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The effect of big data on decision quality: Evidence from telecommunication industry

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A B S T R A C T

The aim of the research is to test the impact of big data on the quality of decision making. The necessary data was collected from telecommunication companies operating in Jordan. Three companies provide telecommunications services in Jordan: Zain, Umniah, and Orange. Non-probability purposive sampling was used. Hence, the study instrument was distributed to managers at the senior and middle levels of these companies. The structured equation modeling (SEM) technique was employed to test the study hypotheses. The results confirmed that big data impacts decision quality. Besides, it was determined that the highest impact was on velocity. The researchers suggest that Jordanian telecom companies invest in information technology that allows them to provide data with accuracy, reliability, and high quality, as well as improve the qualifications of their employees.

1. Introduction

In recent years, a wave of data revolution has been observed in turbulent and highly competitive global environments, affecting all walks of life. Information systems in companies have evolved over the years and moved from being a system in which transactions are recorded to being a system that supports decisions made by businesses at various levels (AlHamad et al., 2022; Tariq et al., 2022; Al-Hawary & Obiadat, 2021; Eldahamsheh et al., 2021; Al-Hawary & Alhajri, 2020). Companies have to adapt more quickly and more aggressively in order to survive and thrive. They are increasingly seeking ways to identify constraints in the progress of business processes that severely hinder their ability to respond. Traditional information systems rely primarily on internal data sources such as enterprise resource planning systems (ERPs) to make business decisions (Allahow et al., 2018; Al-Hawary & Alwan, 2016; Al-Nady et al., 2016; Al-Nady et al., 2013). These data sets are organized and used for management systems through relational databases (RDBMS). These have been used to support internal business decisions such as inventory management, pricing decisions, discovering the most valuable customers, identifying lost products, etc. (AlTaweel & Al-Hawary, 2021; Al-Hawary & Al-Syasneh, 2020; Jeble, Kumari & Patil, 2018).

The buzzword "big data" has gotten a lot of attention and has brought with it not only technological but also management issues. Big data is believed to give a company a competitive advantage and is a "must have" for the day-to-day operations of a corporation (Huang, Wang & Huang, 2018). The data moved from being recorded and organized manually on paper to being

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recorded electronically on computers. With the succession of digital developments and the start of the fourth industrial revolution, which is called digital transformation, the volume of data recorded in the systems has increased, resulting from the digital transformation techniques represented in systems and mobile devices, Physical Cyber Systems (CPS), Cloud Computing, Augmented and Virtual Reality, Artificial Intelligence (AI), Simulation, Internet of Things (IoT), Industrial Internet, Autonomous and Collaborative Robots, Smart Sensors, and many other technologies(Nara, da Costa, Baierle, Schaefer, Benitez, do Santos & Benitez, 2021)

Organizations work in a turbulent, rapidly changing environment, which forces them to try to ensure the quality of their decision-making processes, as they have become an essential component of management (Al-Hawary & Al-Rasheedy, 2021; Al-Hawary & Al-Namlan, 2018). Information support and the way it is organized have gained increasing importance in decision-making processes at all levels of the enterprise. Big data is not only about data collection; it is about data processing and visualization, and most importantly, it is also necessary to gain business advantages (Kocielniak & Puto, 2015). It can be argued that the explosion of knowledge that has accompanied increased access to big data has had a significant impact on both how and what information senior managers use to inform their decision-making (Merendino, Dibb, Meadows, Quinn, Wilson, Simkin & Canhoto, 2018), as well as (Wieder & Ossimitz, 2015) emphasized the overall relationship (total effect) of the direct and indirect effects of the quality of business intelligence management on the quality of administrative decision-making. While business intelligence management does not translate directly into making better management decisions, it does so through a group process. From indirect effects, notably the two-way mediator path across data quality and information quality, the mediating effects of business intelligence solution scope are also revealed.

Big Data Analytics (BDA) capability (in terms of data sources, access, integration, delivery, analytics capabilities, and people experience) along with organizational readiness and design factors (such as BDA strategy, senior management support, financial resources, and employee engagement) facilitated better use of BDA in making manufacturing decisions. Popovi, Hackney, Tassabehji, and Castelli (2018) found that high-value business performance was improved as a result.

2. Theoretical framework and hypotheses development

2.1 Big data

With the increase in digital developments, the amount of data recorded in the systems doubled, which led to the emergence of the term "big data." The amounts of data resulting from search queries, interactions on social networks, sensors, mobile phones, their applications, and others are not insignificant. This data varies between written data such as texts (online transactions, emails, records, publications, etc.), audio such as audio recordings, and visual data such as videos and images. They are stored in massive databases that are becoming increasingly difficult to capture, form, store, manage, share, analyze, and visualize using standard database software tools (Sagiroglu & Sinanc, 2013).

Although big data is a common buzzword in both academia and industry, its meaning remains shrouded in conceptual ambiguity. De Mauro, Greco, and Grimaldi (2015) describe big data as "representing information assets of this magnitude." The large, velocity, and diversity require specific technology and analytical methods to turn them into value. According to Ward and Barker (2013), "big data" is "a term characterized by the storage and processing of huge or complicated data collections utilizing a variety of approaches, including but not limited to: Machine Learning, NoSQL, and Map Reduce," and "big data" is defined as "a term referring to large data sets with a large, diverse, and complex structure with difficulties in storing, analyzing, and visualizing for further operations or outcomes" (Sagiroglu & Sinanc, 2013).

The use of big data may allow companies to demonstrate the efficiency and effectiveness of corporate innovation. Specifically, big data can help companies collect and process market information to better understand consumer preferences, which can play an important role in innovation performance (Ghasemaghaei & Calic, 2020). Big data is measured using a 3V model (Volume, Variety, and Velocity) (Ghasemaghaei & Calic, 2020; Sagiroglu & Sinanc, 2013; Ghasemaghaei, 2021), and the properties of big data have been expanded to 7 Vs (Volume, Variety, Velocity, Value, Variability, Variability, Visualization), and they mean the following (El Alaoui, Gahi & Messoussi, 2019):

Dimension	Definition
Volume	The amount of data increases significantly
Variety	The fact that all data formats are taken into account, the power of big data stems from the ability to process and extract insights from all types of records
Velocity	The speed at which data is generated, stored, and processed.
Value	It relates to the information and ideas that data provides
Variability	Data that is usually of ever-changing meaning (as distinct from diversity).
Veracity	The process of eliminating corrupted records before they can be processed, and consists of understanding big data and producing an accurate data set.
Visualization	The process of displaying and visualizing large amounts of complex data in a readable manner.

We suffice with the 3V model (Volume, Variety, and Velocity) to measure big data.

2.2 Decision quality

Organizations seek to maintain their position and continue their progress in various fields that concern them, and to achieve success at all levels. Its success depends primarily on the decisions taken within it, including administrative decisions that depend on a variety of skills, and one of the most important of these skills is the decision-making process, because of its role in the success of the administrative process. Administrative decisions constitute the main artery between the organizational structure and its various branches for any organization, and without them, small and large institutions are unable to achieve their smallest goals. Companies can compete and succeed if they always make good decisions, or at least better decisions than competitors. Ghasemaghaei (2018) shows the unique importance of the level of development of employee analytical tools and skills in improving company performance through the use of big data.

According to Dooley and Fryxell (1999), the attributes of loyalty and competence do have an impact on how team members process and understand conflicting opinions. Also, that the task of strategic decision-making generates a network of transactions that must be considered throughout the decision-making process and implemented subsequently, to some extent as anticipated. Wieder & Ossimitz (2015) has contributed to both academia and industry by providing evidence for the first time on the direct and indirect determinants of managerial decision support improvements related to the scope of business intelligence solutions and effective management of business intelligence. (Leidner & Elam, 1993) examined the impact of the use of business intelligence systems on executive information systems (EIS) on helping to make executive decisions at the individual level of analysis and determined that the greater the frequency of use and the duration of use of executive information systems (EIS), the faster the problem is identified, the speed of decision-making, and the greater the extent of analysis in decision-making, that is, it is linked to the chief executive officer's decision-making process.

Harri, Maples, Riley & Tack (2020) introduced a new theoretical decision model in the presence of both input and output price uncertainty and used US beef sector data to test theoretical propositions regarding firm behaviour. His findings in two-stage production confirm that the introduction of uncertainty in the price of inputs leads to an increase in the use of inputs and an increase in the level of production in the first stage and a decrease in the level of production in the second stage, and that the increase in price uncertainty since the middle of the first decade of the twenty-first century has become an important factor that experts take into account when making decisions on purchase and production. (Ruschel, Santos & Loures (2017) proposed a framework based on information from the literature, which summarizes the origin and flow of information used in developing models and shows the relationship between application areas for decision-making.

2.3 Big data and decision quality

The success of organizations is affected by the efficiency of their management in making successful decisions. Data is the cornerstone on which decisions are based. The importance of big data in decision-making processes and the essence of integrated data management in organizations has been noted. They are appropriately arranged and can be implemented in institutions (Kocielniak & Puto, 2015). Although the effect of information burden on decision quality is important, experimental outcomes have been mixed. This meta-analysis provided clear evidence of the negative influence of information load on decision quality by combining findings from 31 bankruptcy-predicting trials. The findings revealed that as the diversity or frequency of the set of information signals grows, so does the quality of the decisions (Hwang & Lin, 1999).

Raghunathan (1999) illustrates that the quality of the decision might improve or deteriorate depending on the quality of the decision maker. For the decision maker who understands the links between the problem variables, higher information quality enhances decision quality. However, when the quality of the information improves, the decision quality of a decision maker who is unaware of these links may suffer. Higher decision quality results from simultaneous improvements in information quality and decision-maker quality. Ghasemaghaei et al. (2018) illustrate the unique importance of all five data analysis competence indices (i.e., data quality, data largeness, skills analytical, domain knowledge, and advanced tools), which make a distinctive and important contribution to the efficiency of data analysis. In addition, all of the above five dimensions have a significant effect on both decision quality and decision efficiency (except for the effect of data bulk on decision efficiency). These significant effects, along with the observed strong positive relationship between data analytics efficiency and decision-making performance, indicate that improvement in data analytics efficiency indicators will improve the company's decision-making performance.

(Jeble et al., 2018) showed that big data helps companies gain a competitive advantage by using various analysis techniques, and these techniques help in obtaining insights, patterns, and correlations that cannot be understood through traditional small data. supporting business executives' decision-making with the help of social media data, competitive intelligence, cost and time reduction strategies, supply chain analytics, web analytics, etc. Companies who understand the importance of big data and product development around it have earned huge profits in recent years. Many companies use analytics in almost all aspects of running their business to reap the benefits of analytics-based decision making. Based on the above, we can build the research hypothesis that:

H_1: *There is an effect of big data on decision quality.*

3. Study model

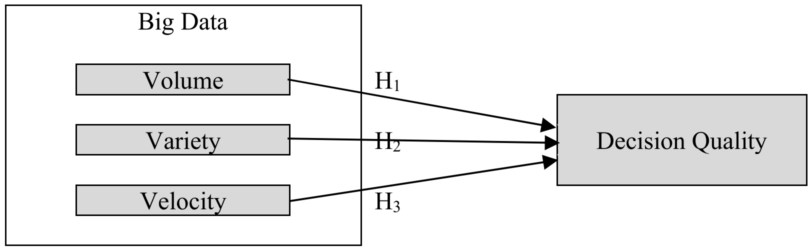

Fig. 1. Research Model

4. Methodology

4.1 Population and Sample

To test the impact of big data on the decision quality, the necessary data was collected from telecommunication companies operating in Jordan. Three companies provide telecommunications services in Jordan that are Zain, Umniah, and Orange. These companies employ approximately 4300 employees in their centres and branches throughout the Kingdom (TRC, 2020). Non-probability purposive sampling was used in the unlimited population according to Sekaran and Bougie (2016). Hence, the study instrument was distributed to 840 managers at the senior and middle levels at these companies. The total responses were 536, as it was found after examination that they had contained 75 responses that did not fit with the statistical analysis procedures. Accordingly, the responses used in this research were 461, where it constituted a response rate 54.88% of the total distribution.

The demographic results of the study sample indicated that the proportion of males was 57.48% compared to 42.52 females. The majority of the sample 71.58% had a bachelor's degree, followed by 21.69% who had a master's degree, then 6.73% had a doctoral degree. Regarding age group, the results showed that 37.96% of the respondents within the category "from 30 to less than 40", followed by 30.37% within the category "less than 30", then 22.99% belonged to the category "from 40 to less than 50", and finally 8.68% belonged to the category "50 and more". Moreover, most of the respondents 41.21% had experience within the category "from 5 to less than 10", while the category "15 and more" ranked last with a percentage of 11.93% of total respondents.

4.2 Measures

An electronic survey was used to collect the primary data for the research, which was designed through Google Forms and distributed via email. This survey included two main sections and an introduction to explain the research purpose and ensure the confidentiality of the provided data. The first section was dedicated to demographic data, which was gender, qualification, experience, and age group. The second section includes items for the main research variables. Items in this section were measured using a five-point Likert scale and they were distributed as follows:

Big data: it was the independent external variable in the research. This variable had 12 items developed according to Ghasemaghaei and Calic (2020). Big data is a second-order construct that subdivides into three first-order constructs. The volume included four items "e.g., the company used large amounts of data in the analysis process". The variety consisted of four items "the company examined data acquired from several sources". The velocity included four items: "e.g., the company used rapid techniques in analysing the explored data".

Decision quality: it was the dependent internal variable in the research. This variable had seven items developed based on Shamim et al. (2019). decision quality is a first-order construct that includes items "e.g., the company achieved the desired results by making sound decisions".

5. Results

5.1 Measurement Model Assessment

The measurement model for the impact of big data on decision quality was tested using the confirmatory factor analysis (CFA) technique. CFA enables the determination of validity and reliability of the instrument used in the research (Brown, 2015). The convergent validity was confirmed by the values of the loadings and the average variance extracted (AVE). Moreover, the discriminant validity was tested by comparing the value of AVE with the maximum shared variance (MSV) of each construct, as well as comparing the square root of AVE (√AVE) with the correlation coefficients. Regarding reliability, the composite reliability (CR) was calculated based on the values of McDonald's Omega coefficients. Table.1 shows the results of the evaluation of the measurement model.

Table 1
Research constructs evaluation

Constructs	Items	Loadings	AVE	MSV	√AVE	CR
Volume	VO1	0.715	0.553	0.418	0.744	0.831
	VO2	0.652				
	VO3	0.773				
	VO3	0.824				
Variety	VA1	0.753	0.562	0.397	0.750	0.836
	VA2	0.846				
	VA3	0.702				
	VA4	0.687				
Velocity	VE1	0.740	0.581	0.422	0.762	0.847
	VE2	0.761				
	VE3	0.811				
	VE4	0.735				
Decision Quality	DQ1	0.716	0.567	0.512	0.753	0.901
	DQ2	0.703				
	DQ3	0.775				
	DQ4	0.806				
	DQ5	0.829				
	DQ6	0.742				
	DQ7	0.691				

The results in Table 1 demonstrated that the loading values were within (0.652-0.846), thus it was greater than 0.50 the minimum value to keep the items (Kephart et al., 2019). The AVE value for each construct exceeded the minimum threshold of 0.50 (Cheah et al., 2018). Hence, the study instrument was characterized by convergent validity. The AVE value was higher than the MSV value for each construct, and √AVE values exceeded the correlation coefficients for the rest of the constructs. Accordingly, it has been verified that the study instrument has an appropriate discriminant validity (Franke & Sarstedt, 2019). Furthermore, McDonald's omega coefficients were within the range (0.831-0.901), therefore exceeding 0.70 the minimum acceptable limit for composite reliability. Subsequently, the study instrument had a good level of reliability (Watkins, 2017).

5.2 Descriptive Statistics Analysis

The respondent's attitudes towards the study variables were determined by extracting the means and standard deviations for each dimension. Besides, the data were tested for confirming that it was free of multicollinearity using correlation coefficients. Table 2 presents the results of the descriptive tests used for these purposes.

Table 2
Results of descriptive statistics and correlations

Constructs	M	SD	1	2	3	4
1. Volume	3.41	0.735	1			
2. Variety	3.58	0.921	0.415**	1		
3. Velocity	3.70	0.890	0.503*	0.482*	1	
4. Decision Quality	3.66	0.847	0.637**	0.603**	0.655**	1

Note: * $P < 0.05$, ** $P \leq 0.01$, *** $P \leq 0.001$.

The results indicated that the levels of big data dimensions were ranged between the high and moderate, where velocity (M= 3.70, SD= 0.890) ranked first at a high level, followed by variety (M= 3.58, SD= 0.921) at the second rank with a moderate level, then volume (M= 3.41, SD= 0.735) at the last rank with a moderate level. The level of decision quality (M= 3.66, SD= 0.847) according to the respondents' opinions in the telecommunications companies operating in Jordan was moderate. Moreover, the results in Table.2 reported that the correlation coefficients between the dimensions of the research variables were within the range (0.415-0.655) which is less than 0.80 the upper limit of the permissible correlation between the variables (Senaviratna & Cooray, 2019). Therefore, the study data did not suffer from the multicollinearity problem.

5.3 Structural Model Assessment

The structured equation modeling (SEM) technique was employed to test the impact of big data on decision quality at telecommunication companies operating in Jordan. Fig. 2 illiterates the structural model for testing the research hypotheses.

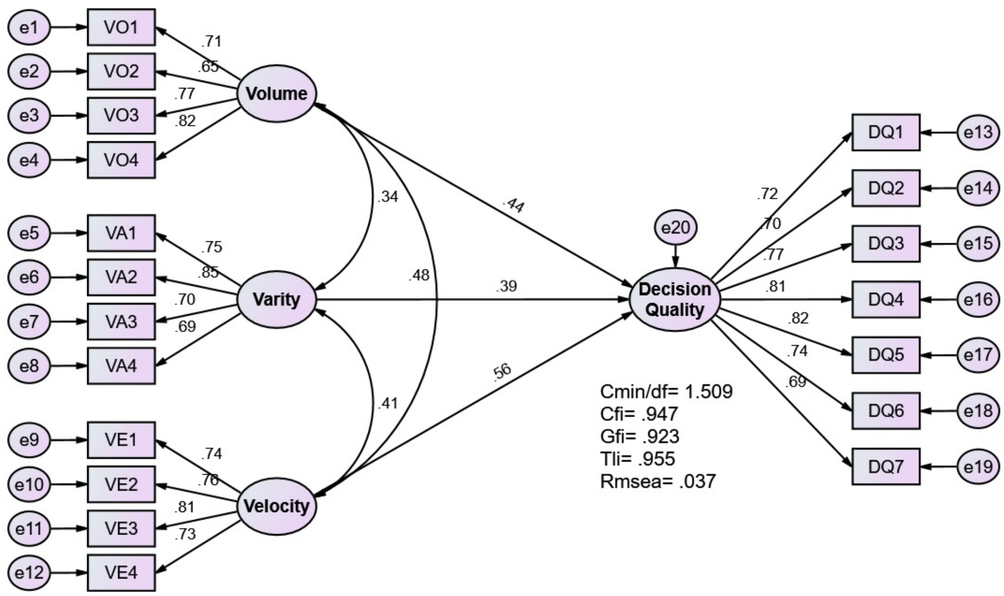

Fig. 2. SEM for testing the impact of big data on decision quality

Fig. 2 demonstrates that the chi-squared ratio was 1.509 which is less than the upper limit of 3 (Shi et al., 2019). The values of the goodness of fit index (GFI), the comparative fit index (CFI), and the Tucker-Lewis index (TLI) exceed the minimum threshold recommended by Niemandand Mai (2018) with a value of 0.90. The root mean square error of approximation (RMSEA) was ()0.037 which is less than 0.08 the highest threshold for this indicator (Xia &Yang, 2019). Hence, the research model used to test hypotheses had constructed validity.

Moreover, Table.3 reports the standardized and unstandardized coefficients calculated for the impact of big data on decision quality at telecommunication companies operating in Jordan.

Table 3
Result of testing hypotheses

Path			**B**	**SE**	**β**	**C.R**	**P**
Volume	→	Decision Quality	0.552	0.038	0.437	14.526***	0.000
Variety	→	Decision Quality	0.517	0.040	0.393	12.925**	0.002
Velocity	→	Decision Quality	0.684	0.035	0.561	19.543***	0.000

Note: * $P < 0.05$, ** $P \leq 0.01$, *** $P \leq 0.001$.

The results presented in Table.3 confirmed that big data impacts decision quality. Besides, it determined that the highest impact was for velocity (β= 0.561, C.R= 19.543, P= 0.000), then volume (β= 0.437, C.R= 14.526, P= 0.000), and the least impact was for variety (β= 0.393, C.R= 12.925, P= 0.002).

6. Conclusion

Based on the results of the study, it was found that there is an adoption of big data in the Jordanian telecom companies, and this is due to the fact that the Jordanian telecom companies own a large volume of data that varies between written, audio, and visual data. It also employs experts and specialists to deal with the large flow of data from data capture, storage, and arrangement appropriately, management, analysis, and other procedures using a series of techniques. The management of Jordanian telecom companies is developing their strategies based on the analysis of data and variables in the business environment, and it was found that they have speed in dealings, which gives an indication of the telecom companies' high investment in technology to support their ability to deal with customers efficiently. It was also found that Jordanian telecommunications companies make decisions that have an impact on the company's performance by making good decisions, and it turns out that wise decisions contribute to risk management and support the decisions they take at various levels of the company, and the company works to enhance its ability to respond to changes through rapid taking Decision-wise, databases are used to support business decisions and promote high-value business performance through quality decisions.

7. Discussion

The study found that big data, with its characteristics of volume, velocity, and variety, has an impact on decision quality. This is because information and communication technology has enabled global logistics and communications services to operate with massive amounts of data moving at faster speeds, allowing for faster decision-making. Companies can also benefit from big data by employing various analysis tools to gain a competitive advantage.

The techniques analyze the data to find patterns and trends and convert them into actionable information, allowing policy-makers to make informed decisions and track improvement and development. And the use of accurate and reliable data in decision-making, which opens up new avenues for making good decisions, as well as improvements in the efficiency indicators of analyzing large amounts of data, leads to access to high-quality data, which helps the company improve its decision-making performance. Employees can swiftly access information thanks to big data technologies that quickly create, store, and process data. It can assist in the collection of market data via social media data, mobile and app data, search queries, web analytics, supply chain analytics, competitive intelligence, and other methods. Furthermore, and processing it to better understand consumer preferences, which helps them make faster decisions. The diversity of big data records available to executives, such as written texts, audio recordings, photographs, visual movies, and so on, aids their decision-making process and contributes to the quality of the decisions made. This study supports the findings of a previous study (Kocielniak & Puto, 2015), which highlighted the importance of big data in decision-making and the importance of integrated data management in businesses. Furthermore, a study (Popovi, Hackney, Tassabehji, & Castelelli, 2018) discovered that organizational readiness and design factors (such as BDA strategy, top management support, financial resources, and employee participation) combined with BDA analysis capacity (in terms of data sources, access, integration, delivery, analytics capabilities, and people experiences) facilitated better use of BDA in making manufacturing decisions, and thus improved high-value business per capita.
The study (Huang, Wang, & Huang, 2018) found that big data adoption is positively associated with improved financial performance and market value, while the study (Ghasemaghaei, 2018) found that when firms process big data, organizational performance is at its peak when companies employ tools. According to the study (Ghasemaghaei, Ebrahimi, & Hassanein, 2018), there is a positive and significant relationship between the efficiency of data analytics and the company's decision-making performance, which contradicts the study (Hwang & Lin, 1999), which found that both dimensions of information (diversity of information and frequency of information) have a negative impact on decision quality. Providing too much different or repetitive information can jeopardize the forecast's accuracy.

8. Recommendations, limitations, and directions for future research

The study found that big data, with its dimensions of volume, velocity, and variety, has an impact on the quality of decisions, and based on this finding, the researcher suggests that Jordanian telecom companies invest in information technology that allows them to provide data with accuracy, reliability, and high quality, as well as improve the qualifications of their employees. It also suggests developing detailed analytical programs that are appropriate for the company's work and provide high-value information, as well as hiring experts and specialists to deal with the information generated by the analysis programs in an optimal manner and present their recommendations to the company's decision-makers. The research looked at the impact of big data on decision quality in terms of volume, velocity, and variety. Another study could look into the impact of big data on organizational performance or customer service, and a third study could look into an intermediate variable like information technology investment or decision maker quality.

Another study can deal with the same title with other measures of big data represented by value, variability, reliability, visualization, and other measures, or data analysis techniques. Because the study focused on telecommunications businesses as a society, another study may focus on the banking sector, the health sector, the service sector, the industrial sector, or other Jordanian governmental sectors. The study focused on Jordanian telecommunications firms, but a comparison analysis with a second country or a comparative study within the same country between two sectors, such as the industrial and service sectors, might be conducted in the future.

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