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The influence of business analytics on the strategy evaluation process by mediating the virtual value chain: Applied to the Egyptian telecommunications sector

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Abstract

This paper seeks to investigate the impact of business analytics on the strategy evaluation process through the mediation effect of virtual value creation in the Egyptian telecommunications sector. A self-administered questionnaire was developed to collect data from a critical sample of the senior managers working in four Egyptian telecommunications corporations—Vodafone, Orange, Etisalat, and Telecom Egypt—and analyzed using structural equation modeling techniques (SEM) by utilizing Amos-25. The results of this research indicated that business analytics has a significant effect on strategy evaluation processes. Also, the results confirmed that the virtual value chain mediates the relationship between BA and strategy evaluation processes. The study contributes to the body of knowledge in BA and strategic management as it is the first to examine the impact of BA on the strategy evaluation process by mediating a virtual value chain.

Keywords

Business analytics; virtual value chain; strategy evaluation process; Egyptian telecommunication sector

Article history

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1. Introduction

In the last few years, there has been a remarkable rise in the adoption of business analytics (BA) in business organizations (Nam *et al.*, 2019a). Most of these organizations seek to leverage BA to enhance business value and sustain competitive advantage (Wixom *et al., 2013;* Gartner, 2014; Wang *et al.*, 2019). According to socio-technical system theory (Bostrom & Heinen, 1977; Dremel *et al.,* 2020), business analytics is a promising field that enables business organizations to make data-driven decisions by leveraging advanced analytics techniques (Vidgen *et al.*, 2017: Rachid et al, 2019). Numerous studies have examined the value BA can create for organizational performance in different areas such as innovation (Duan *et al.*, 2018; *Nam et al., 2019a*) competitive advantage (Sharma et al.,2010*)*, value creation (Wixom *et al., 2013;;* Mikalef *et a*l., 2020; Bhosale and Ukhalkar, 2020), decision-making effectiveness (Cao et al., 2015; Rachid & Thambusamy, 2017; Vidgen *et al.*, 2017; *Pappas et al., 2018),* and agility (Richards *et al.*, 2019; Ashrafi et al., 2019).

Furthermore, some papers hypothesize the potential support of BA for the multiple tasks of strategy processes, such as environmental analysis (Kunc et al 2018; Pröllochs, &. Feuerriegel, 2020) formulating strategic options (Harris et al., 2016; Wang et al., 2016); and implementation strategy (Wang et al., 2016; Nasereddin., 2023). There is a lack of research that thoroughly examines how business organizations can use BA to address the diagnostic and interactive dimensions of the strategy evaluation process, particularly in light of the solid evidence that traditional performance management systems (PMS) are unable to adequately provide the performance data needed to support the strategy evaluation process (Lohman et al., 2004; Micheli & Manzoni, 2010; Melnyk et al., 2010; Franco-Santos et al., 2012).

Today business organizations, particularly those operating in highly volatile environments, need to depend more on the different forms of BA: descriptive, real-time, diagnostic, predictive, and prescriptive, in order to obtain historical and real-time information required to effectively evaluate and improve their performance (Raffoni et al., 2017; Kunc et al., 2018). Yet, there is evidence that business performance analytics could provide better insight into performance dynamics and the critical performance indicators (KPIs) that influence the success of the intended strategy, which addresses the diagnostic dimension of the strategy evaluation process (Simons, 1995; Ferreira & Otley, 2009; Silvi et al., 2012; Raffoni et al., 2017; Kunc et al., 2018). Also, business performance analytics could strongly support innovation and opportunity seeking, which is a core of the interactive dimension of the strategy evaluation process (Simons, 1995; Visani, 2017).

According to Boyer *et al.* (2010) and Williams (2016), the main criterion for improving the benefits of BA is how to leverage BA within the core business processes that drive the value chain process. Today, many business organizations have become more dependent on the virtual value chain than the physical value chain in order to keep pace with customer aspirations (Rayport & Sviokla, 1995; Porter, 2001; Ratnamalala, 2019). VVC is an information-based value activity; thus, effective integration of information during the value chain activities helps to enhance its visibility and sustain its mirroring capabilities (Bertolucci 2014; Gündüz 2015). However, little is known about how value chain activities can be improved by the inclusion of BA (e.g., Gifford 2013; Chai & Olson 2013). Motivated by these concerns, this study examines the effect of BA on the strategy evaluation process by mediating the virtual value chain. This study contributes to calls for more studies on how BA can support strategic management processes. Also, it will substantiate the interdisciplinary efforts in both strategic management and information technology areas.

The Egyptian telecom sector has been chosen as the context for this study for several reasons. First, the Egyptian telecom industry is considered a key driver of implementing Egypt Vision 2030. As Egypt pursues a digital society, Egyptian communication corporations have also implemented a plan, ICT 2030, to further invest in and develop information and communications technology (Katz et al., 2022). Second, telecommunications corporations were among the earliest adopters of business analytics for internal and external metrics to effectively manage and drive their businesses (Yanming & Jianqiu, 2009; Deogaonkar & Washimkar, 2014). Third, currently, the Egyptian business environment is characterized by a high degree of uncertainty and volatility, which can be attributed to various factors such as rapidly evolving technology, escalating customer expectations, and a string of economic crises (Abdelrahan and Kamal). As a result, the four Egyptian telecommunications corporations—Orange, Vodafone, Etisalat, and Telecom Egypt—need to leverage business analytics more to obtain a comprehensive and cohesive view of the data needed to assess their strategies and enhance their performance **(**Capgemini, 2017; Pröllochs & Feuerriegel, 2020).

This paper is organized as follows: The hypotheses regarding the relationships between business analytics, the strategy review process, and the virtual value chain are presented in the next section. The methodology and empirical findings will then be presented, followed by the study's conclusion and limitations.

2. Theoretical background

2.1. Business analytics

Business analytics is defined as the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions (Davenport et al., 2007; Davenport and Harris, 2017; Kumar & Krishnamoorthy, 2020). In recent years, investments in analytics tools and techniques have grown exponentially. Therefore, analytics has become one of the priorities of many business managers (Cosic et al., 2015). Some practitioners use data analytics, business analytics, and business intelligence interchangeably, even though they have different scopes of focus (Williams, 2016; Charles et al., 2023). Data analytics is a broader umbrella that encompasses identifying and sourcing data, preparing data for analysis, visualizing data to make it easier to understand, and presenting data in a compelling way (Beyer and Laney, 2012; Hwang and Chen, 2017; Bhosale & Ukhalkar, 2020), while business intelligence encompasses using historical data to monitor business performance and make informed decisions (Williams, 2016; Alnoukari, & Hananao, 2017; Elhoseny et al., 2020). Business analytics dig deeper into data to uncover insights (Power et al., 2018), identify problems and opportunities (Ashrafi et al., 2019), and predict future outcomes for the business (Krishnamoorthi and Mathew, 2018). Together, BA and BI help to make better decisions (Cao *et al.*, 2021; Al-Sai *et al.*, 2022), improve performance (Gunasekaran et al., 2017; Pappas *et al.*, 2018), and gain a competitive advantage (Sharma et al.,2010: Richads et al.,2019 : Mikalef et al., 2020).

There have been different perspectives that both scholars and practitioners could use to conceptualize BA, but the most common are dynamic capability, orientation, and domain (Holsapple et al., 2014). According to the dynamic capability perspective, BA extends beyond the technological aspects to include tangible, human, and intangible resources, such as data, technology, and data-driven culture (Barney, 1991: Ashrafi et al.,2019; Neill & Brabazon, ,2019).

The orientation perspective of BA describes the direction of thinking or the objective of the analysis. It has divided BA into five stages, which reflect its maturity level: descriptive, real-time, diagnostic, predictive, and prescriptive analytics (Davenport, 2010; Banerjee et al., 2014; Hurwitz et al., 2015; Delen & Zolbanin, 2018; Lawton, 2019; Charles et al., 2023; Peter et al., 2023; Wolniak & Grebski, 2023). The use of the five main categories depends on the nature of business problems (Mikalef et al., 2020), the orientation of the analysis to answer the stated business problem (Lawton, 2019), and also on the availability of data (Wamba et al., 2017). The first , **descriptive analytics,** answers the question, What has happened? It summarizes what has occurred within the internal and external environment of the firm (Davenport, 2010; Lawton, 2019). It also acts as the underlying framework of a continuous monitoring system (Scappini, 2016; Sharma et al., 2020). The most common descriptive tools include business dashboards, visualization types, and KPIs (e.g., Davenport, 2010; Appelbaum et al., 2017; Mikalef et al., 2020). The second is real-time **analytics**, by which decision-makers can examine data as it is produced or received. As a result, it is commonly used in extremely volatile environments, including supply chain management, financial markets, and online customer interactions (Peter et al., 2023; Charles et al., 2023). The third, **inquisitive analysis**, sometimes referred to as diagnostic analysis, aims to provide an explanation for the events that occurred. To find the drivers or root causes of that performance and to learn how to improve procedures and prevent future problems, data analysts employ a variety of diagnostic analysis techniques, including root cause analysis and alerts (Hurwitz et al., 2015; Lawton, 2019; Charles et al., 2023). The fourth **Predictive analytics** help decision-makers to leverage historical data and patterns to make informed predictions by applying different techniques such as regression analysis, time series forecasting, and machine learning models (Harris et al., 2016; Alharthi, 2018). Finally, **prescriptive analytics** answers the question, What should happen? By using optimization models, decision trees, simulation techniques, and machine learning algorithms, strategists could evaluate various scenarios and potential outcomes (Hwang and Chen, 2017; Greasley, 2019; Frazzetto et al., 2019).

According to the domain or the area in which the analytics are being applied, BA covers different functional areas such as marketing, finance, human resources, operations, and production (Holsapple et al., 2014; Colangelo et al., 2018); web analytics (Burby & Atchison, 2007); Google analytics (Hasan et al., 2009); software analytics (Buse and Zimmermann, 2010); crisis analytics (Tomaszewski et al., 2007); marketing analytics (Hauser, 2007); and human resource analytics (Levenson, 2005).

2.2. Strategy evaluation process

Strategy evaluation describes the process of assessing the effectiveness and efficiency of a strategic plan or initiative (Carpenter and Sanders, 2009; Hunger and Helen, 2011). It is an integral part of the strategic management process, serving as a critical feedback mechanism to determine whether the strategy has achieved its intended objectives (David, 2001; Popa et al., 2012; Ivancic, 2013; Elshamly, 2013; Monday et al., 2015).

Business organizations primarily use data-driven performance management systems to meet the interactive and diagnostic approaches of the strategy evaluation process. The diagnostic approach seeks to set strategic objectives and control the system's capacity to attain them, whereas the interactive approach tackles strategic uncertainties and discovers and supports emergent strategies (Simons, 1995; Ferreira & Otley, 2009; Silvi et al., 2015). According to some studies, traditional PMSs are unable to provide adequate performance data, which has a detrimental impact on the ability to accomplish organizational goals (Micheli and Manzoni, 2010), identify critical success factors (Melnyk et al., 2010; Vigfússon et al., 2021), and enhance business performance (Franco-Santos et al., 2012; Wanjiru, ,2016).

Undoubtedly, because of the heightened degree of unpredictability in the business world, firms nowadays have to cope with ever-increasing amounts of information. Therefore, monitoring strategy performance and fostering organizational learning depend heavily on the evaluation of strategic data (Simons, 1995; Galeotti et al., 2016). Business performance analytics have a great potential to improve performance management systems, claim Klatt et al. (2011), Silvi et al. (2012), and Raffoni et al. (2017). The term "business performance analytics" refers to "the application of a data-related analytical approach for gaining a better understanding of performance dynamics and supporting performance." (Page 7, Raffoni et al., 2017). The core of diagnostic evaluation (Simons, 1995; Zhang et al., 2015; Constantiou & Kallinkos, 2015) is addressed by business performance analytics, which allows strategists to gather, analyze, and interpret traditional and structured data in order to identify the key performance indicators (KPIs) and highlight the causal interdependence between them (Simons, 1995; Ferreira & Otley, 2009). Also, business performance analytics facilitate interactive evaluation by analyzing massive amounts of unstructured data that are updated in real time (Bhimani & Willcocks, 2014; Zhang et al., 2015). This analysis reveals evolving strategies and helps detect strategic trends in process. Senior managers' participation in the strategy control process would also be improved by the availability of relevant analytical evaluations that might facilitate the sharing of knowledge, concepts, and opinions across departments and hierarchical levels (Simons, 1995; Raffoni et al., 2017).

2.3. Virtual Value chain

An organization's value chain is the series of sequential activities that produce and provide a good or service to consumers (Porter, 1985; Yan Li, 2013; Staats & Upton, 2015; Kalmykova et al., 2018). The main supply-side activities, like inbound logistics and operations, are closely linked to the demand-side activities, like outbound logistics, marketing, sales, and after-sales services, according to Porter's generic model of the value chain. These activities are supported by four activities: procurement, technology, human resources, and firm infrastructure, which aid in their efficient functionalization (Porter, 1985; McNeish & Kelley, 2019; Strakova et al.,2021). In order to demonstrate how internet-based technologies contribute to the firm's value chain, Porter (2001) later modified his initial physical model to highlight the technology effect.

Furthermore, the concept of the virtual value chain, which was early introduced by Rayport & Sviokla (1995), has arisen as an enabler in the interconnected digital world. According to Rayport & Sviokla (1995) and Lee et al. (2007), VVC is the value chain system driven by information-based value activities, and these activities help to speed up the electronic commerce market space. A series of sequential steps make up the virtual value chain: first, identifying content (what is offered); next, infrastructure (transaction enablers); distribution and transactional support; and finally, identifying the context, which is finished by the customer providing the user interface and customer interactions (Rayport and Sviokla, 1995; Schliffenbacher et al., 1999 ; Swierczek and Kaspersky-Moron, 2016). Similar to the Porter physical value chain itself, value-added information is the driving force behind VVC and is viewed as a source of value rather than as a supporting activity (Raypot & Sviokla, 1995; Weiber and Tobias, 1998). A series of five steps—collecting, organizing, choosing, synthesizing, and distributing—were used throughout the virtual value chain to transform raw data into information with added value (Raypot & Sviokla, 1995; Swierczek & Kaspersky-Moron, 2016).

According to Swierczek and Kaspersky-Moron, (2016), efficiently incorporating value-added information into the value chain improves its visibility and mirroring capabilities. By allowing decision-makers to monitor and coordinate activities in the physical value chain using large-scale information technology, visibility improves their ability to plan, carry out, and assess outcomes with more accuracy (Swierczek & Kaspersky-Moron, 2016). Additionally, mirroring capabilities enable decision-makers to identify the underperformance areas of physical activities and then replace them with virtual activities, which help enhance the value of business operations (Gopalakrishna & Subramanian, 2008; Kim & Chai, 2017;).

With the virtual value chain developing so quickly, a number of scholars have examined ways to evaluate the performance of its primary functions (Gunasekaran & Kobu, 2007; Akyuz & Erkan, 2010). Pierre (2014) have contributed to the field's growing body of research by providing a virtual value chain performance model, which is expected to boost business organizations' overall added value . According to this model, each virtual model activity—upstream, downstream, delivery, and supportive—should be linked to a set of performance indicators so managers may assess how well their departments are performing (Akyuz & Erkan, 2010; Lohman et al., 2013). Furthermore, these indicators aid in identifying the outcomes of ongoing operations and any necessary corrective measures to enhance performance (Gunasekaran and Kobu, 2007; Haryadi, 2016). The potential of business analytics (BA) to enhance value chain performance and support organizational functional areas is currently a topic of much study (e.g., Gifford 2013; Chae & Olson 2013; Bertolucci 2014; Körpeoglu, et al.,2014; Gündüz 2015).

3. Research hypotheses

3.1. Business analytics and strategy evaluation process

According to Raffoni et al. (2017), business performance analytics contribute significantly to both the diagnostic and interactive purposes of the strategy elevation process. With the use of BA, strategists can better handle the deluge of information (Klatt et al., 2011; Ramanathan et al.,2017), assess historical data from various business processes (Pajouh et al., 2013; Torres et al., 2018), and identify performance drivers that are crucial to achieving strategic goals and intended results (Kunc et al., 2018; Krasniqi, et al., 2019).

Additionally, by illuminating the incidental relationships across strategic critical factors, BA helps strategists better understand the reasons behind underperforming areas and offers suggestions for future enhancements (Kazokov & Kunc, 2016; Wolniak & Grebski, 2023), which support the diagnostic dimension of strategy evaluation.

Furthermore, Scappini (2016) and Mardiani et al (2024) argue that BA empowers decision-makers to recognize strategic uncertainties, unveil emerging strategies, and forecast the expected effect and risk associated with a specific managerial action (Scappini, 2016). By leveraging BA, interactive meetings among the senior managers will be facilitated, which will stimulate their participation, foster innovation, and enhance strategic feedback (Angalakudati et al., 2014; Elhoseny et al., 2020).

Depending on the previous discussion, we can develop the following hypothesis:

H1. BA is expected to have a positive impact on the strategy evaluation process

3.2. Business analytics and virtual value chain

Many studies have looked at how decision-makers can access historical and current data about the major activities of the virtual value chain through descriptive analytics and real-time analytics (Gifford, 2013; Chae & Olson, 2013; Ratnamalala, 2019) increasing the chain's visibility.

Additionally, organizations could improve their mirroring capabilities and integrate virtual and physical processes in a balanced manner by using predictive and prescriptive analytics, which help decision-makers identify possible disruptions and their potential impact (Raypot & Sviokla, 1995; Kumar & Rajeev, 2004; Rosenbush & Stevens, 2014; Bertolucci 2014: Müller-Navarra et al., 2015).

By taking advantage of both visibility and mirroring capabilities, decision-makers can monitor the key performance indicators linked to every activity and then make better choices to improve their performance (Akyuz & Erkan, 2010; Lohman et al., 2013; Sadovskyi et al.,2014; Sun et al .,2017). Therefore, we propose the following hypothesis:

H2. ***BA is expected to have a positive impact on the virtual value chain.***

3.3. Virtual value chain and strategy evaluation process

Functional managers can better determine the information hotspots that influence each value creation area's performance and arrange this strategic data into matrices by employing the virtual value chain visibility and mirroring capabilities (Simon, 1995; Gunasekaran & Kobu, 2007).

According to Pierre (2014), functional managers could use performance metrics as a guide to determine if strategic objectives have been met throughout electronic business activities. Unfavorable variances are captured, and significant actions are taken to bring the business activity under control. This back-looking approach addressed the diagnostic purpose of the strategy evaluation process.

Moreover, functional managers become highly involved in data generation, analysis, and interpretation, seeking to mitigate the potential risks entailed in the volatile business environment. This forward-looking approach addresses the interactive purpose of the strategy evaluation process (Simon, 1995; Rayport & Sviokla, 1995; Pierre, 2014; Bradlow et al., 2017). So the following hypothesis will be developed.

H3. ***Virtual value chain is expected to have a positive impact on strategy evaluation process.***

3.4. The mediation effect of virtual value chain in the relationship between business analytics and strategy evaluation

By improving the virtual value chain's visibility and mirroring capabilities, business analytics (BA) make it easier for operational managers to monitor their functions' performance metrics, spot performance gaps, and implement corrective measures (Simon, 1995; Rayport & Sviokla, 1995; Pierre, 2014).

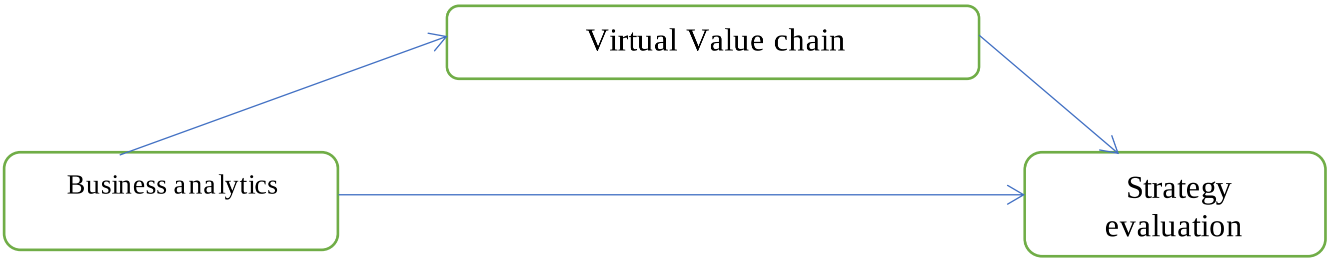
determining the kinds of data to be included in the measurement process, the level of measurement, the definition of each measure, the information's source, the action plan for the frequency of measurement, and the distribution of metric data

(Pierre, 2014). As a result, they become more equipped to assess present performance, recognize prospective opportunities and threats, and reduce associated risks (Simon, 1995; Raypot & Sviokla, 1995; Pierre, 2014).

Therefore, the following hypothesis will be formulated:

H 4: The virtual value chain mediates the relationship between BA and the strategy evaluation process.

According to the above discussion we can develop the proposed research model



4. Research methodology

4.1. Research design Population and Sampling

This study is characterized as descriptive, as it reveals the characteristics of certain populations, establishes a correlation between variables, and defines its nature (Creswell, 2015). A quantitative approach was adopted, wherein an online questionnaire-based survey was used to collect data from senior managers employed in the four Egyptian telecom industries: Vodafone, Orange, Etisalat, and Telecom Egypt. This approach was chosen because it is easy to replicate, facilitates the investigation of multiple constructs simultaneously, and makes it easy to generalize the results of exploratory studies based on predictive models (Boudreau et al., 2001). Critical case sampling was used to identify managers who actually participated in activities related to business analytics integration. Critical case sampling is defined as “choosing settings, groups, and/or individuals based on specific characteristic(s) because their inclusion provides the researcher with compelling insight about a phenomenon of interest (Onwuegbuzie &Collins, 2007). The questionnaires were sent electronically to 135 seniors in the targeted corporations. The data collection process lasted two months (February 2024–March 2024), and the average completion time of the questionnaire was 15 minutes. From the 122 responses collected, 115 were retained for further analysis, 55 were collected from information technology managers, and 60 were from other department managers. Table 1 presents the sample profile

Table (1) Sample profile

Vodafone	Orange	Etisalat,	Telecom Egypt	
3	4	3	3	Strategic planning manager
2	3	3	2	Application manager
4	4	2	3	Project management
3	3	2	2	Data manager
3	3	2	2	Information system manager
2	3	2	2	Information technology manager
2	2	2	2	Network manager
3	3	2	3	Marketing management
3	2	2	2	Quality manager
4	3	3	3	Customer service manager
3	2	2	2	Supply chain manager
32	32	25	26	115

Source: Spss V25 output

4.2. Measures

The theoretical model's variables were assessed using two five-point scales: one for "never" to five for "often" and another for "strongly disagree" to five for "strongly agree." All of the scales came from earlier research. The orientation perspective proposed by (Davenport 2013) and supported by (e.g. Appelbaum et al., 2017; Hwang et al., 2017; Charles et al., 2023; Peter et al., 2023) that BA has five primary types—descriptive, real-time, diagnostic, predictive, and prescriptive analytics—was the foundation upon which the independent variable BA scale was constructed. Both the virtual value chain model offered by Rayport & Sviokla (1995) and the virtual value chain performance metrics model proposed by Pierre et al. (2014) are used in the study to determine the elements that seem significant to assessing the mediating variable virtual value chain. Simons (1995) provided a literature review that we used to evaluate the dependent variable strategy evaluation process. According to Simons, strategy evaluation and control have two primary perspectives: diagnostic and interactive. Additionally, Raffoni et al. (2017)'s business performance analytics methodology has been taken into account while assessing the dependent variable.

4.3. Data analysis

Respondents were made aware that the study was for academic research objectives and that their participation would remain anonymous in order to prevent measurement errors caused by common method bias (CMB). Additionally, following the pre-test, scale items were revised to make the questionnaire easier to read and less ambiguous, which helped to reduce biases associated with the items. In addition, the Harman's single-factor test was run to see if one factor could explain the majority of the variance in the model. Given that the largest variance explained by a single component in this study was 26.8%, the test demonstrated that there is no risk of CMB.

Regarding the reliability and validity of the constructs and their corresponding items, based on Hair et al. (2016), items are reliable if the item loadings are greater than 0.50, and they should have composite reliability (CR) and Cronbach’s alpha (α) values above 0.50. The results show that the reliability of the scales ranged from 0.840

to 0.876, indicating the reliability of the scales. To ensure that the constructs significantly explain the variance of their items, the average variance extracted (AVE) should be greater than 0.50. Regarding validity, one item was removed from the scale measuring business analytics, and two items were removed from the scale measuring the strategy evaluation process because their loading factors were less than 0.5 after the CFA first run. The values of average variance extracted (AVE greater than 0.5) and values of composite reliability are significant and substantial, indicating the validity of the scales (see Tables 2 and 3). According to Fornell and Larcker (1981), convergent validity is satisfactory when constructs have an AVE of at least 0.5. Table 4 presents the results of the discriminant validity, which is based on the Fornell-Larcker criterion with correlations and the square root of AVE values on the diagonal.

Table (2) Outer loading of the items for study constructs

BA Loading				Strategy evaluation Loading				Virtual value chain Loading	
BA1	.950	BA6	.939	SCP1	835	SCP6	.865	VVC1	.832
BA2	.847	BA7	.955	SCP2	.819	SCP7	.876	VVC2	.821
BA3	939	BA8	.834	SCP3	.841	SCP8	.856	VVC3	.845
BA4	935	BA9	.934	SCP4	.831	SCP9	.834	VVC4	.915
BA5	.939	BA10	.849	SCP5	.921	SCP10	.878	VVC5	.838
								VVC6	.923
								VVC7	.865

Source: Spss V25 output

Table 3 reliability and validity statistics

Variables	Cronbach's Alpha	N of Items	AVE	CR
BA	0.862	10	0.736	.862
VVC	0.840	10	0.698	.840
SEP	0.876	7	0.684	.876

Source: Spss V25 output

Table 4 Discriminant validity

	BA	VVC	SEP
BA	0.840		
VVC	0.594	0.815	
SEP	0.611	0.606	0.836

Source: Spss V25 output; The off-diagonal values in the Fornell–Larcker Criterion matrix are the correlations between the latent constructs, and diagonal are square values of AVEs.

4.4. The descriptive results:

According to Table 5, the respondents of the sampled telecom corporations have a remarkable consensus on the level of adoption of different types of BA by their corporations, with a value of 3.98. Also, the respondents believe that their corporation is actively committed to implementing the strategy evaluation process, as evidenced by a mean value of 3.87. The mean of the virtual value chain was the highest, with a 4.13 value.

Table 5 Descriptive statistics

Variables	Mean	Std. Deviation
Business analytics	3.98	1.341
Strategy evaluation process	3.87	1.876
Virtual value chain	4.13	1.987

Source: Spss V25 output

4.5. Model fit indices

The structural model displayed a good fit with the data, compared with the suggested fit criteria. The fit statistics were CMIN $\chi^2 = 213.564$, df = 97, p = 0.0, and CMIN/df = 2.201. The fit indices were all in acceptable ranges, with CFI = 0.94, GFI = 0.94, TLI = 0.95, and RMSEA = 0.057. Models with cut-off values above 0.90 for CFI and below 0.08 for RMSEA are considered to have a good fit between the hypothesized model and the observed data (Hu and Bentler, 1999). Figure 2 displays all of the structural relationships among the studied constructs, and path coefficients are also presented in this figure. As indicated in Figure 2, all hypotheses were supported by the data.

By analyzing the significance of the path coefficients (β) using p-values (p), the model shows that BA significantly affects the strategy evaluation process (β = 0.20, p = 0.000). Also, business analytics (β = 0.29, p = 0.000) significantly affect virtual value chain. Additionally, the virtual value chain also significantly affects the strategy evaluation process (β = 0.33, p = 0.000). Table 5 summarizes the findings of the structural model evaluation.

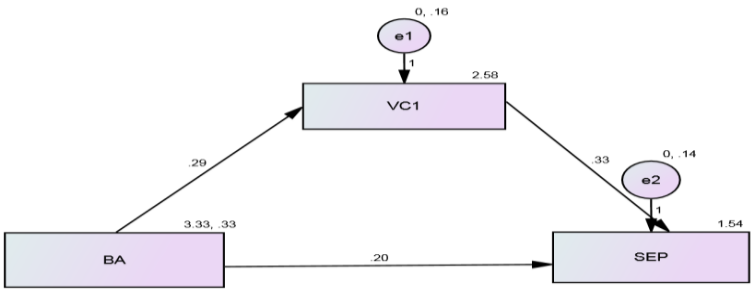


Figure 2 validated model of the study relationships

Table 6 summary of direct effects

	Estimate	S.E.	TV	P	Results
BA → VVC	0.29***	.065	4.382	0.000	H1.Accepted
VVC → SEP	0.33***	.088	3.685	0.000	H2.Accepted
BA → SEP	0.20***	.067	3.061	0.002	H3.Accepted

***p < 0.001

4.6. Mediating effects

The analysis also shows that virtual value chain had a mediating effect in the relationship between BA and the strategy evaluation process; the total effect is 0.228, with a 0.002 p-value < 0.001, and the direct effect is 0.198, and the indirect effect 0.124, with a p-value < 0.001, significant (see table 7).

Table 7 summary of mediation effect

	Total effect	P	Direct effect	p	Indirect Effect	p	Results
BA → VVC → SEP	0.228***	***	0.198***	***	0.124***	***	H4, Accepted

***p < 0.001/ mediator, virtual value chain, dependent variables, strategy evaluation process

5. Discussion and conclusions

This study intends to examine how organizations could leverage BA to fine-tune strategy evaluation processes by mediating virtual value chains. The motivation for this study is to extend the multidisciplinary literature, which mostly focuses on how technology affects firm performance. Firstly, the results of the study show that BA has a significant impact on the strategy evaluation process. Descriptive, real-time, diagnostic, predictive, and prescriptive BA are tools that strategists in various organizations can use to obtain historical and real-time data needed to identify key performance indicators and visualize the connections between various performance areas that support the diagnostic dimension of the strategy evaluation process (Simons, 1995; Ferreira & Otley, 2009). Also, BA promotes the interactive dimension of the strategy evaluation process by incorporating data into management daily interaction, which enables it to deal with strategic uncertainties, track new ideas, trigger organization learning, and properly position the organization in the future. These findings are supported by existing literature, which emphasizes the importance of BA for the strategy evaluation process (Pajouh et al., 2013; Kazokov & Kunc, 2016; Torres et al., 2018; Kunc et al., 2018; Elhoseny et al., 2020).

Second, the study's findings imply that BA has a significant influence on the Egyptian telecom sector's virtual value chain. By capitalizing on value-added information delivered by a variety of BAs, functional managers can improve value chain visibility and mirroring capabilities. Also, BA enables the functional managers to closely monitor the key performance metrics of all upstream, downstream, delivery, and supportive processes in their value chain. This finding is consistent with the literature (e.g., Bertolucci 2014: Sadovskyi et al.,2014: Müller-Navarra et al., 2015; Ratnamalala, 2019) that has demonstrated that BA improves the performance of the virtual value chain by making data-driven decisions more informed and hence more effective.

Thirdly, the virtual value chain was found to be influential in the strategy evaluation process. By capitalizing on the visibility and mirroring capabilities of the virtual value chain, strategists could closely track the key performance metrics, identify gaps between actual performance and standards, and create a variety of scenarios to address underperforming areas. Moreover, strategists become more able to engage effectively in the data creation, analysis, and interpretation processes and gain insightful knowledge about the future. Our findings support existing literature that emphasizes the importance of virtual value chain visibility and mirroring capabilities in tacking the performance metrics of the key processes involved in value creation, which in turn contribute to the strategy evaluation process (Pierre, 2014; Müller-Navarra et al., 2015; Bradlow et al., 2017).

Fourthly, the results confirm that the virtual value chain mediates the relationship between the BA and strategy evaluation process. By utilizing BA, business organizations can improve value chain visibility and mirroring capabilities, allowing strategists to monitor performance metrics and handle the diagnostic and interactive aspects of strategy evaluation. This outcome is supported by previous literature (e.g., Pierre, 2014; Williams, 2016; Mikalef et al., 2020).

6. Limitations and directions for future studies

This study has some limitations, which are also opportunities for future research. First, the study was conducted on the telecommunications sector in Egypt, which is characterized by a virtual value chain that is somewhat different from other sectors; therefore, it is not logical to generalize the results of the study to other sectors. In the future, it would be worth having an in-depth investigation in various sectors or countries.

Second, the study addressed the influence of BA on the strategy evaluation process in general; thus, it would be useful to examine the effect of each type of BA (descriptive, prescriptive, inquisitive, and predictive) on the strategy evaluation process and recognize the most influential one.

Third, the study discussed the virtual value chain as a mediator variable in the relationship between BA and the strategy evaluation process. It would be valuable to incorporate other mediators that may have a substantial mediating effect on the relationship between BA and strategy evaluation, such as the types of competitive strategies adopted, an organization's core competencies, and organizational culture.

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Appendix A

Dear Mr / Miss

I really appreciate your support in filling out this questionnaire on utilizing business analytics in the strategy evaluation process by mediating virtual value chain in the Egyptian telecom industry. It is important to know that this data will be kept confidential and will only be used for scientific research purpose.

Corporation

- Telecom Egypt
- Vodafone
- Orange
- Etisalat

Title

- IT manager
- Information manager
- Technical support manager
- Strategic planning manager
- Marketing manager
- Quality manager
- Customer service manager
- Supply chain manager
- Financial manager
- Human resource manager

A. Kindly indicate to what extent your corporation is using the following BA to fine-tune the process of strategy evaluation by selecting the appropriate responses. The item scales are five-point Likert-type scales, with 1 = never, 2 = rarely, 3 = sometimes, 4 = always, and 5 often.

BA applications	
1.1 Reports, Scorecards and dashboards	
1.2.User-defined analyses	
1.3.Ad hoc analyses	
1.4 real –time analytics	
1.5.Modeling	
1.6.Simulation	
1.7.Multidimensional analysis	
1.8.Alerts analysis	
1.9.Factors analysis	
1.10.forecasting models	

B. Kindly indicate to what extent you agree or disagree with the following statements concerning the effectiveness of the strategy evaluation process, and the characteristics of virtual value chain by selecting the appropriate responses. The item scales are five-point. Likert-type scales with 1 = strongly disagree, 2 = disagree, 3 = either agree or disagree, 4 somewhat agree, and 5 strongly agree

Strategy evaluation process	
1. Our corporation, the foundation of our strategy evaluation process is a data-driven performance management system.	
2. Our corporation has a set of comprehensive performance targets that reflect our strategic priorities.	
3. Our corporation takes the necessary steps and periodically monitors the progress made toward reaching the set objectives.	
4. Our evaluation system enables us to tackle strategic uncertainties and discover external opportunities and threats.	
5. Our corporation keeps the interactive and diagnostic purposes of the strategy evaluation process in check.	
6: Our corporation is interested in gaining a deeper understanding of performance dynamics through the application of a related analytical technique.	
7. Business performance analytics enable the collection, analysis, and interpretation of the data required to address the diagnostic and interactive purpose of the strategy evaluation process.	
8. Business performance analytics enable the elimination of subjective biases and ensure consistency across the strategy evaluation process.	
9. Business performance analytics help identify the critical performance indicators (KPIs) that influence the success of the intended strategy.	
10. Business performance analytics are expected to support innovation and minimize risks that could shock the actual performance of the company	
Virtual value chain	
1. Our corporation has a clear identification of all the basic constituents of our virtual value chain, such as content, infrastructure, and distribution, context, and customer interactions.	
2. Our corporation uses a set of performance metrics to evaluate the effectiveness of our virtual value chain.	
3. Value-added information is the fundamental unit of our virtual value chain.	
4. Our corporation exerts remarkable effort toward gathering, organizing, selecting, synthesizing, and distributing processes in order to convert raw information into value-added information.	
5. Our virtual value chain has a high level of visibility, which helps to monitor performance and evaluate results with greater precision.	
6. Our virtual value chain has high mirroring capabilities, which enable us to effectively maintain the balance between the physical and virtual processes .	
7. Our corporations are concerned with utilizing BA to improve the performance of the different activities of the virtual value chain.	