucidated using the B.I. scope construct. Additionally, this construct predicts the positive influence of content on the quality of executive decision-making processes [40].

Hunt and Madhavaram [41] identify three primary objectives for using B.I.: improving decision-making processes, enhancing corporate transparency, and revealing relationships among isolated pieces of information. The perceived relative advantage, complexity, interoperability, and observability of B.I. features play critical roles in ensuring the success of B.I. implementations [42]. B.I. systems are rooted in the Theory of Effective Use (TEU), which aims to enhance the utilization of information systems that gather, analyze, and present data to support decision-making. TEU underscores the significance of system quality and usability, encompassing aspects like interface design, functionality, and features, to enhance the user experience [43]. Improved user engagement, facilitated by B.I. systems, plays a pivotal role in decision-making, especially when faced with unpredictable environmental factors, ultimately contributing to enhanced scenario building for the future [20].

Azeroual and Theel [5] delineate three dimensions of B.I. data: first, Data Warehouses; these repositories encompass integrated data, historical data, and detailed and consolidated data [44,45]. Secondly, Online Analytical Processing (OLAP) software extracts data from data warehouses or data marts to form knowledge [46,47]. Thirdly, Data Mining employs mathematical and statistical methods, artificial intelligence, and deep learning machines, to locate and extract relevant information and new insights from data warehouses. This technique predicts future outcomes, discovers behavior and trends, and facilitates timely decision-making by swiftly answering pertinent questions [47].

B.I. serves as an offensive approach and can be strategically combined with risk management scenarios to predict competitors' actions [48]. It empowers companies to identify profitable sectors and acquisition opportunities, analyze the impact of technology on product quality and market value, and make informed decisions regarding product enhancement and technological development. Furthermore, B.I. assists organizations in gathering timely and accurate information about their internal and external environments, anticipating industry changes, and making strategic decisions. B.I. tools, such as OLAP, data mining, and data warehousing, play a pivotal role in analyzing vast datasets to identify patterns and opportunities for diversification [9,21].

2.2. Strategic Foresight

As the business environment becomes more turbulent, organizations are increasingly turning to S.F. to respond. Failing to be aware, prepared, and adaptable can impede the ability of organizations to adjust to disruptions, making it crucial to establish an effective intelligence system as part of their strategic plan [18]. Scenarios are useful tools for organizing perspectives on future events where present actions could materialize and are viewed as a crucial instrument for strategic planning toward future goals. Scenarios remain effective tools for decision-making under conditions of ambiguity [18]. S.F. is a structured approach that leverages ideas to anticipate and prepare for future changes [49]. It enables organizations to capture more opportunities while minimizing risks by anticipating the future and developing appropriate responses. S.F. has long been used to comprehend future perspectives, locate essential resources, plan for significant advancements, and even reshape the business environment [44].

S.F. variables have three aspects, namely, method sophistication, people, and networks and organization, as suggested by Schmidt [50]. The foresight process entails gathering data about upcoming innovations, technological shifts, or rivals' technological initiatives, as well as evaluating company information [36]. The people and networks element acknowledges that system disruption is unavoidable and that foresight is about successfully using knowledge [26]. Organization is the third dimension, where innovation management connects with other procedures to fully use future findings. Schmidt [50] stresses the value of formal methods for transforming data into useful insights. The S.F. variables, including method sophistication, people, networks, and organization, play a crucial role in enhancing understanding, facilitating proactive decision-making, supporting robust planning, and fostering collaboration and innovation. By utilizing these variables effectively, organizations develop a forward-looking mindset, navigate uncertainties, and position themselves for future success [44,51].

Telecom companies can enhance the S.F. by capturing the key factors influencing the desired future outcomes. This enables organizations to make informed decisions based on a comprehensive understanding of the complex interplay of various actors and variables. Furthermore, it enhances the effectiveness of their decision-making processes and improves the quality of their S.F. efforts, enabling them to better anticipate and shape future developments [52].

2.3. Impact of Business Intelligence on Strategic Foresight

The existing literature strongly affirms the intrinsic connection between B.I. and S.F. Both disciplines share the commonality of monitoring and reporting on the external business environment, which includes the vital tasks of identifying opportunities and threats, serving as an early warning system, and bolstering the effectiveness of decision-making processes. The amalgamation of B.I. and S.F. offers organizations a powerful mechanism for enhancing their capacity to grasp their current situation comprehensively, discern potential risks and opportunities, and make well-informed decisions that seamlessly align with long-term strategic goals [53].

Prior research, as exemplified by studies such as those conducted by Schmidt [50] and Fleisher and Bensoussan [39], underscores the significance of the symbiotic relationship between B.I. and S.F. In the realm of organizations, they argue that by incorporating real-time data streams into B.I. tools, organizations can have more up-to-date information for S.F. activities. Schmidt's [50] work accentuates the pivotal role of integrating both B.I. and S.F. to facilitate effective planning and decision-making. Schmidt's study explores the application of machine learning and predictive analytics in B.I. for S.F. By using advanced algorithms, B.I. systems can not only analyze historical data but also predict future trends, aiding S.F. practitioners in making more accurate foresight. On a broader scale, Fleisher and Bensoussan's [39] research has sought to seamlessly merge the domains of S.F. and B.I. while concurrently adopting a forward-looking strategy; their approach entails a comprehensive analysis of the future, focusing on uncertainty. This approach underscores the importance of creativity, foresight, and a willingness to embrace calculated risks, which can help in creating various scenarios based on historical data and current market conditions, allowing organizations to prepare for a range of potential futures [52,54].

These recent studies collectively underscore that B.I. goes beyond historical data analysis and is a vital tool for organizations to anticipate, adapt to, and shape their future effectively through S.F. This integration is in line with the existing literature that emphasizes the symbiotic relationship between B.I. and S.F., enhancing organizations' decision-making capabilities in complex and uncertain environments [39,46,50,53]. The seamless integration of B.I. and S.F. strengthens an organization's competitive edge in the ever-evolving business landscape [39,46,52].

In accordance with the previous discussion, the following hypothesis is proposed:

Hypothesis 1. *Business intelligence (OLAP, data mining, and data warehouse) has a positive impact on strategic foresight in telecom companies in Jordan.*

This main hypothesis is further divided into three sub-hypotheses based on strategic foresight elements, as follows:

Hypothesis 1.1. *Business intelligence (OLAP, data mining, and data warehouse) has a positive impact on method sophistication.*

Hypothesis 1.2. *Business intelligence (OLAP, data mining, and data warehouse) has a positive impact on people and networks.*

Hypothesis 1.3. *Business intelligence (OLAP, data mining, and data warehouse) has a positive impact on organizations.*

2.4. Knowledge Management

The field of K.M. has witnessed significant growth and evolution over the past decade [41]. Defining K.M. can be challenging due to its multifaceted nature, which encompasses various viewpoints, including fundamental beliefs, strategies or goals, actions, and facilitators. Additionally, K.M. intersects with numerous aspects of organizational operations and draws from various disciplines. The concept of knowledge itself has been defined and categorized in multiple ways, encompassing both implicit and explicit forms [36,47]. K.M. serves as the fundamental knowledge foundation for Strategic Foresight (S.F.) by capturing and organizing information effectively [26]. This role of K.M. facilitates not only informed decision-making but also sense-making, learning, adaptation, and the support of long-term orientation. Moreover, K.M. plays a critical role in preserving institutional memory and assisting in strategic planning. Organizations can significantly enhance their S.F. capabilities and make more informed decisions about the future by harnessing the power of K.M. [55].

Two main factors influence K.M.: the resource-based view (RBV) and humanistic management theory. The RBV underscores the strategic significance of internal resources, including knowledge, in attaining a competitive advantage. It highlights the imperative for organizations to identify, cultivate, and effectively utilize their knowledge assets. On the other hand, humanistic management theory emphasizes the value and dignity of individuals within organizations, promoting a supportive and empowering work environment that focuses on personal development, collaboration, and ethical considerations [56].

K.M. encompasses the processes of creating, sharing, and utilizing knowledge within and between organizations [46]. Scholars and practitioners across diverse industries recognize the pivotal role of K.M. in the survival and success of a company [34]. Evaluation of K.M. often involves assessing its implementation, transformation, and acquisition [55]. Research by Wang and Wang [13] suggests that sharing both explicit and implicit knowledge can enhance a firm's financial performance. The four processes of organizational knowledge and procedure creation theory continuously generate dimensions of K.M. that lead to knowledge creation [57]. K.M. encompasses not only the processes and tools for managing knowledge but also knowledge diffusion, which deals with how an individual entity applies the information it possesses throughout the entire organization [26,58].

To comprehend the cognitive aspects of foresight, Bootz et al. [59] examined its effects on K.M. They recognized that effective K.M. methods are crucial for fostering innovation and gaining a sustainable competitive edge in today's corporate landscape. There is an increasing emphasis on developing strategies for generating, using, and sharing knowledge within firms [13,60–62].

2.5. The Moderating Role of Knowledge Management on the Relationship of Business Intelligence and Strategic Foresight

The interplay between K.M., B.I., and S.F. has been well established in previous studies. K.M. plays a pivotal role in moderating the relationship between B.I. and S.F. It serves as the foundation for S.F. initiatives by efficiently capturing, organizing, and managing information. This foundational role enables informed decision-making, sense-making, learning, and adaptation. Furthermore, K.M. contributes to maintaining a long-term orientation by preserving institutional memory and providing support for strategic planning. By leveraging K.M., organizations can significantly enhance their S.F. capabilities and make well-informed decisions, thereby shaping their future trajectory effectively [2,32,63,64].

Pouru et al. [32] studied knowledge generation for future scenarios in organizations, analyzing data from 110 Finnish firms. They found that current practices often treat future knowledge narrowly. They recommended improving by using diverse networks, re-evaluating the framework for future scenarios, and adopting a dynamic approach to foresight. Canongia [19] explored the link between competitive intelligence, K.M., and technological foresight, emphasizing the importance of foresight. The study found that technological foresight depends on strategic data analysis, and the prospecting strategy model, which includes variables, trend analysis, and stakeholder engagement, helps in understanding future conditions for global market success. Djuricic and Bootz [56] found that both effectuation and foresight help create valuable networks for experiential learning and knowledge expansion. Pauget and Dammak [8] studied the impact of B.I. and S.F. in the context of the Internet of Things, enhancing foresight through real-time data collection for trend anticipation and informed decision-making.

In a rapidly changing and complex business environment, companies often face challenges in anticipating and adapting to evolving circumstances. In this context, top management's ability to predict potential consequences and suggest appropriate actions is under immense pressure. S.F. plays a crucial role in supporting strategic thinking and decision-making by facilitating learning, establishing connections and networks, enabling knowledge flows, and generating knowledge, ideas, and visions. Pietruszka-Ortyl et al. [58] identified a strong association between the use of modern technologies for K.M. and the application of S.F. for future success. Kaivo-oja and Laureus [23] discussed the contribution of foresight tools to K.M. and knowledge collaboration. This relationship has garnered increased attention in the field, with scholars exploring the impact of individual and group cognition on achieving desired goals [26,65–67]. Research has also delved into how foresight technologies or scenarios can influence cognitive processes [59,68]. These explorations have led to the development of new techniques, gadgets, and tools for creating, exchanging, and disseminating information within foresight processes, reflecting changes in the field of S.F. [69–71].

The integration of foresight and K.M. is now widely recognized, underscoring the strong relationship between these two areas of study [41,72,73]. Moreover, incorporating B.I. proves vital in preventing unintentional disclosure of confidential data while efficiently gathering necessary information about partners. B.I. offers a range of methodologies and tools that assist in managing vast amounts of data required for prompt and informed decision-making [28,74]. Chopra et al. [31] emphasized the strong correlation between B.I. and K.M., highlighting how B.I. involves transferring and integrating crucial business information within an organization, while K.M. enables businesses to maintain a framework of critical capabilities for optimizing commercial opportunities. Leveraging B.I. as a K.M. tool can simplify information discovery, processing, and sharing, ultimately improving an organization's competitive edge [52,75]. Furthermore, mature market companies can utilize B.I.

to expand their offerings beyond the current market by analyzing the industry landscape, identifying profitable opportunities, and evaluating potential acquisition targets [61,76].

Given the above discussion, the following hypotheses are formulated:

Hypothesis 2. *Knowledge management moderates the relationship between business intelligence and strategic foresight.*

This main hypothesis is further divided into three sub-hypotheses, as follows:

Hypothesis 2.1. *Knowledge management moderates the relationship between business intelligence and method sophistication.*

Hypothesis 2.2. *Knowledge management moderates the relationship between business intelligence and people and networks.*

Hypothesis 2.3. *Knowledge management moderates the relationship between business intelligence and organization.*

Figure 1 below shows the research conceptual model based on the previously formulated hypotheses.

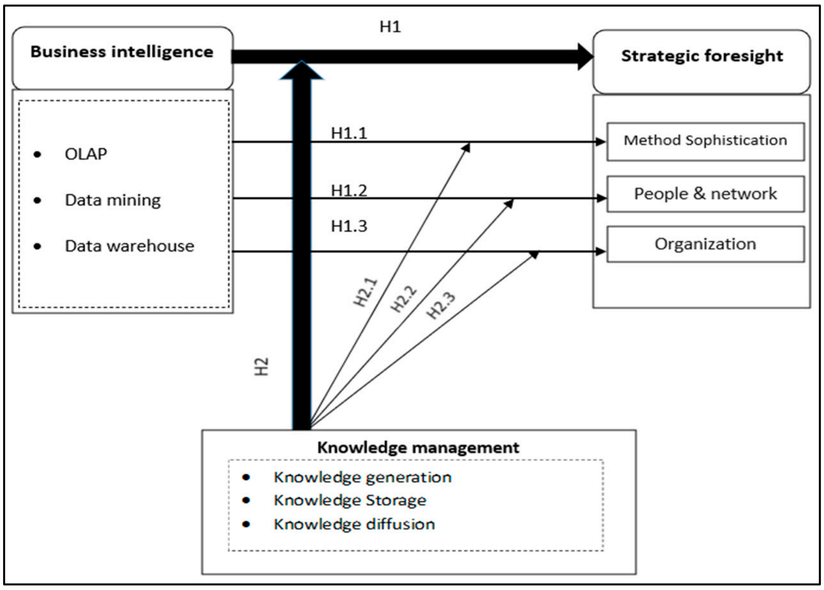

Figure 1. Conceptual research model of the study. The research model was developed by the researchers based on [4,11,77].

3. Methodology

3.1. Population and Sample

The research population of this study involves employees (n = 3886) working for three telecom companies in Jordan (i.e., Umniah, Orange, and Zain). Data were collected from a simple random sample of 350 employees, who were approached using a self-administered questionnaire survey. A total of 307 valid and complete questionnaires were retrieved for data analysis.

3.2. Instrument Development and Design

Established measures validated in previous studies were adapted in the current research to capture the research variables. Particularly, B.I. was assessed using three dimensions, including data warehouse, data mining, and OLAP, and a total of 15 items were borrowed from different studies [77] to cover the aforementioned dimensions. S.F. was evaluated using 15 items related equally to people and networks, method sophistication, and organization, adapted from [4]. Finally, K.M. was operationalized using 15 items relating to knowledge generation, knowledge storage, and knowledge diffusion, which were adapted from Ode and Ayavoo [11]. All research variables were assessed on a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. The questionnaire was translated using the back-translating technique, which involved two business professors proficient in both languages (English and Arabic). Following the translation, the questionnaire was thoroughly tested and refined through academic and field piloting to validate the measures, ensure their reliability, and enhance the clarity of the questions for the participants.

4. Data Analysis and Results

A dataset of 307 valid questionnaires was considered to carry out the data analysis. In accordance with the two-step approach suggested by Anderson and Garbing [27]. The measurement model was assessed first, and then afterwards, the structural model was considered to report the findings of the hypothesis testing. Accordingly, confirmatory factor analysis (CFA) was used to validate the measurement model, followed by scale reliability and validity checks.

4.1. Respondents' Demographics

A dataset consisting of 307 valid and complete questionnaires was generated for analysis. Prior to analysis, the dataset was examined to ensure data completeness and adherence to a normal distribution. Descriptive statistics were used to assess the completeness and validity of the data. The skewness and kurtosis values of all observed variables fell within the acceptable range for a normal distribution (skewness < ± 3 and kurtosis < ± 10) [78]. The demographic profile of the sample is presented in Table 1. The descriptive measures indicate that 60.9% of the respondents were male, with the majority falling within the age range of 30–34 years (34.2%). Among the respondents, 74.3% held a first degree, and a significant proportion held a senior position (57.8%) with 5–10 years of experience (48.2%).

Table 1. Respondents' Demographics.

Variable	Category	Count	%
Gender	Female	120	39.1
	Male	187	60.9
	Total	307	100
Age	<30	32	10.4
	30–34	105	34.2
	35–39	104	33.9
	40–44	54	17.6
	>45	12	3.9
	Total	307	100
Educational level	Bachelor	228	74.3
	Diploma	8	2.6
	Higher Diploma	12	3.9
	Masters	57	18.6
	Ph.D.	2	0.7
	Total	307	100

Table 1. *Cont.*

Variable	Category	Count	%
Nature of work	Department or unit director	12	3.9
	Expert in the department	79	25.7
	General Manager/Assistant General Manager	26	8.5
	Senior of the department	140	45.6
	Team leaders of the department	50	16.3
	Total	307	100
Experience	<5 years	97	31.6
	5–9 years	148	48.2
	10–14 years	36	11.7
	>15 years	26	8.5
	Total	307	100

4.2. Measurement Model

Structural equation modeling (SEM) was employed to evaluate the measurement model, which consisted of five latent variables measured by 45 observed indicators. Following the model-building process of [79], the measurement model was developed as the initial step, according to Hair et al. [80]. The measurement model demonstrated a satisfactory fit based on recommended criteria (RMSEA < 0.08, GFI ≥ 0.90, CFI ≥ 0.90, NFI ≥ 0.90, and IFI ≥ 0.90). CFA was subsequently conducted to validate the model, with convergent and discriminant validity indicators used to establish construct validity. All measurement items exhibited factor loadings above the acceptable threshold of 0.50, as suggested by Hair et al. [80] and shown in Table 2. The average variance extracted (AVE) for all variables in the model, also presented in Table 2, is within the recommended cut-off value of >50% [81].

Table 2. Factor loadings and reliability analysis results C.A., C.R., and AVE for the factors.

Variables	Items				Factor		
	Code	Mean	Sd	Loadings	CA	CR	AVE
Business Intelligence	O1.1	4.03	0.68	0.739	0.77	0.78	0.57
	O1.2	4.13	0.64	0.829			
	O1.3	4.12	0.70	0.746			
	O1.4	4.03	0.70	0.739			
	O1.5	4.09	0.66	0.708			
	DM.1	4.12	0.63	0.717			
	DM.2	4.01	0.68	0.713			
	DM.3	4.06	0.65	0.886			
	DM.4	3.98	0.73	0.729			
	DM.5	3.96	0.66	0.704			
	DW.1	4.06	0.62	0.844			
	DW.2	4.04	0.58	0.728			

Table 2. *Cont.*

Variables	Items				Factor		
	Code	Mean	Sd	Loadings	CA	CR	AVE
	DW.3	4.07	0.62	0.753			
	DW.4	4.06	0.65	0.760			
	DW.5	4.10	0.63	0.716			
Knowledge Management	KG.1	4.01	0.70	0.749	0.79	0.80	0.59
	KG.2	3.99	0.69	0.885			
	KG.3	3.96	0.66	0.751			
	KG.4	3.98	0.68	0.739			
	KG.5	3.99	0.65	0.722			
	KS.1	4.03	0.68	0.753			
	KS.2	4.03	0.70	0.719			
	KS.3	3.61	0.90	0.729			
	KS.4	3.65	0.98	0.730			
	KS.5	3.97	0.66	0.787			
	KD.1	3.92	0.65	0.716			
	KD.2	4.01	0.63	0.748			
	KD.3	3.98	0.61	0.818			
	KD.4	3.93	0.62	0.761			
	KD.5	3.85	0.74	0.724			
Method Sophistication	MS.1	4.02	0.71	0.819	0.74	0.75	0.59
	MS.2	3.96	0.68	0.875			
	MS.3	3.95	0.67	0.841			
	MS.4	3.97	0.69	0.748			
	MS.5	3.93	0.66	0.832			
People and Networks	PN.1	4.02	0.62	0.812	0.79	0.80	0.55
	PN.2	4.09	0.70	0.819			
	PN.3	3.79	0.90	0.718			
	PN.4	3.78	0.98	0.725			
	PN.5	3.65	0.66	0.767			
Organization	O.1	3.97	0.66	0.724	0.80	0.87	0.56
	O.2	4.06	0.67	0.767			
	O.3	3.93	0.64	0.828			
	O.4	3.91	0.63	0.752			
	O.5	3.87	0.72	0.714			

Reliability measures, as depicted in Table 2, likewise demonstrated good internal consistency for all constructs, with Cronbach's alpha coefficients greater than the recommended threshold of 0.70 as suggested by Hair et al. [80].

Additionally, Table 3 represents the examination of inter-correlations among the variables in the model.

Table 3. Inter-correlations of constructs.

	Variables	1	2	3	4	5
1.	Business Intelligence	1.00				
2.	Knowledge Management	0.37	1.00			
3.	Methods Sophistication	0.46	0.35	1.00		
4.	People and Networks	0.44	0.42	0.36	1.00	
5.	Organization	0.40	0.37	0.39	0.43	1.00

The comparison of squared correlations with the AVE for each variable, as shown in Table 4, indicated that the variables are distinct from one another [31]. This analysis provided evidence for both the convergent and discriminant validity of the model's constructs.

Table 4. Assessment of discriminant validity.

	Variables	1	2	3	4	5
1.	Business Intelligence	0.57				
2.	Knowledge Management	0.14	0.59			
3.	Methods Sophistication	0.21	0.12	0.59		
4.	People and Networks	0.19	0.17	0.13	0.56	
5.	Organization	0.16	0.14	0.15	0.18	0.55

Diagonal values = AVE; off-diagonal values = squared inter-correlations among variables.

As can be noticed from the previous table, the AVE for each variable exceeds the squared correlation between the respective variables, suggesting that the variables are distinctive enough from one another.

4.3. Hypothesis Testing and Structural Model

The structural research model demonstrated a satisfactory goodness of fit to the observed data, as indicated by the model fit indices presented in Table 5, consistent with the recommendations of Hayes and Byrne [82,83].

Table 5. Structural model fit.

Chi sq (df)	Chi sq/df	RMSEA	GFI	CFI	NFI	IFI
52.95 * (28)	1.76	0.058	0.942	0.941	0.902	0.952

* p-value < 0.01, df: degree of freedom.

Based on the model fit indices presented in Table 5, the structural research model demonstrated a favorable fit to the observed data, in accordance with recommendations from Hayes and Byrne [82,83]. Path analysis provided evidence in support of three direct structural paths, confirming the corresponding research hypotheses. Specifically, B.I. was found to have a significant impact on Method Sophistication ($\beta = 0.65$, $p < 0.001$), People and Networks (β = 0.58, $p < 0.001$), and Organization (β = 0.47, $p < 0.001$), suggesting full support for the main Hypothesis (1), which points out that B.I. has a positive effect on S.F. dimensions (Method Sophistication, People and Networks, Organization). The findings of hypothesis testing are shown in Table 6.

Table 6. Results of hypothesis testing (direct paths).

Hypotheses		Impact Direction		B	*p*	Hypothesis Result
H1.1	BI	--->	Method Sophistication	0.65		Supported
H1.2	BI	--->	People and Networks	0.58		Supported
H1.3	BI	--->	Organization	0.47		Supported

Furthermore, to examine H2 concerning the indirect moderation effect of K.M. on the relationships between B.I. and the S.F. dimensions (Method Sophistication, People and Networks, Organization), the process macro model proposed by Hayes [82] was utilized. The product indicator method, which incorporates all the indicators of the latent predictor and moderator, as well as all possible combinations of pairs, was employed to calculate the interaction term in the structural model. As depicted in Table 7, the results indicate a significant influence of K.M. on the three paths between B.I. and the S.F. dimensions (Method Sophistication, People and Networks, Organization). The *p*-value for each indirect path was found to be 0.000 ($p \leq 0.05$), indicating statistical acceptance (supported) of the indirect hypothesis for all three paths. Thus, the indirect hypothesis test is statistically accepted (supported) for the three paths. Table 7 also shows the R2 rate for Method Sophistication (0.305), for People and Networks (0.305), and for Organization (0.239), indicating that K.M. has an appositive effect and enhances the relationship between B.I. and S.F. based on its dimensions (Method Sophistications, People and Networks, Organization). These values have a moderate effect, which is reliable and can be utilized in the interpretation and prediction process.

Table 7. Results of hypothesis testing (moderated paths).

Hypothesis	Indirect (Moderated) Effect	Estimated Coefficients	S.E.	*P*	R	Hypothesis Result
H2.1	Moderated effect (BI - KM) ---> Method Sophistication	0.658	0.21	0.000	0.305	Supported
H2.2	Moderated effect (BI - KM) ---> People and Networks	0.469	0.32	0.000	0.305	Supported
H2.3	Moderated effect (BI - KM) ---> Organization	0.551	0.23	0.000	0.239	Supported

5. Discussion

The review of literature in this research reveals that in the face of challenges in uncertain business environments, such as the highly competitive landscape of telecom companies in Jordan, companies must invest in change and development to achieve sustainability. However, relatively few empirical studies have examined the influence of the role of B.I. in driving S.F. with K.M. as a moderator variable [18,56,67,70]. To fill this gap, the current study examined the impact of B.I. on S.F., with an emphasis on the moderating role of K.M. on this impact in the telecom companies in Jordan. SEM was used to test the two research hypotheses proposed in the study. The first hypothesis related to the impact of B.I. (OLAP, data mining, data warehouse) on S.F. (method sophistication, people and networks, organization) was fully supported. The study posits that B.I. positively impacts S.F. This aligns with prior research [50,77], which emphasizes the symbiotic relationship between B.I. and S.F. These studies suggest that integrating both B.I. and S.F. can empower companies to navigate complex and uncertain environments effectively. The research results indicated that B.I. systems provide a framework for utilizing data to support decision-making in unpredictable environments, which enhances the building of future scenarios [46,53,54]. Furthermore, companies must cultivate foresight in comparison to their rivals and proactively respond based on insights and alerts to ensure their survival and ongoing operations. This result is aligned with the outcomes reported in prior empirical research [20,49,52,54]

The second main hypothesis was that K.M. moderates the relationship between B.I. and the S.F. dimensions (Method Sophistication, People and Networks, Organization), which was fully supported. Such findings support the research that recognizes K.M.'s pivotal role in capturing and organizing information effectively, fostering innovation, and supporting strategic planning. Pouru et al., Djuricic and Bootz, and Pauget and Dammak [8,32,56] support the study results and emphasize the importance of knowledge creation, sharing, and diffusion in enhancing S.F.

K.M. provides a structured approach for capturing and disseminating knowledge, fostering learning, and promoting innovation. It equips organizations with the capability to anticipate, monitor, and respond to changes in the market environment, thereby enhancing their competitive advantage and achieving sustainability in Jordan [4,61]. This finding is aligned with the outcomes reported in previous empirical research [21,25,47,65,67,77].

The study contributes to the existing body of knowledge in several ways. While prior research has acknowledged the importance of K.M. in relation to B.I. and S.F. [51,56,59,62], this study confirmed the relationship between the moderating role of K.M. This provides a deeper understanding of how K.M. can influence the relationship between B.I. and S.F., offering practical insights for organizations seeking to optimize these processes. Moreover, by focusing on the telecom sector in Jordan, the study provides context-specific insights that can be valuable for organizations operating in this industry. It also addresses the research gap where empirical evidence from such regions is limited.

6. Research Contributions and Implications

Although research has been conducted on telecom companies in Jordan, where there is limited empirical evidence on this topic in uncertain business environments, organizations must invest in change and development to achieve sustainability and provide a structured approach for capturing, sharing, and utilizing knowledge to improve future planning scenarios. The theoretical model proposed in this research was developed based on the findings of empirical studies conducted in Western contexts. The novelty of this paper lies in conducting an empirical test of the model specifically within the context of telecom companies in Jordan. This approach becomes crucial considering the growing uncertainty in the external environment, which must address challenges such as the COVID-19 pandemic. Unlike the majority of previous research, this study considers the challenges faced by the environment and the competition between telecom companies to succeed, the need for future planning to achieve sustainability, the significance of S.F. in envisioning future scenarios, the role of B.I. in managing data and supporting decision-making, and the importance of K.M. in knowledge sharing and new technology adoption.

Therefore, the findings presented provide a more comprehensive and practical S.F., which allows the organization to increase its awareness of potential dangers that result from foresight and provide a foundation for more effective emergency preparedness and the development of appropriate types of resilience. Telecom companies that employ foresight are more adaptable to change. K.M. also fosters employee expansion and development, boosts organizational agility, accelerates innovation, enhances business processes, shares expert knowledge, and facilitates quicker problem-solving. B.I. organizes efforts to gather, process, and disseminate information that can boost the competitiveness of the business. As a result, the company takes into account new problems, trends, and technologies; employs mathematical forecasting and econometric modeling; develops scenarios of potential futures; gathers signals and trends within and outside the industry; and hosts future workshops to challenge conventional ways of thinking. Moreover, S.F. establishes a focal point that examines potential futures as well as a desired future that informs the implementation to provide a strategic framework and structure. Finally, B.I. assists in setting up a convenient position, identifies consumer habits and trends, aids in investigating new opportunities in an unpredictable future, and relates to strategic planning as well as modifications in a business environment.

7. Recommendations and Limitations

The research recommends that telecom companies implement data analysis methods and reports on the performance of the present organization over time to provide further operational solutions on its capacity for forward-looking analysis to better comprehend internal opportunities or dangers in the company. Companies also need a place to hold enormous volumes and gain simple access to data. Additionally, the data warehouses must include details about the company's external environment (suppliers and competitors), provide comprehensive information to fulfill the beneficiaries' demands, and assist stakeholders in reaching emergency response decisions. Finally, the study advises benchmarking performance, getting market information, and sharing knowledge with business partners. Systems for sharing information, looking for novel methods to complete tasks, and reacting to relevant technological activity and unanticipated rival moves should be in place in the organization.

In the end, this study is limited in its geographical and specific industrial context. That is, the focus has been mainly on the telecom industry, which makes it difficult to extrapolate its results to other types of industrial enterprises. Therefore, it is imperative to expand the research sample to encompass a more diverse range of telecom companies, both within and beyond Jordan. This would allow for a more comprehensive understanding of data management practices and their variations. Furthermore, cross-industry studies can be undertaken to identify similarities and differences in data management approaches across sectors, providing valuable insights for telecom companies looking to adapt and innovate. International comparative studies can shed light on how data management practices are influenced by regional factors, regulatory frameworks, and market dynamics. Lastly, longitudinal studies should be pursued to track the evolution of data management practices over time, helping telecom companies stay agile in an ever-changing landscape.

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