Department of IMPRESA E MANAGEMENT

Master in MANAGEMENT

Chair of MANAGERIAL DECISION MAKING

The Effect of Implementing Business Intelligence on the Quality of Decision Making In the Telecommunication Sector in Jordan

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ACCADEMIC YEAR 2021/2022

ABSTRACT

Purpose: The purpose of this study is to investigate the impact of business intelligence (BI) on the quality of decision-making in the telecommunications sector in Jordan. Because BI is used in many areas, and decision-making is one of the most important administrative functions.

Methodology: To conduct this study, data was gathered from 324 managers, supervisors and employees who work for the Jordan's telecommunications sector (Zain, Orange, and Umniah) were surveyed. After establishing the tool's normality, validity, and reliability, descriptive analysis was performed, and the relationship between variables was examined. Finally, multiple regressions were used to test the impact using SPSS.

Findings: The result shows that Jordanian telecommunication sector (Zain, Orange and Umniah) implement BI its dimensions. It also shows that there is a correlation between BI dimensions and the quality of decision- making dimensions. Finally, results indicate that there is a significant impact of the total BI on the quality of decision-making in the Jordanian telecommunication sector (Zain, Orange and Umniah). Data analysis has rated the highest impact on the quality of decision-making, followed by data warehouse, predictive analysis and data exploration.

Limitations/Recommendations: The current study was conducted in the Jordanian telecommunication sector (Zain, Orange and Umniah). As a result, it recommends future researches to explore more data over a longer period of time to ensure the current model validity and the measuring instrument. It also recommends carrying out similar studies on other sectors in Jordan and the same sector outside Jordan to ensure that the findings are generalizable.

Key Word: Business intelligence, data exploration, data warehouse, data analysis, predictive analysis, Quality of decision-making, Telecommunication sector, Jordan

ACKNOWLEDGMENT

This thesis is the result of a learning experience at the University of Luiss, and many people have participated in its completion at various times, either directly or indirectly, and any effort to thank them all would be inadequate.

To begin, I'd want to offer my heartfelt thanks to Prof. Luigi Marengo and Prof.Valentina Meliciani for their advice, effort, and patience, as well as for their unwavering support for me and this thesis throughout its development.

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AUTHORIZATION FORM

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Rami Samer Al-Nimer

Date: June/2022

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Abbreviations	Meaning
BI	Business Intelligence
DSS	Decision Support Systems
OLAP	Online Analytical Processing
BI&A	Business Intelligence and Analytics
KMO	Kaiser-Meyer-Olkin

CHAPTER 1: Introduction, Scope, and Objectives

1.1. Background:

Due to the increased accessibility of information through electronic methods, Business Intelligence (BI) has gotten a lot of attention. Information is collected, processed, and presented in a relevant manner throughout this process, which also serves as the foundation for a company's intelligence activities. Furthermore, information consumption must be enhanced, particularly in light of global social and political changes, rapid change in technology, and increased competitiveness. The heightened uncertainty among companies, on the other hand, has given rise to information processing operations, which could otherwise threaten the companies' market viability.

The significance of BI is obvious in the use of advanced technologies to gather information to enhance commercial efficiency and improve staff members to acquire the starting point of information they require to do their jobs effectively, and also the skill to analyze and effortlessly communicate this information with others. The BI software, it is used to aid in the analysis of data. Data warehouse software, digital dashboard software, and data mining software are just a few examples. (Rahahleh, & Omoush, 2020). Because companies in the telecommunications and technology sector are revealed to more data, perhaps more than others, decisions must be straightforward, perfectly reasonable, accurate, and prepared to be displayed in a manner that contributes value to decision-makers. This necessitates the use of BI and its implementation to improve the quality of decision-making by attempting to make effective and efficient decisions based on an ongoing flow of quality information (Zraqat, 2020).

It has become more difficult for process management systems to sustain their efficiency as data amount and complexity have increased (Shaheen, et al. 2020). Therefore, BI provides a variety of characteristics that enable them to combine, link, organize, and analyze data from various sources, including consumers', distribution networks', and rivals' behaviors, and to present that information as knowledge for managerial decisions. (Yiu, Yeung, & Cheng, 2021).

As the BI definition indicates, data is one of the most essential elements; it's regarded as the backbone of BI, and the current trend is to utilize data warehouse as a database management approach in BI environments (Mousa, Mohammed, & Raheem, 2018). Moreover, companies rely on good decision-making to accomplish business strategies such as development and profitability for the company and its shareholders, as well as to address challenges (Alkatheeri, et al 2020). Never the less, data exploration and data analysis are two BI techniques that aim to make data observation and processing, as well as information retrieval and assumption, easier for decision-makers (Bikakis, et al.2019). Therefore, the relationship between BI and decision-making quality is strongly linked. As a result, BI has shown to be a valuable addition to the quality of company decision-making (Ilmudeen, 2022).

1.2. Problem Statement:

The problem of the study arises when the Covid-19 pandemic occurred in Jordan, all sectors were negatively affected, including the telecommunications sector. Some employees worked online and some employees did not work because they got infected. Moreover, during that period the use of telecommunications services was intense because people started to work online, teaching online, taking classes online and running businesses online. Resulting in intensive data reception, which caused pressure on the telecommunication sector and led to the lack of efficient and effective decisions at that time (Al-Dmour, AlShaar, Al-Dmour, et al 2021).

Information and communications technology industry is one of the most important industries in Jordan, it accounts for about 12% of gross domestic product, has grown into one of the region's most significant, with over 600 active companies employing about 16,000 people directly and contributing to an overall economy of about 84,000 workers. Moreover, The ICT industry is divided into sub-sectors, each with valuable investment options. For instance, IT software, Telecom, IT infrastructure, and Gaming (Jordan's Investment Commission, 2018).

Therefore, this study investigated the impact of implementing BI on the quality of decision-making in the telecommunication sector (Zain,Orange and Umniah) in Jordan. Which is one of Jordan's most valuable industries.

1.3. Study's Questions:

Based on the arguments above, this study aims to answer the following research question:

Do BI dimensions (data exploration, data warehouse, data analysis, and predictive analysis) have an impact on the quality of decision-making in telecommunication sector (Zain, Orange and Umniah) in Jordan?

Based on BI dimensions above, we divided the main question into the following sub-questions:

1.3.1 Sub Questions:

1- What is the effect of data exploration on the quality of decision-making in the telecommunication sector (Zain, Orange and Umniah) in Jordan?

2- What is the effect of data warehouse on the quality of decision-making in the telecommunication sector (Zain, Orange and Umniah) in Jordan?

3- What is the effect of a data analysis on the quality of decision-making in the telecommunication sector (Zain, Orange and Umniah) in Jordan?

4- What is the effect of predictive Analysis on the quality of decision-making in the telecommunication sector (Zain, Orange and Umniah) in Jordan?

1.4. Study's Purpose and Objectives:

The purpose of this study is to investigate the impact of BI on the quality of decision-making in the telecommunication sector (Zain, Orange and Umniah) in Jordan.

1.4.1 Main Objective:

To identify the effect of implementing BI (data exploration, data warehouse, data analysis, and predictive analysis) on the quality of decision-making in the telecommunication sector (Zain, Orange and Umniah) in Jordan.

1.4.2 Sub Objectives:

1- To identify the effect of data exploration on the quality of decision-making in the telecommunication sector (Zain, Orange and Umniah) in Jordan.

2- To identify the effect of data warehouse on the quality of decision-making in the telecommunication sector (Zain, Orange and Umniah) in Jordan.

3- To identify the effect of the data analysis on the quality of decision-making in the telecommunication sector (Zain, Orange and Umniah) in Jordan.

4- To identify the effect of predictive Analysis on the quality of decision-making in the telecommunication sector (Zain, Orange and Umniah) in Jordan.

1.5. Significance of the Study:

1.5.1 Theoretical Significance of the Study:

The study is contributing positively towards a growing body of literature about the effects of implementing BI on the quality of decision-making by highlighting the key factors of BI that contribute positively or negatively to the quality of decision making: the case of telecommunication sector in Jordan.

1.5.2 Practical Significance of the study:

This study can be used to give a recent recommendation for the telecommunication sector on the importance of BI in quality decision-making. Especially, in terms of exploring, storing, and analyzing the data for a better decision-making quality. Therefore, this study can assist the telecommunication sector to be more aware and understand BI.

1.6. Study's Hypotheses:

According to the study's questions, the following hypotheses are formulated as follows:

1.6.1. Main Hypothesis

H0: There is no significant effect of implementing BI (data exploration, data warehouse, data analysis, and predictive analysis) on the quality of decision-making in the telecommunication sector (Zain, Orange and Umniah) in Jordan at a level ($\alpha \leq 0.05$)

1.6.2. Sub hypotheses:

H0.1: There is no significant effect of data exploration on the quality of decision-making in the telecommunication sector (Zain, Orange and Umniah) in Jordan at a level ($\alpha \leq 0.05$)

H0.2: There is no significant effect of data analysis on the quality of decision-making in the telecommunication sector (Zain, Orange and Umniah) in Jordan at a level ($\alpha \leq 0.05$)

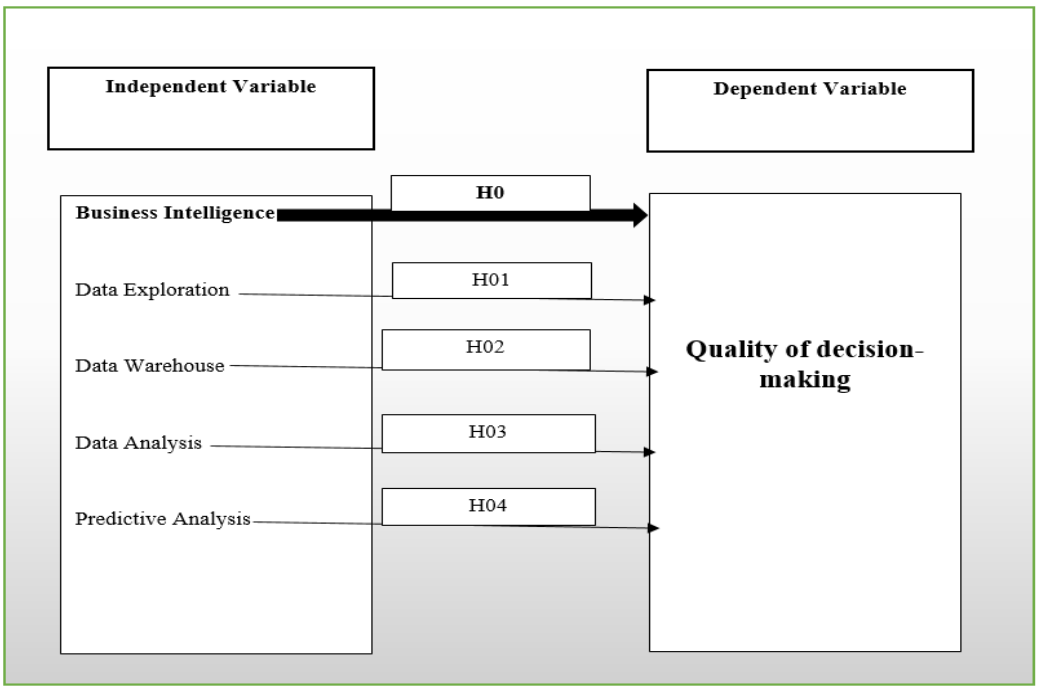
H0.3: There is no significant effect of data warehouse on the quality of decision-making in the telecommunication sector (Zain, Orange and Umniah) in Jordan at a level ($\alpha \leq 0.05$)

H0.4: There is no significant effect of predictive analysis on the quality of decision-making in the telecommunication sector (Zain, Orange and Umniah) in Jordan at a level ($\alpha \leq 0.05$)

1.7. Conceptual Framework:

This framework demonstrates the independent variable BI and its dimensions (data exploration, data warehouse, data analysis, and predictive analysis) impact on the dependent variable (the quality of decision-making).

Figure 1: The study model



The study model as shown in Figure 1 was developed based on the following studies:

<u>Independent Variable:</u>

1- [Hassan, S., Dhali, M., Zaman, F., & Tanveer, M. (2021).] "Data Warehouse, Predictive analysis"

2- [Yang, N. (2021).] "Business intelligence and data analysis"

3- [Vaish, M. P., Shrivastava, S., & Sen, S. (2020)] “Business intelligence and Data Warehouse”

4- [Kumar, M., Shenbagaraman, V. M., Shaw, R. N., & Ghosh, A. (2021).] “Predictive analysis”

5- [Van Capelleveen, G., van Wieren, et al (2021).] “Data exploration”

Dependent Variable:

1- [Vaish, M. P., Shrivastava, S., & Sen, S. (2020)] “Business intelligence, Data Warehouse effect on decision-making”

2- [Negash, S., & Gray, P. (2008).] “Business intelligence, data exploration impact on decision-making”

1.8. Procedural Definitions of Terms:

1.8.1. BI: is the infrastructure that discovers, collects, stores and analyzes the data to enhance the decision-making process.

1.8.2. Data Exploration: is discovering and collecting the needed data.

1.8.3. Data Warehouse: is where the current and historical data is stored in order to be analyzed to make decisions.

1.8.4. Data Analysis: is turning the raw data to information by clearing, filtering and modeling the data to make decisions.

1.8.5. Predictive Analysis: is the ability for forecast based on the analyzed data in order to reduce the uncertainty and discover what might occur later on in the firm.

1.8.6. Quality of Decision-Making: it confirms of both effectiveness and efficiency of the decision. Effectiveness is reaching the wanted results and efficiency is reaching the wanted results with a least cost possible.

1.9. Study Limitations:

- *Human Limitation:* This study was carried out in the telecommunication sector. The study's sample size was regarded to be a large sample size; therefore, the study sample was (Zain, Orange, and Umniah)
- *Place Limitation: The study was carried out in Jordan.*
- *Time Limitation: The study was implemented in 2021 and 2022.*

1.10. Study Delimitation:

The study contains several Delimitations which includes the following:

- *Human Delimitations:* The scope of this study was carried out on all employees at Jordanian telecommunication sector (Zain, Orange, and Umniah)
- *Place Delimitations*: This study was carried on the Jordanian telecommunication companies (Zain, Orange and Umniah).
- *Time Delimitations*: The time is limited to the academic year of 2021-2022.
- *Scientific Delimitations*: This study was determined the impact of BI on the quality of decision-making and adapt the prior's studies recommendations.

CHAPTER 2: Literature Review and Previous Studies

2.1. Introduction:

Because of the enhanced access to information through technological methods, BI has attracted a lot of attention. Information is collected, analyzed, and displayed in a usable fashion throughout this process, which also serves as the foundation for intelligence practices within businesses (Nuseir, Aljumah, & Alshurideh, 2021). Business decisions at various levels necessitate the analysis of various types of data. The use of appropriate techniques will aid in making good business decisions in this regard. The goal of a BI system is to effectively assist such decisions (Borissova, Cvetkova, et al 2020). This section goes through BI and its dimensions. In addition, this section includes a summary of previous studies on BI.

2.2. BI:

BI is defined as a phrase that includes the applications, infrastructure, tools, and best practices that enable access to and analysis of data in order to improve and optimize decisions and performance (Hamad, Al-Aamr, et al. 2021).

In today's fast-paced technological environment, the BI industry is gaining traction by empowering industries to meet client demands (Nithya, & Kiruthika, 2021). "What happened in the past" and "how it occurred leading up to the present moment" assessments are part of BI. Although large trends and patterns can be recognized, their motive cannot be determined, and no forecasts can be made. Furthermore, BI determines the cause of what occurred (the why) and uses this information to make short- and long-term business predictions (Muntean, Dănăiaţă, et al. 2021). Therefore, BI makes use of data to generate information that may be used to trigger knowledge, which then thrives as explicit knowledge (Jayakrishnan, Mohamad, & Yusof. 2022).

In modern industry, BI applications are widely used or in the process of being used to facilitate practices such as management decisions, data analysis, and market success assessment. Many companies are now spending trillions of US dollars to incorporate BI programs to complete the challenge (Cheng, Zhong & Cao 2020). Moreover, over the last thirty years, BI processes research has evolved tremendously, resulting in a fractured state that draws on a diversified range of studies with vastly disparate contributions (Talaoui & Kohtamäki, 2020).

BI provides the data and tools needed for statistical and trend analysis, as well as assessing the present state of the company using key performance indicators in order to establish a plan of action. As a result, companies are increasingly turning to BI to boost their performance (Duarte, Guimarães, & Santos, M 2022).

Integrating BI into daily processes and therefore cultivating a company's culture among personnel may greatly improve a company's operational skills, resulting in difficult-to-copy competitiveness. Moreover, the practical usage of a BI tool may provide an organization with immediate and comprehensive market and organizational data, resulting in distinctive time-constrained, route competitive advantages (Yiu, Yeung, & Cheng, 2021).

BI can be thought of as a decision-support system that encompasses the entire process of collecting large amounts of data, extracting usable information, and offering analytical capabilities. Other research has defined BI as an information system that helps people make better decisions. It consists of four basic steps: analysis, insight, action, and performance monitoring (Alnoukari 2022).

Companies utilizing BI systems are better at coordinating resources, which improves operational capabilities and results. Although BI software licenses are widely available, integrating BI systems into production and manufacturing operations has proven to be a significant barrier for companies. The operational use of BI, in particular, necessitates significant internal staff support. Furthermore, while BI tools are important for evaluating and integrating data, their true value comes from integrating them into daily operations (Yiu, Yeung, & Cheng, 2021).

Companies may get a competitive market advantage and long-term consistency by classifying great possibilities and adopting an effective plan (Zhang, Qi, & Meng. 2022). Companies are focusing on enhancement today, and enterprises are growing. One of the benefits of BI is the accessibility of large, accurate data (Zafary, 2020).

2.2.1. Data Exploration:

Ever since the invention of information systems and the documenting of their properties to provide the right information to the right individual at the appropriate Time and Location. It contributes to the development of a large database and the study of that database. The right information will be translated into knowledge, and this knowledge will assist the companies in thriving, rising, and capturing new markets, and they will be able to offer improved customer-oriented services, helping them to maintain their current customers. Almost every company today sees the importance of exploring data in terms of making decisions. Data Exploration not only aids in discovering data from many sources, but it also aids in the reduction of various costs, such as the cost of computing resources, as well as the reduction of time for decision-making and knowledge exploration to produce the best results and output (Gautam, Singh& Shaikh 2017). Data exploration aims to discover and collect data as quickly as possible (Maciejewski, & Lukasczyk. 2021).

Each group of data units with the same data structure is organized in a separate layer by the data exploration scheme and process. Furthermore, the data exploration device collects and tries to control data units from each framework as a whole (Maciejewski, & Lukasczyk. 2021).

To gain ideas from a dataset, the company should first create a selected and relevant data collection that can be readily plotted, examined, maintained, and understood. To begin, demonstrating evidence from a questionnaire showing a representative sample is the sole approach widely employed by data researchers to quickly acquire ideas from a dataset, contradicting conceptual and practical arguments from the experiential learning field that alternative sampling strategies have benefits. (Rojas, 2017).

Data exploration entails several steps, including data ingestion, visualization, statistical analysis, and narrative. Even though these activities are complimentary, researchers frequently carry them out with different tools. Furthermore, because they rely on human query definition, these technologies have huge learning curves (Hu, Orghian, & Hidalgo. 2018).

A long history of office and web programs aimed at making data exploration more available exists. Polaris was renamed Tableau, it enables people to establish visualizations by dragging and dropping data columns onto "shelves." Spotfire is a set of BI products (Qlik. 2017.).

Comparable drag-and-drop tools for creating dashboards with numerous visualization styles are available, among many others. Even though these technologies are extensively used, the majority are still associated with manual descriptions (Hu, Orghian, & Hidalgo. 2018).

One of the data exploration tools is Power Query, since 2013, it has been a free utility that may be used as an add-in in Microsoft Excel. Because of the high quality and wide variety of capabilities that PQ demonstrated immediately after its release, Microsoft has included it among the basic MS Excel features since 2016, and it may be turned on in the options. PQ also referred to as "Data Explorer" or "Get & Transform," was created by a specialized Microsoft team of developers. The goal of PQ is to be able to gather and examine data from many sources, as well as convert the data for possible evaluation. The most essential aspect of this system is that it can simply automate the entire data collecting and conversion process (Cempírek Václava, Fedorko Gabrielb, et al 2021).

2.2.2. Data Warehouse:

In the 1980s, data warehouse was introduced as a way of storing and arranging data in a unified and coordinated way, enabling users to do the scientific analysis and BI (Salinas, & Lemus. 2017).

Data warehouse is a suitable platforms for meeting the needs of various decision-makers (Ferreira, Almeida .and Monterio, 2017). It serves as a decision support tool, providing conclusions to the company's decision-maker(s) dependent on the examined data pattern. For any company, a data warehouse is established to enable decision-making activities through data aggregation, storage, and examination (Jayashree & Priya 2020).

A data warehouse is a set of technologies for converting vast volumes of data into usable information (Efendi & Krisanty.2020). Various, outlets such as everyday business processes and detectors from various Operating systems, produce a large amount of data regularly. They're mostly loaded into a data warehouse facility so that sophisticated research can be performed on them (Zhao, Li & Liu. 2020).

Decision-making is aided by a data warehouse. DSS stands for Decision Support Systems, as it is a computer-based framework that assists decision-makers with using datasets to solve issues, DSS functions integrate each person's abilities with the computer's ability to maximize the accuracy of the decision. To solve the problem, DSS needs data from a variety of places. Any issue must be resolved, and any chance and plan necessarily require the collection of data (Santoso. 2017). Therefore, data warehouse is a well-established organizational concept that is backed up by well-known techniques (Salinas, & Lemus. 2017).

Data warehouse is indeed one of the elements of a BI approach, it is a set of data that is a specific topic, interconnected, and time-variant (brum, et al 2019). Therefore, it is a respectful technique that has been proven at the company’s level in a variety of industrial environments and is heavily accepted in the academic community (salinas & lemus 2017).

The key model for flexibly and pleasant accessing the knowledge contained in a data warehouse is Online Analytical Processing (OLAP), OLAP has evolved into a suite of specialized visualization techniques for describing the collected data set, as well as an efficient navigation and interface scheme for defining, optimizing, and modifying the category of concern (Golfarelli & Rizzi, 2018).

2.2.3. Data Analysis:

The concept of data analysis is always changing, and there is no universally accepted definition. Data analysis for business is a broad term that covers a wide range of operations carried out by companies. It essentially defines how data processing is used to solve business problems. This entails gathering, formalizing, and analyzing data in order to recover business-oriented information for managerial decision-making (Gökalp et al., 2021). While the rapid evolution of data analysis has helped companies to achieve more success, the speed with which technology innovations occur has also contributed to an increase in company failure. According to a Credit Suisse analysis (2017), the speed and complexity of recent disruptions are unprecedented, since several business sectors are being touched by multiple disruptive forces at the same time.

Data analysis and BI in the context of company performance have recently gained significant attention in major information systems (IS) outlets, including calls for special issues, editorials, reviews, and academic notes. This is because companies see data as a strategic asset that can be handled and integrated by information technology (IT) to improve executive decision-making and data-driven processes. Because of its tremendous operational and strategic potential, data analysis is thought to be an enabler, as it increases company effectiveness. Data analysis has now become a crucial sector for businesses (Qaffas, Ilmudeen, Almazmomi, et al 2022).

Every company now relies heavily on data analysis, there are companies that specialize in analytics software and analyze data for their clients. Data can be found in a variety of formats, including text, audio, photos, and video. Never the less, data analysis is the discipline of transforming unorganized data into organized data, allowing analysts to spot patterns and generate conclusions based on data that is used for the organization's long-term sustainability, improvement, and growth (Bhat. 2020).

The compilation, storing, interpretation, and simulation of data is all part of the data analysis phase. Each phase, however, serves a different function. (Mahajan, & Gokhale 2017). It is the process of using data in connection with structured analysis (quantitative or artificial learning) to derive insights that aid in the creation of informed management actions, rather than predicting one probabilistic result with precision, it can help produce odds for a variety of results (Amarasinghe, et al. 2020).

Data analysis uncovers new relationships between data, reveal previously unseen patterns, and lead to the development of new information, that can then be used to enhance the company's efficiency, and increase profitability, it is also often used to gain valuable insights into vast and potentially dispersed datasets to improve firm decision-making. However, different firm resources can play critical roles in successfully using these tools. Therefore, not all firms investing in data analytics can enhance their decision-making (Ghasemaghaei, Hassanein, & Turel, 2017).

2.2.4. Predictive Analysis:

Predictive analysis is a decision-making technique that takes the uncertainty out of the system and utilizes analytical processes to identify the best answers. The predictive analysis gives insight into the likelihood of potential breakdowns and rejections, allowing for proactive measures to be taken before problems arise. Predictive analytics solutions may be used to anticipate a variety of behaviors and trends, sparing companies money and effort. R, scikit-learn, Konstanz Information Miner (KNIME), Orange, RapidMiner, Waikato Environment for Knowledge Analytic (WEKA), and other accessible predictive analysis technologies are publicly accessible to anyone (Virkar, & Shinde. 2020).

Predictive analysis has shifted the focus of decision-making, especially the company's strategic decisions, away from "gut instincts" and emotion toward fact- and scientific proof decision-making (Ignatius, Selvakumar, Spandana, & Govindarajan. 2022). Therefore, Predictive analysis tracking may assist with intellectually demanding decision-making activities and set the road for future developments (Jessica Keim-Malpass, Liza & Moorman. 2021). Never the less, Predictive analysis entails predicting predicted behavior and consequences using historical evidence (Shaheen, et al. 2020).

It enables early intervention if variations from the planned series of events are expected to happen, and it could affect strategic resource allocation decisions. As a result, mistakes and the resulting economic losses can be eliminated or minimized. Case administrators recognizing continuing compliance violations to reduce company threats or production managers for whom the future course of events is critical for resource budgeting are two possible target groups, The fundamental issue in all of these jobs is predicting what will happen next. Event logs are often used to retain data acquired during previous process executions, these logs are useful for training predictive models, with the underlying premise that previous occurrences are a good predictor of how a process will go in the future (Philipp, Jacob, Robert, & Beyerer. 2020).

Predictive analysis isn't a brand-new concept. The idea had been available for quite a while and had been widely adopted by major corporations functioning in a limited range of industries, including financial institutions and grocery stores. Nevertheless, owing to the phenomenon of big data, the advantages and promise of predictive analysis have only lately been recognized (Concepción Burgos, María, Campanario, et al. 2018).

Machine learning algorithms are used in predictive analysis (Ajmer Singh, Rajesh Bhatia, & Anita Singhrova. 2018). As a result, the two are connected. Predictive models could be built on a collection of data and then applied to fresh data or values, these effects might include market shifts or client behavior. It aids in the prediction of future events based on previous events. (Aggarwal, Bali, & Mittal. 2019).

Predictive analysis blends individual skills and experience with technologies such as computer training of trends in present and previous data and the use of algorithms not only to detect patterns and trends but also to model the potential probability of those patterns' outcomes (Ignatius, Selvakumar, Spandana, & Govindarajan. 2022). Business, information systems, and modeling are all brought together in predictive analysis (Kahlawi. 2022).

Predictive analysis is a collection of quantitative and analytical approaches for devising new tactics for predicting future outcomes. As a result, the predictive analysis gets critical when dealing with a large amount of extremely critical data. Upcoming probability and measurements are projected depending on the expected occurrences. There are two types of predictive models: 1-categorization models, which are used to predict which category an individual belongs to; and 2- regression models, which are used to forecast a number, the predictive models are made up of procedures that are used in data mining and statistical analysis to find movements and patterns in data (Aggarwal, Bali, & Mittal. 2019).

Predictive analysis is a type of advanced analytics that may forecast future occurrences and provide suggestions Decision trees, clustering, neural nets, market basket analysis, regression modeling, hypothesis testing, decision analytics, genetic algorithms, and text mining are all examples of predictive analysis that may be used to analyze data with numerous factors systematically (Poornima & Pushpalatha. 2018).

2.3. Quality of Decision-Making:

Planning, finding alternatives, evaluating alternatives in terms of the purpose wanted, and selecting options that will best achieve the goal are all part of the quality decision-making process. It is the process of choosing one course of action among two or more alternatives (Goetsch & Davis 2014). The quality of decision-making process is defined by Sousa et al. (2019) as the process of recognizing an issue, defining it, and selecting the best options to solve the problem and its outcomes.

In recent years, data quality and its application in efficient and effective decision-making has become a vital aspect in determining the long-term viability and success of modern companies. The quality and accuracy of data, information, and expertise are often essential in the decision-making process. Companies rely on good decision-making to achieve strategic objectives such as growth and profitability for the company and its shareholders, as well as to solve challenges (Alkatheeri, Ameen, Isaac, et al. 2020).

Decision-making frequently entails brainstorming ideas and presenting proposals and suggestions aimed at improving the company's operations and achieving its goals. Furthermore, identifying the relevant facts and expressing the merits and weaknesses of each idea or proposal aids in determining the best proposal and making adjustments until the best option is reached. As a result, the company is able to meet its objectives in the shortest amount of time while still operating at the highest degree of efficiency and effectiveness (Alkatheeri, Ameen, Isaac, et al 2020).

2.4. Relationship between BI and Quality of Decision-Making

BI applies to the technology, tools, and processes that are used to gather, integrate, analyze, and display business data. The fundamental goal of BI is to assist all employees to make better and faster decisions. Companies are being pushed to gather, interpret, and use their knowledge to help them make better decisions (Balachandran & Prasad. 2017). Never the less, businesses must take complexity and change in the environment into consideration. Therefore, businesses must be proactive and monitor the business environment for the process of decision-making (Vugec, et al .2020).

BI assists decision-makers in seeing ideas to enhance productivity or make faster and smarter decisions. Furthermore, it can help improve the efficacy of operational standards and their impact on supervision mechanisms, organizational decisions, budgeting, financial and administrative recordkeeping, and strategic decision-making in a dynamic organizational environment (Richards, Yeoh, Chong & Popoviˇc. 2017).

The most successful task of BI systems is enabling access to data, analyzing massive amounts of data, and quickly sending related subsets of data to the company's management. All companies are affected by decision-making and analysis based on the facts of BI. We are in an environment that is overflowing with data and technologies (Pall & Ogan 2018). Therefore, any company's decision-making process is critical. Computer software developers design and implement software in the age of information technology to meet current business needs. Therefore, the goal of BI software is to improve the efficiency and effectiveness of business processes, procedures, and decision-making for the advantage of the company (Bhat. 2020).

BI can be looked at from a technological perspective and a knowledge search perspective (Ghaida 2018). The study considers the maturity of BI, there is a positive relationship between the maturity of BI and the overall quality of decision- making, especially in large companies (Chen & Nath, 2018). It improves operational efficiency by producing more insightful and intelligent results for decision-makers (Richards, Yeoh, & Chong 2017).

2.5. Previous Studies:

This section discussed previous studies demonstrating the role and the importance of BI.

-*Nuseir's (2021) study titled "**Designing business intelligence (BI) for production, distribution and customer services: a case study of a UAE-based organization**":*

Centered on the National Food Products Company (NFPC) in the United Arab Emirates, this study illustrates the mechanism of BI in processing, delivery, and customer support (UAE). This research examines the BI planning process step by step and points to schematic representations of company requirements and the organization's goal primary success metrics Key Performance Indicators (KPI).

The BI method of a UAE-based company, National Food Products Company (NFPC), was clarified in this study, with a focus on integrating BI elements into its development and delivery processes, as well as customer services. The BI tool reveals that the "star system" is the most suitable one based on the company's needs and preferred KPIs to increase efficiency and enhance delivery and customer service.

-*Kusmantini et al.'s (2021) study titled **"Analysis of the Effect of Business Intelligence on Competitive Advantage through Knowledge Sharing and Organizational Innovation in Export Companies**":*

The purpose of this study is to look at how BI affects competitive advantage in export organizations in Yogyakarta's Special Region via knowledge exchange and organizational creativity. BI, knowledge exchange, competitive advantage, and corporate creativity were the variables examined in this study.

This recommendation is directed at the export organizations that are the focus of this study. The direct impact of BI on competitive advantage has a lower coefficient value than the effect of BI on information exchange and corporate creativity, according to the study findings. As a result, businesses are required to enhance their direct use of BI. Developing a company's strategic strategy and assessing business success indices are two ways to improve BI. The development of a business strategy is supposed to improve competitiveness.

- *Yiu, L. D., et al (2021) study titled. "**The impact of business intelligence systems on profitability and risks of firms**":*

Fact-based decision-making has long been promoted by researchers in the field of operations management (OM). Manufacturers can enhance profitability and minimize risk by implementing BI solutions. However, because integrating BI systems into production and manufacturing activities is challenging, the real commercial value of BI systems has remained a point of contention. The findings demonstrate that when a company employs a BI system, its profitability rises and its risks decrease. When compared to control businesses, sample firms achieve considerably better profitability shortly after using BI tools and in the year after their implementation. According to the researchers' findings, improved employee connections and more process standardization can help sample businesses increase profits and reduce risk. The effect of BI on reducing risk is greater in companies with strong staff connections. This could suggest that better staff connections assist a company in cultivating an effective communication climate to get more accurate data from multiple sources, resulting in more intelligent analysis using BI systems. Firms that use BI solutions in an established process context have better profit improvements and reduced profit variance. Process institutionalization creates a consistent workplace environment with well-defined processes, which streamlines the data gathering process and makes BI system integration easier.

- *Hamad, F., (2021) study titled. “**Business intelligence in academic libraries in Jordan**”:*
Data is critical in gaining a comprehensive understanding of the changing demands of academics’ college libraries and in assisting libraries in adapting their services and operations to meet those needs. For decision-making and long-term planning, data must be converted into information. BI provides sophisticated analytical capabilities, such as visualization and data-mining tools, which lead to improved recommendations and, as a result, improve usability. This research looks at the notion of BI through the eyes of information department workers in Jordanian academic libraries. It also is examined and investigated in terms of the potential plus difficulties that come with it. Academic libraries do not use the term "BI" as a term, even if they use intelligent technologies and incorporate intelligence into their everyday operations. Academic libraries do not use the term "BI" as a term, even if they use intelligent technologies and incorporate intelligence into their everyday operations. This research was successful in gaining thorough knowledge from information technology department personnel at several Jordanian university libraries. According to their replies, BI offers data on various library operations, such as the cost of doing business operations, and system use statistics are already an element of the library's practice. Furthermore, BI influences library managerial decision-making as well as the assessment of educational resources to make data-driven judgments. BI can help libraries enhance their efficiency and outcomes, giving them a competitive edge. At both the management and individual levels, BI may improve the quality of work, the decision-making mechanism, and effectiveness.

- *Mathrani, S. (2021). The study titled “**Critical business intelligence practices to create meta-knowledge**”:*
Companies have implemented BI tools to help in targeted analytical evaluations for the implementation of important decisions to effectively execute plans and adapt to business changes in real-time. Even though organizations have recognized the value of BI, little research has looked into their analytical decision-making capacities in addition to business processes. This research looks at the BI techniques that are necessary for successfully producing meta-knowledge for strategic objective analytical decision-making. To begin, major BI vendors are interviewed to have a better knowledge of their capabilities and existing implementation patterns. Following that, two big BI installation research papers

are carried out to analyze their data processing methods. The essential activities in the BI process for generating meta-knowledge were discovered in this research, as well as organizational initiatives that have a beneficial influence on operational performance and business achievement. These procedures aid in the implementation of the BI procedure for systematic measurement and monitoring of the underlying concerns. Through graphics (tabular data, graphical models) or summary reports, BI technologies can increase the reporting forms of analytical quantifiable components necessary for fulfilling corporate goals. However, the researchers discovered that BI methods differ in terms of efficacy and utilization among companies, indicating several technical problems and missed possibilities.

- *Cempírek Václava, et al (2021) study titled "**Utilization of Business Intelligence Tools in Cargo Control**":*

The study outlines the use of BI in a shipping firm to regulate intermodal freight. It consists of a BI foundation, which includes concise specifications for computer program construction and the stated program, which is used to manage cargo on dedicated railways or other kinds of cargo in intermodal transportation. The developed application accomplishes its goal. The initial plan was to build a program in MS Access or Power BI; both efforts have been saved in their final forms. Power Query, Power Pivot, and DAX, all of which are available in MS Excel, were ultimately better for working with data from dedicated trains. The use of contemporary equipment allowed for the mechanization of the cargo control procedure. The program was developed to handle intermodal data about trains and other intermodal commodities. The program efficiently integrates data about train intermodal transportation, and as a consequence, we have a sophisticated reporting capability that is available online and allows us to evaluate the entire cargo according to a container unit, train, both trains allocated for "roundtrip," or a commodity. This application contributes to our system's enhanced design for commercial transportation.

- *Abu-Rashed, J., et al (2020) study titled "**The role of business intelligence in a knowledge-based economy**":*

The role of BI in Saudi Arabia's transformation into a knowledge-based economy is examined in this article. It identifies important enablers that might be utilized to overcome the present gap between market and strategic intelligence. The research looks at the fundamentals of Saudi Arabia's economy to give long-term recommendations for the country. The study ideas are based on our own experiences with Saudi culture and the present economic circumstances. With the National Transformation Program and Vision 2030, Saudi Arabia has demonstrated its governmental commitment to advancing its economy. The Kingdom has a strategy and a purpose for moving away from an oil-based economy and toward a knowledge-based one. The study emphasized the use of BI tools and contemporary educational institutions to establish a knowledge-driven and knowledge-based economy.

- *Llave, M. R. (2020). The study titled" **Business Intelligence and Analytics in Small and Medium-Sized Enterprises**":*

This research explores the adoption of Business Intelligence and Analytics (BI&A) in small and medium-sized organizations (SMEs). Even though the importance of BI&A is widely acknowledged, observational data reveals that SMEs are still lagging in terms of BI&A adoption. As a result, understanding the phenomena of BI&A adoption in SMEs is crucial. The research approach looks at the factors that influence BI&A adoption in small businesses. The study examines the factors that impact the adoption of BI&A in small firms. The study looked at how SMEs invest in, execute, utilize, and add value to BI&A inventions. A thematic analysis was done to assemble the qualitative expert interview data and explore potential subjects. Using the grounded Delphi system, the Delphi survey results were studied further. The conclusions of the study were explained using three scientific viewpoints: resource-based perspective theory, complex capabilities, and IS worth process models.

Because BI&A and related advancements are seen as some of the most critical IT expenditures in enterprises, research interest in them has increased. The purpose of this study was to learn more about BI&A adoption in small organizations. The most significant drivers and impediments of adoption were identified and graded in a Delphi study by a panel of 39 BI&A specialists. To understand more about how these difficulties affect adoption, follow-up interviews were conducted.

- *Huynh, T. N. G. (2020). The study titled "**Business intelligence in the electrical power industry**":*

Due to its critical role in everyday life, the electrical power industry has attracted the interest of both entrepreneurs and researchers in recent years. However, present sources of electricity generation are rapidly diminishing, posing new problems for the power industry. According to the perspective of sustainable development, the solution should maintain three layers: economically, ecologically, and socially; enhance business decision-making, raise organizational productivity, and improve operational energy efficiency at the same time. In the context of smart and creative technology, a BI solution is seen as a viable alternative in a data-rich environment where theoretical advancement is still fragmented. As a result, the goal of this study was to perform a comprehensive literature review and establish a body of knowledge in the electrical power industry connected to BI. In the electrical power industry, the author also created an integrative framework that shows relationships between antecedents and results of BI. Finally, the article highlighted under-researched areas of the literature as well as the research objectives in terms of theoretical and practical consequences.

Table (2-1): Previous Studies

Previous study	Factors (independent variables)	Dependent variables	Objective	Sector
Nuseir. 2021 "Designing business intelligence (BI) for production, distribution and customer services: a case study of a UAE-based organization"	BI (sources of information, extraction, transformation and loading (ETL) process, data warehouse, OLAP engine, and visualization)	Production, distribution and customer services	To determine the impact of BI on production, distribution and customer services	National food products companies (NFPC) in the United Arab Emirates
Kusmantini, et al. 2021	BI (knowledge sharing, organization and	Competitive advantage	To analyze the effect of BI on	Export companies

“Analysis of the Effect of Business Intelligence on Competitive Advantage through Knowledge Sharing and Organizational Innovation in Export Companies”	Innovation)		competitive advantage	
Yiu, L. D., et al. 2021 “The impact of business intelligence systems on profitability and risks of firms”	BI systems, and employee relationships	Profitability and risks of firms	To investigate the impact of BI systems on profitability and risks of firms	Manufacturing Firms
Hamad, F. 2021 “Business intelligence in academic libraries in Jordan”	BI (data analytics)	Quality of work, management process, and performance	To analyze BI in academic libraries at the Jordanian universities	Jordanian Universities
Mathrani, S. 2021 “Critical business intelligence practices to create meta-knowledge”	BI (knowledge management	Meta-knowledge	To investigate the BI practices in creating meta-knowledge successfully for strategy-focused analytical decision-making	Electronics manufacturing companies
Cempírek Václava, et al. 2021 “Utilization of Business Intelligence Tools in Cargo Control”	BI (data integration, and data analysis expressions	Cargo control	To determine intermodal cargo control with the utilization of BI in a shipping company	Shipping company
Abu-Rashed, J., et al. 2020 “The role of business intelligence in a knowledge-based economy”	BI	Economic diversification	To examine the role of BI in creating a more knowledge-based economy in Saudi Arabia.	Economic diversification in all Saudi Arabia sectors
Llave, M.R. 2020 “Business Intelligence and Analytics in Small and Medium-Sized Enterprises”	BI (data analytics)	Small and medium-sized enterprises	To analyze the impact of implementing BI and analytics on Small and Medium-Sized Enterprises	Medium-sized enterprises

Huynh, T. N. G. 2020 "Business intelligence in the electrical power industry"	BI (OLAP, data mining, process mining, and analytics	Generations, transmissions and distributions	To analyze the impact of BI on generations, transmissions and distributions in the electrical power industry	Electrical power industry
Current study and what distinguish it from previous studies				
"The effect of implementing business intelligence on the quality of decision making in the telecommunication sector in Jordan"	BI (data exploration, data warehouse, data analysis, predictive analysis)	Quality of decision-making	To determine the effect of implementing business intelligence on the quality of decision- making	Telecommunication Sector

2.4. Study Contribution to Knowledge

Many studies have researched BI but they have paid little attention to BI dimensions (data exploration, data warehouse, data analysis, predictive analysis) and the relationship between BI and decision-making quality in telecommunication sector (Zain, Orange, and Umniah) in Jordan. As a result, the study was shedding light on the indirect relationship between business intelligence and the quality of decision-making.

CHAPTER 3: Study Methodology

3.1. Introduction:

This chapter described a variety of strategies and procedures that were employed to achieve the study's goals. To begin, it includes a description of the study methodology, the study sample as well as the population, the study tool, and methods used to verify the validity and reliability of the study's data, the study's variables, and the statistical treatments used in analyzing the study's data in order to address the study's hypotheses. Finally, the researcher addressed the statistical treatment that was used in the analysis of the gathered data.

3.2. Study's Design:

This study conducted a quantitative survey using a questionnaire to collect primary data to see the impact of BI on the quality of making decisions. The questionnaire was distributed to all employees and managers.

3.3. Population and Sample:

It is necessary to select a sample that will represent the population to enhance reliability.

Population: The study's population was the Jordanian telecommunication sector.

Sample: The study's sample was the three companies of the Jordanian telecommunication sector (Zain, Orange and Umniah).

Unit of analysis: After sending (422) questionnaires to all the employees of three Jordanian telecommunications companies on a continuous basis (Zain, Orange, and Umniah). A total of 378 questionnaires were retrieved from a total of 422, with 54 being deleted due to large gaps in data. As a result, the validity of (324) completed questionnaires from the research unit of analysis was determined. The Cochran formula which helps to provide an adequate sample size for the purpose of determining the target population is provided below: $n = \frac{z^2 \times p \times q}{e^2}$ (Ahmad, & Halim. 2017. Cochran. 1977)

Where, z: denotes to the z-score which is estimated at 1.96 and confidence interval is computed at 95%.

p: is considered as the variability proportion which is computed at 50%.

q: denotes to the population which has not been considered in the study.

e: refers to the error which is estimated at 5%

$$n = \frac{(1.96)^2 \times 0.5 \times 0.5}{(0.05)^2} = 384$$

Per the result above, 384 would be the adequate sample size.

3.4. The Study's Instruments:

The study contains two fields, practical and theoretical. In the practical aspect, the study relies on collecting and analyzing data via a questionnaire to test the hypotheses. And in the theoretical aspect, the research relies on previous scientific studies. The current study's data collection, research methods, and programs have focused on a questionnaire created to illustrate the objectives of the study and questions.

The model's data will be gathered via a questionnaire, following a detailed analysis of the literature on the topic of this study. The instrumental parts of the questionnaire are as follows:

- The first section consists of demographic factors. Closed-ended questions were used to gather demographic data from (6) variables (age, gender, educational background, years of service in the telecommunications sector, Job level, and company's name).
- BI is the second section. This section will assess BI and its dimensions (Data Exploration, Data Warehouse, Data Analysis, and Predictive Analysis). To assess BI using twenty-one items (five for Data Exploration, 5 for Data Warehouse, six for Data Analysis, and five for Predictive Analysis). on a five-point Likert scale as follows:

Strongly Implemented	Implemented	Neutral	Not Implemented	Strongly Not Implemented
5	4	3	2	1

$$Class\ Interval = \frac{\text{Maximum Class – Minimum Class}}{\text{Number of Level}} = \frac{5-1}{3} = \frac{4}{3} = 1.33$$

The low degree ranges from (1.00- 2.33), the medium degree from (2.34 – 3.67), and the high degree from 3.67 – 5.00. (Ivanov, Ivanova, & Saltan. 2018).

The quality of decision -making is the third section and it will contain six questions

3.5. Procedure for Data Collection:

The current study is divided into two parts: theoretical and practical. In terms of theory, the researcher collected data from different sources such as journals, working papers, research, thesis, articles, and the worldwide web that were relevant to the current investigation. In the practical element, the researcher relied on descriptive and analytical approaches to collect, analyze, and test hypotheses in a practical manner.

The current study's data collecting, analysis methods, and programs are based on two sources:

1-To write the theoretical framework of the study, use secondary materials such as books, journals, and theses.

2. Primary source: a questionnaire that was created with the study's goals and questions in mind. This study is based on a quantitative approach. The steps of collecting data will be as follows:

3.5.1. Create a questionnaire related to the subject:

The questionnaire included multiple-choice questions asking them simple questions.

3.5.2. Distribute the questionnaire:

The questionnaire was distributed to all employees to answer the questions and collect the data.

3.5.3. Data Analysis:

For a p-value less than 0.05, a statistically valid test would be applied when analyzing the data to ensure validity and reliability. To explain the distribution of study participants, descriptive statistics will be used to calculate the mean and standard deviation for quantitative variables. The R-square (R^2). In a regression model, R-square (R^2) is a statistical measure that represents the proportion of the dependent variable's variance that can be explained by the independent variable. To measure the variations between factors, the chi-squared test or independent sample t-test will be used. Cronbach's alpha is a reliability coefficient that measures internal consistency, or how closely a group of objects is related.

3.6. Statistical Techniques in Data Analysis:

The data acquired from the study questionnaire responses was analyzed and conclusions were drawn using the Statistical Package for Social Sciences (SPSS). Finally, the researcher employed statistical approaches that were appropriate for the situation.

The Statistical Techniques were:

1. Cronbach Alpha reliability (α) is a method for determining the strength of correlation and coherence between questionnaire items.
2. Kaiser-Meyer-Olkin (KMO) analysis is to establish the sampling validity of data to be used in Factor Analysis
3. Mathematical operations Means of determining the level of reaction of the study sample to the study factors.
4. The standard deviation is used to calculate the degree of response spacing around the arithmetic mean.

3.7. Demographic Analysis

According to Stapor, (2020), there are two methods for statistical analysis which are descriptive and inferential statistics. Descriptive statistics are used for the description of the sample characteristics and variables of study, where inferential statistics are used for examining the relationships between the variables, in order to test the hypotheses. Consequently, a questionnaire was used to collect the needed data, then a descriptive statistic was used to describe the demographic characteristics of the sample, after that the inferential statistics were used to examine the relationships between the variables and test the suggested hypotheses.

The sample of the study includes employees, IT employees, supervisors, and heads of departments. The total number of staff members who completed the questionnaire is 324 respondents.

The first section of the questionnaire was targeted to collect data such as gender, age, educational background, work experience, and current position. The following tables and sections present a summary and discuss these characteristics in detail.

To start by, the results in table (3-1) shows that the percentage of males (65.1 %, n=211) is higher than that of females (34.9 %, n=113) in the sample of the study which total is 324 respondents. These results might be justified by the fact that in the Middle Eastern countries.

Furthermore, according to the table (3-1) results, a large percentage of respondents were between 25 and less than 35 years old (46.9 %, n=152), followed by the ages between 35 and less than 45 years old (21%, n=68). While, the lowest percentage of respondents were 55 years old or above (2.5%, n=8) followed by 45 and less than 55 years old (11.1 %, n=36). However, given the table (3-1), it is obvious that the employees in the telecommunication industry in Jordan are of different ages and hence, different backgrounds and experiences are expected.

The information regarding the educational level of the respondents in table (3-1) show a comparatively high level of formal education among respondents, with 67.6% having a bachelor's degree, 21.9 % having a master's degree, 8.6 % having a higher diploma, and 1.9 % having a PhD degree. These results show that the company's employees are well-educated and interested in enhancing their skills.

In addition, table (3-1) shows that 46.9 % of the respondents had between 5 and less than 10 experience years, 29.6 % had between 1 less than 5 years, 13.6 % had more than 10 years, and 9.9 % had less than a year.

Finally, the results in table (3-1) preview the frequency distribution of job level among the respondents. As shown in the table 38.3 % of the respondents were employees, 25.9 % worked as supervisors, 16.7 % were head of a department, 11.4 % were IT employees, and 7.7 % were senior managers.

Table (3-1): Frequency Distribution by Demographic Characteristics

		Frequency	Percent
Gender	Female	113	34.9%
	Male	211	65.1%
	Total	324	100.0%
Age	Less than 25	60	18.5%
	25 - Less than 35	152	46.9%
	35 - Less than 45	68	21.0%
	45 - Less than 55	36	11.1%
	55 or above	8	2.5%
	Total	324	100.0%
Educational background	Diploma	28	8.6%
	Bachelor's degree	219	67.6%
	Master's degree	71	21.9%
	Doctoral degree	6	1.9%
	Total	324	100.0%
Years of experience in the telecommunication sector	Less than a year	32	9.9%
	1 - Less than 5 years	96	29.6%
	5 - Less than 10 years	152	46.9%
	10 years or more	44	13.6%
	Total	324	100.0%
Job-Level	Head of a department	54	16.7%
	Senior Manager	25	7.7%

	Supervisor	84	25.9%
	Employee	124	38.3%
	IT employee	37	11.4%
	Total	324	100.0%
Telecommunication company	Umniah	88	27.2%
	Orange	113	34.9%
	Zain	123	38.0%
	Total	324	100.0%

CHAPTER 4: Data Analysis and Hypothesis Testing

4.1. Introduction:

The descriptive analysis and hypothesis testing are provided in chapter four. The chapter is structured as follows, section 4.2 presents the reliability, and section 4.3 presents validity, section 4.4. presents the descriptive statistics analysis for the independent variable (BI), then section 4.5 presents the descriptive statistics analysis for the dependent variable (quality of decision-making section), after that section 4.6 examines the relationship between dependent and independent variables, followed by testing multicollinearity in section 4.7. And finally, testing hypothesis in section 4.8. The importance degree was determined based on the following five categories as depicted in the formula in section 3.4 (Ivanov, Ivanova, & Saltan. 2018).

- Very Low: (1- 1.8)
- Low: (1.81- 2.6)
- Medium: (2.61- 3.4)
- High: (3.41- 4.2)
- Very High: (4.21- 5)

4.2. Reliability:

The amount to which a questionnaire, test, observation, or any measurement process gives the same results on multiple tries is known as reliability (Sürücü & Maslakçi, 2020). On the other hand, to validate if something is measured properly is known as validity. A good measurement must be both reliable and valid. Accordingly, Cronbach’s alpha (α), which is a measurement used to test reliability, is applied in the current study. Cronbach's alpha is a score that varies from 0 to 1, with 0 representing complete unreliability and 1 representing perfect reliability and values of less than 0.70 are generally unfavorable (Bell, et al. 2022).

Table (4-1) shows the Cronbach's Alpha for each of the study constructs, there is a high level of internal consistency between the independent variables with Cronbach alpha values ranging from 0.817 to 0.919. Besides the Cronbach alpha value for the dependent variable is 0.927. Accordingly, the overall results imply a satisfactory level of reliability for the study model.

Table (4-1): Reliability Statistics

	Cronbach's Alpha	N of Items
Data Exploration	.817	5
Data warehouse	.900	5
Data analysis	.919	6
Predictive analysis	.917	5
Independent variable	.962	21
Quality of decision-making	.927	6

4.3. Validity:

To evaluate construct validity and measure sample adequacy, the Kaiser-Meyer-Olkin (KMO) test was used. According to the findings in Table (4-2), it is obvious that the value of KMO is range between (0.794 – 0.918) for the independent variables (data exploration, data warehouse, data analysis, and predictive analysis). While the value of KMO for the dependent variable (quality of decision-making section) is (0.918), which suggests that the data is suitable for factor analysis, since the values of KMO are all above (0.5).

According to the findings in Table (4-2), it is obvious that the value of KMO is range between (0.794 – 0.918) for the independent variables (data exploration, data warehouse, data analysis, and predictive analysis). While the value of KMO for the dependent variable (quality of decision-making section) is (0.918), which suggests that the data is suitable for factor analysis, since the values of KMO are all above (0.5). Furthermore, all chi2 are higher than 600 which indicates the fitness of model, also, the test produced an explanatory value of ranging between 61.483 and 75.247 that explain the variance. Finally, Bartlett test results were statistically significant, as was the p-value of all variables is (0.000), supporting the same idea that the data is suitable for factor analysis.

Table (4-2): KMO analysis

	Statements	KMO	Chi2	BTS	Var%	Sig.
Data Exploration	1-5	.794	654.884	10	61.483	.000
Data Warehouse	6-10	.879	967.547	10	72.052	.000
Data Analysis	11-16	.918	1298.509	15	71.419	.000
Predictive analysis	17-21	.882	1127.700	10	75.247	.000
Quality of decision-making	22-27	.918	1418.812	15	73.557	.000

4.4. Descriptive Statistics Analysis for Independent Variable

4.4.1. Data Exploration

The Table (4-3) describes the mean, standard deviation, and the importance of the items that evaluate respondents' answers towards the data exploration variable. Respondents were asked to reply to five statements on data exploration in order to decide the depth of their observation of the construct in their organization.

As shown in Table (4-3), the highest mean value which is 3.948 was obtained by the statement 'The company explores data from reliable sources to ensure collecting high-quality data' with a standard deviation of 0.7171 which indicate that the majority of respondents are supportive of the current situation. However, the lowest mean value which is 3.389 was obtained by the statement 'The company uses data exploration to help in developing strategies' with a standard deviation of 0.8272 which also is considered medium in terms of level and confirms the same findings.

The average mean value of data exploration scores was 3.704 and the descriptive statistics for the variable revealed that the respondents were not very dispersed around their mean scores on individual items with standard deviations between 0.7010 and 0.8272. All these results indicate that the respondents have a high implementation agreement on that data exploration dimension in the Jordanian telecommunication sector.

Table (4-3) Mean, Std. Deviation, and Importance Level of Data Exploration

	Data Exploration	Mean	Std. Deviation	Statement Importance	Importance Degree
1	The company adopts data exploration as a business intelligence process to collect data from various sources	3.756	.7624	2	High
2	The company explores data from reliable sources to ensure collecting high-quality data	3.948	.7171	1	High
3	The company implements data exploration for identifying and developing working routines	3.691	.7773	4	High
4	The company's managers may use data exploration to help them make efficient and effective decisions	3.738	.7010	3	High
	Overall mean	**3.704**	**.5764**		**High**

4.4.2. Data Warehouse

The Table (4-4) describes the mean, standard deviation, and the importance of the items that evaluate respondents' answers towards the data warehouse variable.

As shown in Table (4-4), the variable achieved a high overall mean value of 3.865 which shows that respondents agreed about the importance of data warehouses in Jordanian telecommunications firms. More specifically, the highest mean value was achieved by the statement "The company uses data warehouse as a historical and large data repository" with a mean value of 4.062 and a standard deviation of 0.7793, the lowest mean value was 3.751 and standard deviation of 0.6354 was achieved by the statement 'The company adopts Online Analytical Processing (OLAP) for organizing and analysing significant databases to enhance the decision-making process" and the replies are generally concentrated around the mean with average standard deviation 0.5749, indicating that respondents agreed on the importance of using data warehouse in telecommunications firms in Jordan.

Table (4-4): Mean, Std. Deviation, and Importance Level of Data Warehouse

NO.	Data Warehouse	Mean	Std. Dev.	Statement Importance	Importance Degree
1	The company uses data warehouse as a historical and large data repository	4.062	.7793	1	High
2	The company enhances the business intelligence process by using a data warehouse as an analytical tool	3.834	.6917	3	High
3	The conflict decisions are reduced in the company by using a data warehouse (due to the availability of useful information in the data warehouse)	3.849	.6276	2	High
4	The implementation of a data warehouse by the company aids in the efficient and effective decision- making process	3.831	.6566	4	High
5	The company adopts Online Analytical Processing (OLAP) for organizing and analyzing significant databases to enhance the decision-making process	3.751	.6354	5	High
	Overall mean	**3.865**	**.5749**		**High**

4.4.3. Data Analysis

The descriptive analysis of the data analysis variable is provided in the table above. Looking at Table (4-5), a high level of agreement among Jordanian telecommunication companies on the importance of data analysis implementation can be observed. The average mean value is 3.979 starting from 3.803 to 4.132, with related standard deviation values between 0.6511 and 0.7843.

More specifically, the statement ‘The company employs data analysis to transform raw data into useful information was ranked first with the highest mean value of 4.132 which shows that employees are seen as being highly motivated and aware of the need for data analysis in the Jordanian telecommunications sector. On the other hand, the statement 'The company uses data analysis during Covid-19 to reduce the number of difficulties and risks was ranked last based on the mean value which is 3.803 and thus is considered high in terms of level, which confirms and support the above-mentioned results. Furthermore, Jordanian telecommunications use data analysis as statistical and visualization approaches to filter, analyze and explain data (mean 4.052), as well as to make data more understandable (mean 4.003).

Table (4-5): Mean, Std. Deviation, and Importance Level of Data Analysis

	Data Analysis	Mean	Std. Dev.	Statement Importance	Importance Degree
1	The company employs data analysis to transform raw data into useful information (insights)	4.132	.7843	1	High
2	The company uses data analysis as statistical and visualization approaches to filter, analyze and explain data	4.052	.7700	2	High
3	The company uses data analysis to speed up the execution of tasks	3.957	.7399	4	High
4	The company implements data analysis to make data more understandable	4.003	.7678	3	High
5	The company uses data analysis during Covid-19 to reduce the number of difficulties and risks	3.803	.6925	6	High
6	The company's managers and staff use data analysis in making efficient and effective decisions	3.929	.6511	5	High
	Overall mean	**3.979**	**.620**		**High**

4.4.4. Predictive analysis

As shown in Table (4-6), the mean values of predictive analysis items are between 3.671 and 3.834, with related standard deviation values between 0.6736 and 0.7233, and a high level of an overall mean of 3.754. Therefore, the gained results indicate the agreement of employees working in Jordanian telecommunication companies on the importance of implementing predictive analysis in the company.

For instance, the statement ‘The company applies predictive analysis to forecast the future trends based on extracting useful information gained the highest mean value 3.834 which reflects the high level of awareness among the employees of the importance of predictive analysis in the Jordanian telecommunications sector. On the other hand, the statement ‘The company adopted predictive analysis during Covid-19 to identify changes in the environment in a timely manner’ obtained the last rank among others (mean 3.671) and thus is still considered high in terms of level, which confirms and support the above-mentioned results. Additionally, Jordanian telecommunications companies use data analysis predictive analysis to enhance decision-making process effectively and efficiently as well as to reduce decisions uncertainty, which accordingly will be reducing time and effort.

Table (4-6): Mean, Std. Deviation, and Importance level of Predictive Analysis

	Predictive analysis	Mean	Std. Dev.	Statement Importance	Importance Degree
1	The company applies predictive analysis to forecast the future trends based on extracting useful information	3.834	.6736	1	High
2	The company uses predictive analysis for reducing time and effort	3.726	.7214	4	High
3	The company uses predictive analysis to enhance decision-making process effectively and efficiently	3.782	.7233	2	High
4	The company enhances predictive analysis as a business intelligence tool to reduce decisions uncertainty	3.760	.7011	3	High
5	The company adopted predictive analysis during Covid-19 to identify changes in the environment in a timely manner	3.671	.6934	5	High
	Overall mean	**3.754**	**.6093**		**High**

4.5. Descriptive Statistics Analysis for Dependent Variable

This section presents the results of the descriptive analysis of the dependent variable (quality of decision-making). Respondents were asked to state on a five Likert scale their agreement or disagreement with the given statements concerning the dimension of quality of the decision-making.

As shown in Table (4-7), the quality of decision-making is a variable with high importance from the viewpoint of the majority of the respondents. This was shown by the high mean values range of 3.775 to 4.157 and an average mean value of 3.966. Moreover, employees stated that Jordanian telecommunications companies handle uncertainty, by providing accurate information, and take the right actions result in a high-quality decision, where the decisions made in the company can be implemented and aid in the achievement of the company's purpose. The respondents also asserted that Jordanian telecommunications made measurable decisions by using feedback, where these decisions are compatible with the telecommunications sector's policies as well as in accordance with its strategic plan. Finally, the obtained results reflect the high agreement among the employees working in the Jordanian telecommunications sector on the important quality of decision-making dimensions.

Table (4-7): Mean, Std. Deviation, and Importance level of Quality of Decision-Making

	Quality of decision-making	**Mean**	**Std. Dev.**	**Statement Importance**	**Importance Degree**
1	The company handles uncertainty, by providing accurate information, and take the right actions result in a high-quality decision	4.157	.8296	1	High
2	Decisions made in the company can be implemented	4.043	.7962	2	High
3	The decisions made aid in the achievement of the company's purpose	3.969	.7611	3	High
4	The company's decisions are measurable by using feedbacks	3.942	.7326	4	High
5	The company's decisions are compatible with the telecommunications sector's policies	3.911	.7036	5	High
6	The company's decisions are made in accordance with its strategic plan	3.775	.7466	6	High
	Overall mean	**3.966**	**.652**		**High**

4.6. Relationship between Variables

In the study, correlation analysis is a statistical approach for measuring the association between two variables and measuring the strength of the linear relationship between them. Simply defined, correlation analysis determines how much one variable changes as a result of the change in another. A high correlation indicates a strong association between the two variables, whereas a low correlation indicates the opposite (Wooditch, et al. 2021).

The findings of the correlation test that attempts to examine the relationship between data exploration, data warehouse, data analysis, predictive analysis, BI, with quality of decision-making in the Jordanian telecommunications sector are presented in table Table (4-8).According to the results in Table (4-8), the correlations between dependent and independent variables are strong, where the Pearson Correlation Coefficients range between (0.727 Quality of decision- making with predictive analysis) and (0.856 Quality of decision-making with Data Analysis).

Table (4-8): Correlations Test

	Data Exploration	Data Warehouse	Data Analysis	Predictive Analysis	Quality of decision-making
Data Exploration	1	.760**	.740**	.748**	.736**
Data Warehouse	.760**	1	.875**	.759**	.842**
Data Analysis	.740**	.875**	1	.732**	.856**
Predictive Analysis	.748**	.759**	.732**	1	.727**
Quality of decision-making	.736**	.842**	.856**	.727**	1
**. Correlation is significant at the 0.05 level (2-tailed).					

4.7. Test of Multicollinearity

This study used the Variable inflation factor (VIF) and the tolerance test for each dimension of the study independent variables to evaluate the assumption of multicollinearity, as indicated in Table (4-9).

Table (4-9) shows that the VIF values for each variable are less than 10, and the tolerance values are all greater than 0.1, implying that there is no multicollinearity in the current study's independent variables.

Table (4-9): Collinearity Statistics Matrix

Coefficients		
Model	**Collinearity Statistics**	
	Tolerance	**VIF**
(Constant)		
Data Exploration	.343	2.914
Data Warehouse	.193	5.176
Data Analysis	.216	4.625
Predictive analysis	.349	2.865

4.8. The Findings of Main Testing Hypotheses

Determining which multivariate approach will be used to analyze the hypotheses is the most crucial element of the findings. The primary goal of this study is to evaluate the effect of implementing BI on the quality of decision- making in the telecommunication sector in Jordan. As a result, the most appropriate analysis method was selected is multiple regression analysis in order to test the main hypothesis and sub-hypotheses.

Table (4-10) illustrate the results of the multiple regressions analysis to test the main null hypothesis which states that there is an insignificant impact of BI on the quality of decision-making of telecommunication firms in Jordan at a significant level ($\alpha \leq 0.05$). The fitness of the model for multiple regressions is demonstrated by the value of R^2, which is 0.781. This indicates that BI can explain 0.781 of variance in the quality of decision- making of telecommunication firms in Jordan. This is also supported by the results of the f-test, which is significant at a 5% level (f-test =283.595, sig.=0.000).

Consequently, the main null hypothesis that states there is no significant effect of implementing BI on the quality of decision- making in the telecommunication sector in Jordan should be rejected at a 5% significant level. Therefore, the findings in table 4.8

confirm that there is a significant impact of the BI on the quality of decisions making of telecommunication firms in Jordan at a significant level ($\alpha \leq 0.05$), indicating that using BI in Jordanian telecommunication firms will enhance the quality of decisions making.

Table (4-10): Regression Analysis for Testing Main Hypotheses

Model Summary	**R^2**	**Adjusted. R^2**	**F**	**Sig.**
	.781	.778	283.595	0.000
R	Unstandardized Coefficients		t	Sig.
0.883	B	Std. Err.		
(Constant)	-.036	.123	-.294	.769
Data Exploration	.126	.051	2.494	.013
Data Analysis	.467	.059	7.874	.000
Data Warehouse	.337	.068	4.984	.000
Predictive analysis	.100	.047	2.100	.037

Results pertaining to the sub hypothesis H0.1

H01: There is no significant effect of data exploration on the quality of decision- making in telecommunication sector in Jordan at level ($\alpha \leq 0.05$)

As shown in Table (4-10), the beta coefficient for the data exploration variable is 0.126 with a calculated t-value (2.949) that higher than the critical t-value (1.96), and the significant level is lower than 5%. This demonstrates that there is high importance of data exploration and its effect on the quality of decisions making for telecommunication firms in Jordan. Consequently, the first sub-null hypothesis should be rejected and conclude that there is a significant impact of data exploration on the quality of decision- making of telecommunication firms in Jordan at a significant level ($\alpha \leq 0.05$).

Results pertaining to the sub hypothesis H0.2

H02: There is no significant effect of data analysis on the quality of decision-making in telecommunication sector in Jordan at level ($\alpha \leq 0.05$)

As shown in Table (4-10), the beta coefficient for the data analysis variable is 0.467, with a calculated t-value (7.874) that higher than the critical t-value (1.96), and the significant level is less than 5% (Sign. =0.000). This demonstrates that there is very high importance of data analysis. Consequently, the second sub-null hypothesis should be rejected and conclude that there is a significant positive impact of data analysis on the quality of decisions of telecommunication firms in Jordan at a significant level ($\alpha \leq 0.05$), indicating that using data analysis in Jordanian telecommunication firms will enhance the quality of decisions making.

Results pertaining to the sub hypothesis H0.3

H03: There is no significant effect of data warehouse on the quality of decision-making in telecommunication sector in Jordan at level ($\alpha \leq 0.05$)

As shown in Table (4-10), the beta coefficient for the data warehouse variable is 0.337, with a calculated t-value (4.984) that higher than the critical t-value (1.96), and the significant level is less than 5% (Sign. =0.000). This demonstrates that there is high importance of data warehouse and its effect on the quality of decisions of telecommunication firms in Jordan. Thus, the third sub-null hypothesis should be rejected and conclude that there is a significant positive impact of data warehouse on the quality of decision-making of telecommunication firms in Jordan at a significant level ($\alpha \leq 0.05$), indicating that using data warehouse in Jordanian telecommunication firms will enhance the quality of decisions making.

Results pertaining to the sub hypothesis H0.4

H04: There is no significant effect of predictive analysis on the quality of decision-making in telecommunication sector in Jordan at level ($\alpha \leq 0.05$)

As shown in Table (4-10), the beta coefficient for the predictive analysis variable is 0.100, with a calculated t-value (2.100) that higher than the critical t-value (1.96), and the significant level is less than 5% (Sign. =0.037). This reveals that there is high importance of predictive analysis on the quality of decision-making of telecommunication firms in Jordan. Therefore, the fourth sub-null hypothesis should be rejected and conclude that there is a significant impact of predictive analysis on the quality of decision-making of telecommunication firms in Jordan at a significant level ($\alpha \leq 0.05$), indicating that using predictive analysis in Jordanian telecommunication firms will enhance the quality of decisions making.

Table (4-11): The Results of Hypotheses

Number	Hypotheses	Results
H01:	There is no significant effect of data exploration on the quality of decision-making in telecommunication sector in Jordan at level ($\alpha \leq 0.05$)	REJECT
H02:	There is no significant effect of data analysis on the quality of decision-making in telecommunication sector in Jordan at level ($\alpha \leq 0.05$)	REJECT
H03:	There is no significant effect of data warehouse on the quality of decision-making in telecommunication sector in Jordan at level ($\alpha \leq 0.05$)	REJECT
H04:	There is no significant effect of predictive analysis on the quality of-decision-making in telecommunication sector in Jordan at level ($\alpha \leq 0.05$)	REJECT

CHAPTER 5: Results Discussion, Conclusion, and Recommendations

5.1. Introduction

The main purpose of this study is to investigate the effect of implementing BI on the quality of decision-making in the Jordanian telecommunication sector. The study has built a framework to quantify the effect of BI on the quality of decision-making to achieve the study's purposes. The research methodology was created after a thorough evaluation of the literature. The model comprises two types of variables: dependent variables (quality of decision-making) and independent variables (BI) and its dimensions (data exploration, data warehouse, data analysis, and predictive analysis). The Jordanian telecommunications sector has confirmed the model. The study, on the other hand, looked into the significance of BI. In addition, the researchers determined how much BI influences the quality of decision-making at the organizations in question.

5.2. The Results

The results confirm that BI has a positive direct impact quality of decision-making in the Jordanian telecommunication sector (Zain, Orange, and Umniah)

We also find that the effects of implementing the BI dimensions (data exploration, data warehouse, data analysis, and predictive analysis) in combination into a positive effect on the quality of decision-making. In particular, the results reveal a significant path from BI to decision-making quality via data exploration, data warehouse, data analysis, and predictive analysis which substantiates the calls for proper BI.

5.2. Results' Discussion:

The results of this study show the implementation of BI dimensions in the telecommunication sector (Zain, Orange, and Umniah). Data analysis has the highest implementation rate among the dimensions, then data warehouse, followed by predictive analysis, finally data exploration which all have a high implementation rate.

1. The significant impact of the total BI on the quality of decision-making, which was supported by previous studies Tripathi, Bagga, & Aggarwal. (2020), & Borissova, Cvetkova. et al (2020).

2. The significant impact of the total BI on quality of decision-making, which was supported by the previous study (Cheng, Zhong & Cao 2020). BI would impact the quality of decision making, and lead to better outcomes.
3. The significant impact of BI dimensions on the quality of decision-making which was supported by a previous study Vaish, Shrivastava, & Sen. (2020), Van Capelleveen, van Wieren, et al (2021), Yang. (2021), & Vaish, Shrivastava, & Sen. (2020). BI technologies affect the company's decision-making process efficiently and effectively. Moreover, BI provides better insights and reduces the uncertainty.
4. Data exploration has a significant impact on the quality of decision-making, which was supported by a previous study (Gautam, Singh& Shaikh 2017).

The results and findings of this study have shown that there is a positive significant impact of implementing BI on the quality of decision-making in the Jordanian telecommunication sector.

The study gave guidelines to all employees in the telecommunication sector (Zain, Orange, and Umniah) seeking to enhance and implement BI by exploring, storing, and analyzing the data. The study also showed the importance of BI in terms of predicting to reduce uncertainty, especially during the Covid-19 pandemic. Therefore, the study showed that regardless of merging jobs and/or doing the tasks online, BI enhanced the decision-making process efficiently and effectively.

Overall, the study contributes to both academia and industry by providing evidence of determinants of organizational benefits from BI solutions on the quality of decision-making.

5.3. Conclusions:

This study is devoted to answering the study main question: do BI dimensions (Data exploration, Data warehouse, Data analysis, and predictive analysis) have an impact on the quality of decision-making in telecommunication sector (Zain, Orange and Umniah) in Jordan? Data was gathered using a questionnaire that was evaluated for validity and reliability. The hypotheses were then tested using correlation and multiple regressions.

The results of this study showed that the implementation of BI dimensions is high in telecommunication sector (Zain, Orange, and Umniah) in Jordan, data analysis has rated high implementation, followed by data warehouse, predictive analysis, and then data exploration, respectively. Moreover, the findings show that implementation of quality of decision-making is high. The results also showed that the correlation between BI dimensions is strong and positive, and the correlation between independent and dependent variables is strong and positive.

Finally, results indicate that there is a significant impact of the total BI on the quality of decision-making in the telecommunication sector in Jordan.

Based on the conclusion above, several critical company tasks, including those that set future plans and goals, require a decision-making process. As a result, the information used to make these decisions is a valuable asset that can affect a company's success. BI is a strong tool that facilitates decision-making by allowing information to be processed and translated into knowledge quickly and simply.

5.4. Recommendations:

This study was conducted in Jordan's telecommunications sector. To be able to generalize the current study's findings, it is suggested that a similar study be conducted in other nations, particularly in Arab countries.

Because this study was completed in a short amount of time, it is recommended that it be repeated at a later date to check on industry development.

Extending the analyses to other industries and countries represents future research opportunities, which can be accomplished by conducting additional tests with larger samples within the same industry, and including other industries will help mitigate the problem of generalizing conclusions to other organizations and industries. As a result, more study is required, as well as data collection from a variety of countries. Furthermore, the focus of this study is on the telecommunications sector. Further research is required to determine whether the findings may be applied to other business sectors.

Finally, further studies in this field should be investigated because the same study characteristics can be applied to other sectors. Industrial, insurance, banking, and education are among them.

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Appendices

Appendix (1)

Questionnaire

The master's thesis aims to study “The Effect of Implementing Business Intelligence on The Quality of Decision Making in The Telecommunication sector in Jordan”

This survey contains 38 questions.

Your answers will be top secret and will be used for search purposes only.

Appreciate your participation in this research. Please, if you have any questions or comments, please contact me at this number (0795614573) or on the email mentioned (rami.alnimer@hotmail.com)

Thank you so much for your cooperation.

Researcher: Rami Samer Al-Nimer

Academic Supervisor: Prof. Luigi Marengo

FIRST SECTION: Demographics Information

Age: □ Less than 25 □ 25 - Less than 35 □ 35 - Less than 45 □ 45 - Less than 55 □ 55 or above

Gender: □Male □Female

Educational background: □Diploma □ Bachelor's degree □ Master's degree □ Doctoral degree

Years of experience in the telecommunication sector: □Less than a year □1 - Less than 5 years □ 5 - Less than 10 years □10 years or more

Job-Level: □Senior Manager □ Head of a department □Supervisor □IT employee □Employee

Telecommunication Company: □Zain □Orange □ Umniah

SECOND SECTION: The following 21 questions tap into your perception about the actual implementation of Business Intelligence variable (data exploration, data warehouse, data analysis, predictive analysis). Please answer the following questions based on your knowledge and experience about the statement taking into consideration that:

[1 = strongly not implemented, 2 = not implemented, 3 = neutral, 4 = implemented, 5 = strongly implemented].

Data Exploration

1	The company adopts data exploration as a business intelligence process to collect data from various sources.	1	2	3	4	5
2	The company explores data from reliable sources to ensure collecting high-quality data.	1	2	3	4	5
3	The company implements data exploration for identifying and developing working routines.	1	2	3	4	5
4	The company's managers may use data exploration to help them make efficient and effective decisions.	1	2	3	4	5
5	The company uses data exploration to help in developing strategies.	1	2	3	4	5

Data Warehouse

1	The company uses data warehouse as a historical and large data repository.	1	2	3	4	5
2	The company enhances the business intelligence process by using a data warehouse as an analytical tool.	1	2	3	4	5
3	The conflict decisions are reduced in the company by using a data warehouse (due to the availability of useful information in the data warehouse).	1	2	3	4	5
4	The implementation of a data warehouse by the company aids in the efficient and effective decision- making process.	1	2	3	4	5
5	The company adopts Online Analytical Processing (OLAP) for organizing and analyzing significant databases to enhance the decision-making process.	1	2	3	4	5

Data Analysis

1	The company employs data analysis to transform raw data into useful information (insights).	1	2	3	4	5
2	The company uses data analysis as statistical and visualization approaches to filter, analyze and explain data.	1	2	3	4	5
3	The company uses data analysis to speed up the execution of tasks.	1	2	3	4	5
4	The company implements data analysis to make data more understandable.	1	2	3	4	5
5	The company uses data analysis during Covid-19 to reduce the number of difficulties and risks.	1	2	3	4	5
6	The company’s managers and staff use data analysis in making efficient and effective decisions	1	2	3	4	5

Predictive Analysis

1	The company applies predictive analysis to forecast the future trends based on extracting useful information	1	2	3	4	5
2	The company uses predictive analysis for reducing time and effort.	1	2	3	4	5
3	The company uses predictive analysis to enhance decision-making process effectively and efficiently.	1	2	3	4	5
4	The company enhances predictive analysis as a business intelligence tool to reduce decisions uncertainty.	1	2	3	4	5
5	The company adopted predictive analysis during Covid-19 to identify changes in the environment in a timely manner.	1	2	3	4	5

THIRD SECTION: The following 6 questions regarding the quality of decision making.

Quality of decision-making

1	The company handles uncertainty, by providing accurate information, and take the right actions result in a high-quality decision.	1	2	3	4	5
2	Decisions made in the company can be implemented.	1	2	3	4	5
3	The decisions made aid in the achievement of the company's purpose.	1	2	3	4	5
4	The company's decisions are measurable by using feedbacks.	1	2	3	4	5
5	The company's decisions are compatible with the telecommunications sector's policies.	1	2	3	4	5
6	The company's decisions are made in accordance with its strategic plan.	1	2	3	4	5

Appendix (2): Names of Arbitrators

No.	Name	Academic Rank	Specialization	University
1	Prof. Faisal Aburub	Professor	Management Information Systems	University of Petra
2	Dr. Anas Aloudat	Associate Professor	Management Information Systems	University of Jordan
3	Dr. Nasim Matar	Assistant Professor	Software Engineering	University of Petra
4	Dr. Hazem Qattous	Assistant professor	Software Engineering	Princess Sumya University for Technology
5	Dr. Enas Al-Lozi	Assistant Professor	Management Information Systems	Al-Zaytoonah Private University
6	Dr. Wasef Matar	Assistant Professor	Management Information Systems	University of Petra

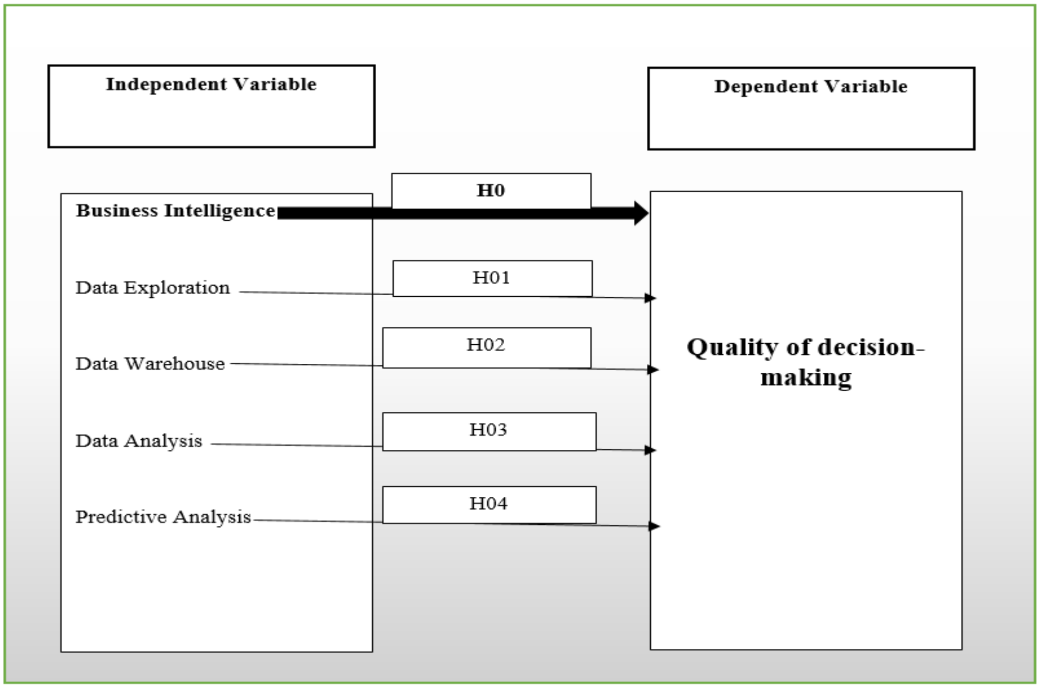
Summary:

The importance of BI is evident in the use of advanced technologies to gather information in order to improve commercial efficiency and improve staff members' ability to obtain the starting point of information they need to do their jobs effectively, as well as the ability to analyze and communicate this information with others. The BI software is used to assist with data analysis. Software for data warehouses, digital dashboards, and data mining are just a few examples. Because telecommunications and technology companies are exposed to more data than other industries, their conclusions must be simple, completely rational, accurate, and ready to be displayed in a way that adds value to decision-makers.

As the amount and complexity of data has grown, it has become more challenging for process management systems to maintain their efficiency. As a result, BI offers a number of features that allow them to collect, link, classify, and analyze data from a variety of sources, such as customer, distribution network, and competitor behavior, and display that data as knowledge for managerial decisions.

The study's concern is that when the Covid-19 outbreak struck Jordan, it had a detrimental impact on all industries, including telecommunications. Some staff worked online, while others were unable to work due to infection. Furthermore, during that time, people began to work online, teach online, take lessons online, and manage businesses online, which increased the use of telecommunications services. As a result, there was a lot of data reception, which put a lot of strain on the telecommunications sector and produced a lack of efficient and effective decisions at the time.

The goal of this study is to see how BI affects the quality of decision-making in Jordan's telecoms sector. Because BI is employed in so many areas, and one of the most crucial administrative roles is decision-making. In order to perform this study, 324 managers, supervisors, and employees from Jordan's telecommunications sector (Zain, Orange, and Umniah) were polled. Following the validation of the tool's normality, validity, and reliability, descriptive analysis was used to analyze the association between variables. Finally, employing SPSS, multiple regressions were employed to examine the impact.



BI is a term that refers to the applications, infrastructure, tools, and best practices that enable data access and analysis in order to improve and optimize decisions and performance.

The BI industry is gaining headway in today's fast-paced technology world by empowering industries to meet client requests. BI includes judgments of "what happened in the past" and "how it happened leading up to the present time." Although huge trends and patterns can be identified, their causes are unknown, and no predictions can be made. Furthermore, BI examines the reason for what happened (the why) and applies this knowledge to develop short- and long-term business predictions.

Since the inception of information systems and the documentation of their attributes, the goal has been to deliver the correct information to the right person at the right time and place. It aids in the creation of a huge database as well as the analysis of that database. The appropriate information will be transformed into knowledge, and this knowledge will help businesses thrive, rise, and capture new markets. They will also be able to provide better customer-oriented services, which will help them retain their current clients. Almost every firm now recognizes the value of data exploration in decision-making. **Data exploration** not only aids in the discovery of data from a variety of sources, but it also aids in the reduction of various costs, such as the cost of computer resources, as well as the time required for decision-making and knowledge research in order to create the best outcomes and output. The goal of data exploration is to find and collect information as soon as feasible.

The data exploration scheme and procedure organize each set of data units with the same data structure into a separate layer. Furthermore, the data exploration gadget gathers and attempts to govern data units across all frameworks.

A **data warehouse** is a good platform for serving the needs of different decision-makers. It acts as a decision-making aid, delivering conclusions to the company's decision-makers based on the data pattern reviewed. A data warehouse is created for any firm to allow decision-making operations through data gathering, storage, and analysis.

A data warehouse is a collection of tools for turning large amounts of data into useful information. A great volume of data is generated on a regular basis by numerous outlets, such as routine business processes and detectors from various operating systems. They're mostly stored into a data warehouse so that advanced study can be conducted on them.

A data warehouse assists in decision-making. Decision Support Systems (DSS) is a computer-based framework that assists decision-makers in using datasets to solve problems. DSS functions combine each person's abilities with the computer's capacity to maximize the correctness of the decision. DSS need data from a variety of sources in order to address the problem. Any problem must be answered, and any chance or strategy necessitates the gathering of data. As a result, data warehouse is a well-known organizational idea backed by well-known practices.

Data analysis is a constantly evolving concept with no universally accepted definition, data analysis for business is a broad word that encompasses a wide range of commercial operations. It basically explains how data processing is utilized to solve business issues. Collecting, standardizing, and analyzing data in order to recover business-oriented information for managerial decision-making are all part of this process. While the rapid evolution of data analysis has aided companies in achieving greater success, the rate at which technological innovations occur has also contributed to an increase in company failure. The speed and complexity of recent disruptions are unprecedented, as multiple business sectors are simultaneously impacted by multiple disruptive forces. Data analysis and BI in the context of firm performance have recently gotten a lot of press in major information systems (IS) publications, such as special issue calls, editorials, reviews, and academic notes. This is because businesses view data as a strategic asset that can be managed and integrated by information technology (IT) to help executives make better decisions and implement data-driven procedures. Data analysis is regarded to be an enabler since it boosts organizational effectiveness and has significant operational and strategic possibilities. For firms, data analysis has become increasingly important.

Predictive analysis is a technique for making decisions that removes uncertainty from the system and uses analytical processes to find the best solutions. The predictive analysis provides insight into the likelihood of probable breakdowns and rejections, allowing proactive actions to be made before issues develop. Predictive analytics solutions can be used to foresee a wide range of behaviors and trends, saving businesses time and money. Moreover, predictive analysis has changed the focus of decision-making, particularly strategic ones, away from "gut instincts" and emotion and toward fact-based and scientifically validated decisions. As a result, predictive analytical tracking could help with mentally taxing decision-making and pave the way for future advances. Predictive analysis, on the other hand, comprises analyzing previous evidence to forecast predicted behavior and effects.

The quality decision-making process includes planning, identifying alternatives, evaluating alternatives in terms of the desired purpose, and selecting solutions that will best achieve the goal. It is the process of selecting one course of action from a set of two or more options. The process of recognizing an issue, defining it, and picking the best solutions to handle the problem and its consequences is defined as the quality of decision-making process. Data quality and its application in efficient and effective decision-making has become an increasingly important factor in determining the long-term viability and success of modern businesses in recent years. In the decision-making process, the quality and accuracy of facts, information, and knowledge are frequently critical.

Decision-makers can use BI to find new ways to improve productivity or make faster, more informed decisions. Furthermore, in a dynamic organizational context, it can aid in improving the efficacy of operational standards and their impact on oversight mechanisms, organizational decisions, budgeting, financial and administrative recordkeeping, and strategic decision-making.

The most successful task of BI systems is providing data access, processing large amounts of data, and sending related subsets of data to the company's management fast. Decision-making and analysis based on BI facts have an impact on all businesses. We live in a world that is bursting at the seams with data and technology. As a result, the decision-making process of any company is crucial. In the age of information technology, computer software developers design and install software to satisfy contemporary business needs. BI can be seen from both a technological and an information search standpoint. According to the study, there is a favorable association between the maturity of BI and the overall quality of decision-making, particularly in large corporations. It increases operational efficiency by providing decision-makers with more understanding and intelligent results.

The findings show that BI has a direct positive impact on the quality of decision-making in Jordan's telecommunications sector (Zain, Orange, and Umniah)

The researcher also discovered that combining the benefits of the BI dimensions (data exploration, data warehouse, data analysis, and predictive analysis) had a beneficial effect on decision-making quality. The findings, in particular, show a clear path from BI to decision-making quality via data exploration, data warehousing, data analysis, and predictive analysis, substantiating the need for proper BI.

The point of the study is to determine whether BI dimensions (data exploration, data warehousing, data analysis, and predictive analysis) have an impact on the quality of decision-making in Jordan's telecommunications sector (Zain, Orange, and Umniah). A questionnaire was used to collect data, and its validity and reliability were assessed. After that, correlation and multiple regressions were used to assess the hypotheses.

The findings of this study revealed that in Jordan's telecommunications sector (Zain, Orange, and Umniah), data analysis has the highest implementation rate, followed by data warehouse, predictive analysis, and data exploration, in that order. Furthermore, the outcomes suggest that high-quality decision-making is implemented. The findings also revealed that there is a strong and positive link between BI dimensions, as well as a strong and positive correlation between independent and dependent factors.

The findings show that the overall BI has a considerable impact on the quality of decision-making in Jordan's telecommunications sector. Several key organizational tasks, including those that determine future objectives and goals, require a decision-making process, according to the conclusion above. As a result, the data utilized to make these decisions is a valuable asset that can have a significant impact on a company's success. BI is a powerful tool that aids decision-making by allowing information to be rapidly and easily analyzed and transformed into knowledge.

Jordan's telecommunications sector was the subject of the study. It is advised that a comparable study be undertaken in other countries, particularly in Arab countries, in order to generalize the current study's findings.

Because this study was done in such a short amount of time, it is suggested that it be repeated at a later date to monitor industry growth.

Extending the analyses to other industries and countries represents future research opportunities, which can be achieved by conducting additional tests with larger samples within the same industry, and including other industries will help mitigate the issue of generalizing conclusions to other organizations and industries. As a result, further research and data collecting from a range of countries are required. Furthermore, this study focuses on the telecoms industry. To see if the findings can be applied to other business areas, more research is needed.

Finally, more research in this area is needed because the same study criteria can be applied to different industries. Among them are the industries of manufacturing, insurance, banking, and education.