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The Effect of Data Visualization on the Quality of Decision-Making at Pharmaceutical Companies

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Abstract
Data visualization techniques can potentially support the decision-making process for many organizations, especially pharmaceutical companies dealing with a massive volume of data, but they use them at less-than-expected levels. However, this review summarizes the science and evidence regarding data visualization and its impact on decision-making behavior as identified by much previous literature. The current study aimed to determine the effect of the following data visualization techniques (temporal, geographic or spatial, hierarchical, network, multidimensional) on the quality of decision-making at Jordanian pharmaceutical companies. The quality of decision-making was measured by accuracy, confidence, and calibration. The study sample consists of (3) pharmaceutical companies listed on the Amman stock exchange. The researcher chose a random sample of (450) workers at these companies from different administrative levels as a sample for the study. The study found that data visualization techniques positively affect the quality of decision-making (accuracy, confidence, and calibration) at these companies. The study recommends the need for decision-makers in pharmaceutical companies to obtain as much accurate data as possible, impartial and timely information that helps diagnose the problem or situation on exact scientific and objective bases, to enhance the accuracy of their decisions.

Keywords: data visualization, data visualization techniques, decision making, quality of decision making.

Introduction:
With the technology advancements like social media platforms, data is deeply ingrained in our daily lives. Data has historically been equated with structured data in the enterprise area because it can be easily and precisely identified, categorized, stored, and queried (Siddiqa et al., 2016). The amount of data generated over time and as information technology advanced from various sources increased, leading to a "data explosion." This increase in data volume and complexity, or "big data," poses new organizational challenges because traditional data management philosophies and infrastructure cannot keep up with, process, and support significant data needs (Moore, 2017). Big data was divided into structured, semi-structured, unstructured, and streaming data by Kaur & Monga (2015); when used all together, this type of data is known as multi-structured data. Pictures and videos are examples of unstructured data because they are irregular and need to be organized systematically.

According to Siddiqa et al. (2016), Today, data has become notably embedded in our daily lives, propelled by technological advances such as social media platforms. In the enterprise domain, data has traditionally been synonymous with structured data, capable of being distinct, identified, categorized, stored, and queried. Its nature and type were homogenous, such as text, and was derived from limited sources, such as relational databases. Eberhard (2021) also stated that with the development of affordable and potent computer graphics, information visualization has expanded to become ingrained in our professional and personal lives daily. It can enhance human intellect and, eventually, decision-making. Data visualization has recently attracted a lot of attention and has found widespread use in various fields, according to Xin et al. (2018). Data is a treasure since it contains a wealth of important information. At the same time, it's a crucial duty to clearly and intuitively visualize the concealed information. However, with numerous recent innovations in system development and new research findings, data visualization is a rapidly expanding discipline. The fantastic success of data visualization, fueled by the majority (if not all) of domains and applications, has been made possible by research and practitioners from many other fields (Qin et al., 2020). Data visualization is defined as the graphical show of data to furnish the watcher with a subjective comprehension of the data substance. It is additionally the way to change items, ideas, and numbers into a structure that is apparent to the natural eyes (Khot et al., 2021).

Data analysis for decision-making in industrial settings close to the assembly line has transferred from the IT department to business units and operations in recent decades. It now employs more user-friendly tools and more powerful visual representations. Data visualization approaches can facilitate decision-making processes. Data transmitted to decision-makers is frequently most valuable when translated into values, gaining significance through formal rules and subsequent analysis. When confronted with visualization of specific types of knowledge, decision-makers may rely on their ability to interpret discontinuities, objects that stick out, and color and shape variations or to discern patterns using visual cues (Canonico et al., 2022). All organizations assigned the duty of choosing any action to a decision maker with relevant expertise, experience, and context understanding. Decision-makers rely on data analysis delegated to analysts or performed by decision-makers. Frequently, the decision maker blends ambiguous or partial facts with non-formalized knowledge within a multi-objective issue space, weighing analyst recommendations against broader contexts and goals (Dimara et al., 2022). Decisions making is crucial for every business, regardless of size or type, and it impacts every system component. However, for any decision-maker to make wise and precise decisions demands access to reliable information and an understanding of what information is crucial and how to use it in an information-intensive environment (Piri et al., 2020). Larose (2014) indicated that knowledge gives the decision-maker meaning, which entails a collection of information that has value or benefits the decision-maker, such as helping to solve an issue. According to Khatri & Gupta (2022), all types of managers require data and data visualization tools Today, particularly CEOs and other top executives who can view high-resolution screens with dashboard reports and analytics to check on whether projected trends for customer demand, market share, profitable decision making, and other factors are playing out as predicted. Additionally, marketing executives are putting in place cockpits to track the effectiveness of advertising campaigns across various media and to examine user sentiment on social media.

However, there needs to be more understanding of data visualization interventions particular to public health leaders' decision-making (Park et al., 2021). The effect of data visualization on the quality of decision-making at pharmacy companies also has not been thoroughly studied. Additionally, only a few researchers have looked at how data visualization affects human comprehension, perception, or behavior concerning decision-making using formal experimental methods (such as randomized controlled trials) and the effect of it on the quality of decision-making. Park et al. (2021) stated that the comprehensive data visualization literature analysis found little theoretical or methodological to support the impact of data visualization. Most studies needed more theoretical foundations for their research, which would have clarified why and how data visualization tools affect cognitive functions and decision-making behavior. This study focuses on data visualization definitions, processes, and techniques, their benefits to organizations, and their effect on the quality of decision-making at Jordanian pharmacy companies.

Data visualization concept:

The use of computer-supported, interactive, visual representations of abstract data to enhance cognition is known as data visualization or information visualization. Simple graphs like bar charts and modern visualizations like tree maps are among these depictions (Kim, 2022). Data visualization has been widely utilized to assist comprehension of complicated phenomena by integrating graphic production with picture understanding and enabling more efficient communication (Wang, 2015). Data visualization is a visual representation of information or concepts designed to effectively communicate the content or message and improve understanding in the audience (Padilla et al. 2018). Visualization, according to Eberhard (2021), is defined as the process of representing data in a range of imagery, from quantitative graphs to qualitative diagrams, to abstract visual metaphors or artistic imagery, to promote a specific behavior in the audience, and that is associated with effective communication in terms of clarity, speed, and the understanding of complex concepts. According to Gavrilova et al. (2017), knowledge visualization has a long history in visual communication and has lately been connected to visualization management. Knowledge visualization shares conceptual similarities with several basic administrative concepts.

Data visualization is also described as using a computer-supported, interactive visual depiction of data to enhance cognition, where the fundamental goal of insight is discovery, decision-making, and explanation (Card et al., 1999). According to Khot et al. (2021), data visualization is a brand-new and exciting field of study in software engineering. It involves presenting data in a graphical or pictorial format to make it easier to understand. Telea (2015) also defines data visualization as using visual aids like graphs and maps to help people comprehend, discuss, and promote group decision-making and collaborative engagement with data and information. Decision-makers can use data visualizations to understand data, acquire insight, find answers to particular queries, and uncover underlying truths. While according to Cardoso et al. (2018), data visualization explores, judges, and communicates ideas and messages through graphs, bar charts, or other comparable models often employed in financial reporting and controlling. Data visualization, according to Dasgupta et al. (2015), is a carefully designed graphic that depicts data in a way that allows one to get insights, improve understanding, detect patterns, trends, or anomalies faster, and promote engaging discussions.

Padilla et al. (2018) describe data visualization as a graphical representation of information consistently tied to the information it represents. The data could be about objects, events, or more abstract data. According to Khatri & Gupta (2022), data visualization is the graphical presentation of chosen data or abstract information for a variety of purposes, including describing the current problem or situation, comparing options and obtaining brief justifications for each, and gathering information about the level of uncertainty in both the internal and external environments to improve the quality of the decision-making process. Data visualization is also defined by Lurie & Mason (2007) as the selection, disclosure, or display of data using visual formats (pictures, tables, and graphs) to aid in decision-making. According to the dual coding hypothesis, high visualization is supposed to increase decision-making performance and accuracy. According to Eppler's (2013) definition, data visualization refers to all (interactive) graphic techniques that can create or communicate new understandings, procedures, or abilities. The primary goal of data visualization, enhancing the (inherently social) processes of knowledge creation and information exchange with others, is implied to extend beyond computer-based pictures.

Data visualization process:

Beginning with data collection in raw format, Fekete et al. (2008) have structured unified ways of successful data display. Given the nature of big data, source data must be automatically gathered using contemporary data collection techniques. After the data has been organized into categories, the sorting and analysis stage is next applied. The revision and abstraction stage is the next step, during which the focal data is chosen as necessary. Calculating the rates for some data categories or determining by taking small and large values of each group are two possible methods of analysis and selection. The following Figure (1) illustrates significant data visualization steps.

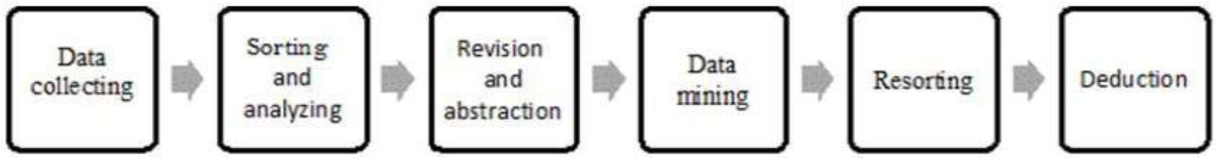

Figure (1)
Big data visualization steps

Data visualization technologies give decision-makers the pertinent and precise knowledge they need for the formulation and selection of options, according to Canonico et al. (2022). The translation of learning, sharing knowledge, and decision-making are all considered long and complex processes intimately tied to data visualization. When visualization tools are employed, they cannot be viewed as a single instance. The dynamic processes of data visualization are depicted in the following Figure (2).

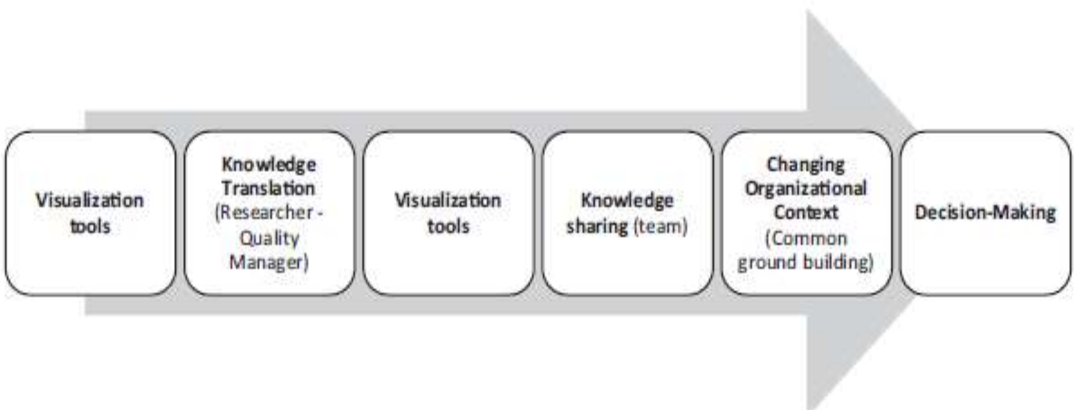

Figure (2)
The dynamic processes of data visualization

Several steps and pipelines are involved in data visualization, according to Qin et al. (2020), starting with data importation, which consists in obtaining the necessary data from a desired data source, followed by preparing the imported data for visualization, for example, normalizing values, correcting incorrect entries, and interpolating missing values, followed by data manipulation, which involves choosing the data to be visualized, and finally, mapping, in which the data obtained will be mapped. The following Figure (3) illustrates data visualization steps.

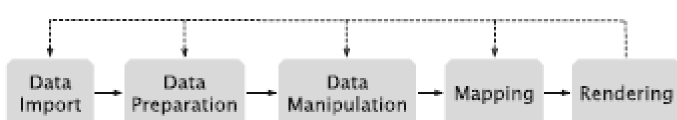

Figure (3)
data visualization steps

According to Patnaik and Vladicesco (2017), there are four fundamental steps in data preparation to ensure clean and quality data: data cleaning, which involves finding and fixing errors in the data, such as filling in missing values, smoothing noisy data, and identifying or removing outliers; data integration, which aims to combine multiple sources like databases, data cubes, or files into a single unified view, for example, cleaning, ETL mapping, and other transformations; and finally, data reduction which involves collecting a smaller sample of the data without sacrificing the accuracy of the research findings. This process also consists in improving classification performance by removing redundant or irrelevant records.

According to Khot et al. (2021), data visualization is a method of presenting and displaying data that encourages accurate comprehension, determination, and association. It uses human propensities for pattern recognition and design recognition, and it tests people's ability to quickly extract large amounts of information from pictures presented in a standardized manner. The Figure provides the data visualization flow (4)

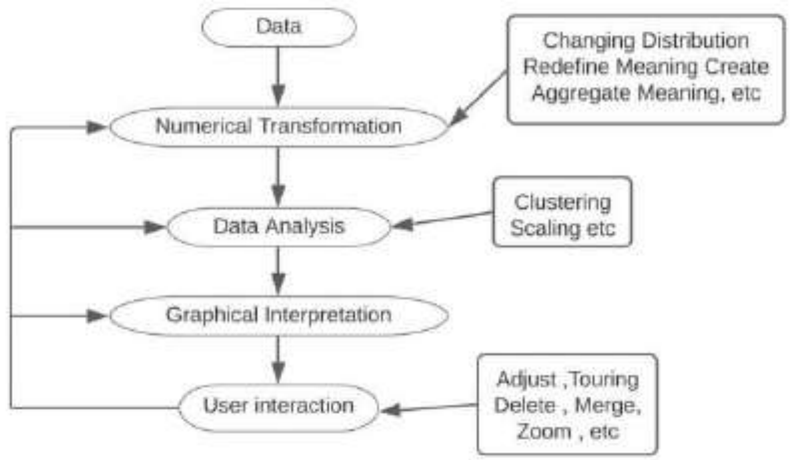

Figure (4)

Data visualization flow

According to Kaushik & Naithani (2016), there are standard processes in the visualization process. The process begins with data collecting from all accessible sources, the discovery of aggregate meaning for the data, and data analysis to start the process of interpreting the data graphically. The user then interacts with the graphical interpretation in the final stage. These actions are demonstrated in the following Figure (5).

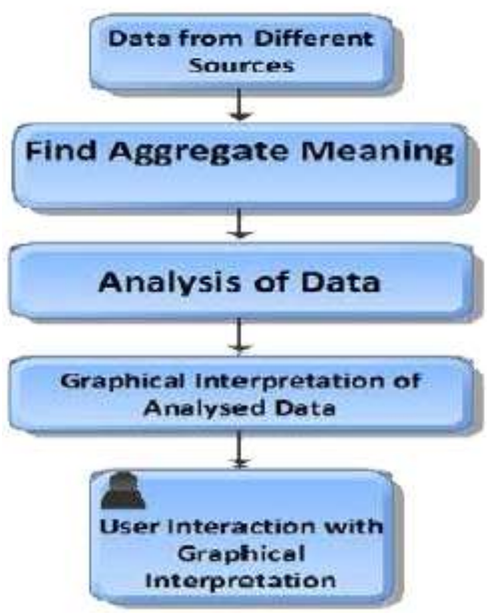

Figure (5)

Data visualization steps

Data visualization benefits:

Across social science research, many findings have supported the importance of data visualization for decision-making. Joshi et al. (2012) concluded that visual displays aid in effective and efficient decision-making by enhancing knowledge of complicated real-world problems using visual data and information from many sources. Decision makers can utilize information derived from data visualization techniques to effectively perform tasks they perform and improve the quality of their decisions. Savikhin et al. (2016) stated that by enhancing the amount of information presented and reducing the cognitive and intellectual load associated with interpreting information for decision-making. Data visualization uses specialized tools, technologies, and techniques to reflect information into visual representations that can be easily, efficiently, accurately, and meaningfully decoded to reduce the time, effort, and cost needed for accessing, reporting, and analyzing data as well as to improve the quality, precision, and effectiveness of decision-making. The strengths of data visualization come from our ability to process visual information much more quickly than verbal information (Khatri & Gupta, 2022).

Data visualization has played a significant role in understanding data, improving communication, and aiding the decision-making process, according to Jeong et al. (2021). Visualizations are also proven to reduce the cognitive burden when using mobile applications, allowing users to quickly scan the material while still fully understanding it. According to Khot et al. (2021), data visualization helps to clarify reality and choose blueprints. It will benefit any field of study that calls for creative ways to introduce vast, complex data. While according to Eberhard (2021), information visualization is a frequently utilized tool to enhance understanding and decision-making in strategic management decisions and a wide range of other fields.

Meanwhile, according to Dasgupta et al. (2015), dashboards are a type of data visualization technique that is also regarded as a particular decision support system. They serve as a visually appealing and intelligent tool for tracking KPIs and can gather essential data from various systems and display it in a condensed form. It can be characterized as a sophisticated user interface that uses graphs, gauges, tables, and other graphical elements to present data.

Almilia & Anas Hartika (2022), In their examination of chemical companies in the chemical industries, discovered that data visualization is frequently used, with information being provided in tables and graphs for their annual report. (1) Financial Summary, which includes an income statement, financial position statement, and ratio analysis; (2) Stock Information, which describes all of the company's shares traded on the stock market during a specific period; (3) Human Resources, which describes the enhancement of employee capability, maintenance, and welfare services for all employees, technically, functionally, and managerially; and (4) Management Information In contrast, the information that is graphically displayed is limited to financial summaries and stock information. Tang et al. (2014), information users can view the raw data in two different formats: graphical charts and numerical tables. It is intended for deeper knowledge installation, and greater understanding since the information in the graph engages the imaging system. The information in the number table activates the verbal system.

Dimara et al. (2018) presented various visualization tools to enhance decision-making tasks' quality. General-purpose tools often assist with any multi-attribute choice problem by displaying displays such as decision trees, interactive querying, algorithmic support, or more specific solutions allowing users to communicate attribute priority visually. According to Moore (2017), the benefits of data visualization include knowledge sharing by externalizing internal understanding, improving thinking capacity, and assisting in new idea formulation by decreasing a person's working memory; visualization can also create deeper relationship understanding and enhance the quality of decision making. While according to Dimara et al. (2022), data visualization purposes range from validating data authenticity or confirming a suspected trend to open-ended exploration in pursuit of insight or fun. Within organizations, these processes frequently serve the end aim of making decisions that will impact the company's structure, processes, or outcomes.

Even though many researchers have created unique data visualization strategies, according to Xin et al. (2018), visualization strategy is only appropriate to solve some issues. Visualization techniques differ according to many features and contexts, such as comparison; distribution; deviation; and part to the whole, as illustrated in the following Table (1).

Visualization feature	Visualization techniques
Comparison	Bar chart
	Box-plot chart
	Butterfly chart
	Scatter plot
	Stacked bar chart
	Table
	Line chart
Distribution	Bubble chart
	Box plot
	Parallel sets
	Circle view
	Scatter plot
Deviation	Box-plot chart
	Parallel sets
	Circle view
	Scatter plot
	Butterfly chart
	Waterfall chart
Part to the whole	Pie chart
	Parallel sets
	Stacked bar chart
	Treemap
	Waterfall chart
	Bar chart

According to Khot et al. (2021), big data visualization frequently surpasses the conventional techniques used in standard visualization, such as pie diagrams, histograms, and corporate charts. Instead, it uses murkier representations like heat maps and fever graphs. Some examples of the most popular strategies for data visualization are shown in the following Figure (6) and explanation.

- **A line graph:** that illustrates how items are related. It can be used to examine changes over time.
- **Bar graph**: This is used to analyze quantities of different kinds.
- **Scatter plot**: This two-dimensional diagram displays a range of two objects.
- **A pie chart:** is used to examine the constituent parts of a whole.
- **Maps**: Popular methods for imagining how data is used in various businesses are maps. The most well-known map visualizations include heat maps, dot distribution maps, and cartograms. They enable users to locate components on significant products and places, including topographical maps, architectural plans, site formats, and more.
- **Diagrams and matrices**: are frequently used to illustrate intricate data relationships and interfaces and to keep track of several data types for a single depiction. They may be tree-like, progressive, and multifaceted. One of the advanced data visualization techniques that helps

determine the relationship between several continuously updating (steaming) data sets is a matrix.

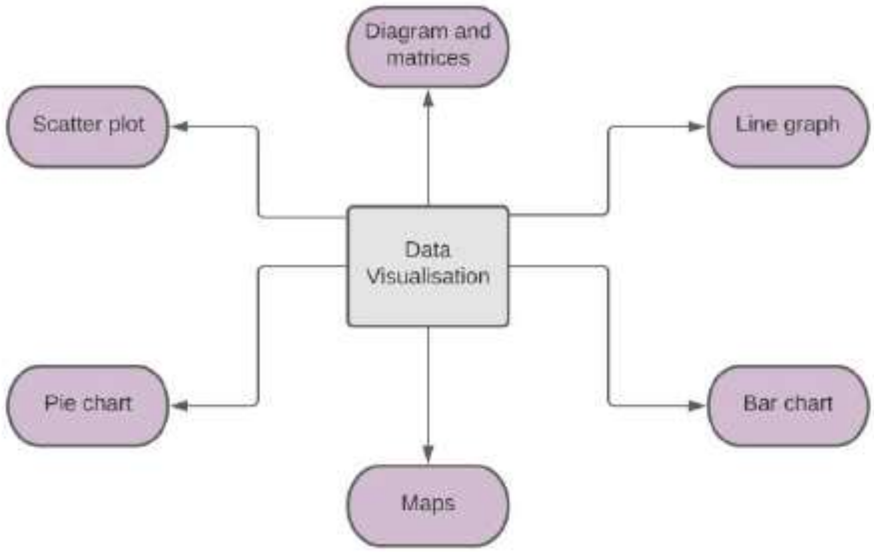

Figure (6)

Data visualization techniques

Data visualization Techniques and types:

Researchers' classifications and types of data visualization approaches vary, but they all agree that every kind of data corresponds to a particular visualization methodology. According to Kaushik & Naithani (2016), the most popular categories of data visualization techniques are temporal visualization, spatial visualization, Spatio-temporal visualization, describing data, viewing the relationship, picturing data (Icons, Glyphs, and Color Coding), and Spatio-temporal visualization. According to Shneiderman (1996), categorizing the data primarily into dimensions (i.e., 1D, 2D, 3D, multidimensional) while handling temporal and node-link data as specific examples is necessary for classifying data visualization kinds or methodologies. But the most efficient DV techniques are dimensional sets and sequences, like text or program source code; dimensional maps, like floor plans or other layouts; dimensional shapes, like molecules, buildings, or the human body; temporal timelines, like medical records, project management data, or historical presentations; multidimensional cases-by-variables structures with more than three variables. Schottler et al. (2021) reviewed 95 papers to survey visualization and interaction methods for geospatial networks. According to the study, the best types of data visualization depict spatial and network information. The combination of web and geographic information and extra information like node and connection properties, time, and uncertainty provide various issues when visualizing geospatial networks.

According to Stalph & Heravi (2021), each family of data visualization approaches posits a variety of various charts kinds that are organized according to their primary objectives. An overview of the elements of data visualizations in the analytical framework, along with their operationalized variables, is shown in the accompanying Figure (7).

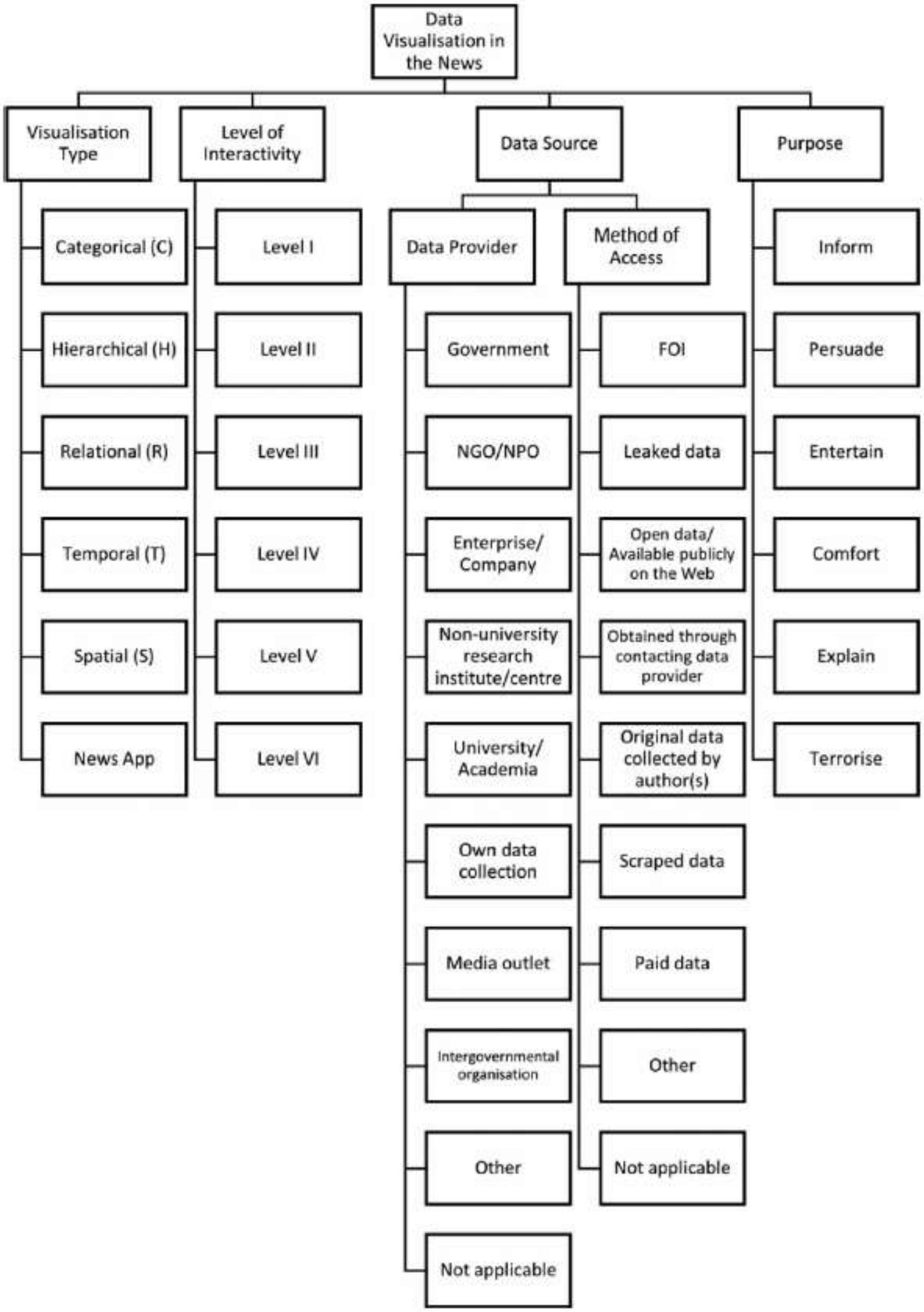

Figure (7)

Components of the Data Visualization Analytical Framework

Numerous methods are currently being used or developed to visualize spatial and spatiotemporal data. Innumerable fields, including daily life activities, the weather, health care, economics, social media, politics, and science, frequently use visualization techniques. The history of temporal data management is long. People have utilized timelines (a method of displaying a list of events in chronological order) since the very beginning to record their transaction data in log files or tables, and scholars frequently use such files or tables to study the events or trends of the transaction.

However, most temporal approaches emphasize philosophical or illustrative themes rather than rationally moving toward understanding events while considering temporal data (TabinHasan et al., 2013). With the use of analytic data techniques and interactive technologies, Spatiotemporal data visualization technology enables users to have a more immersive virtual experience by allowing them to more intuitively and effectively comprehend the information, knowledge, and wisdom hidden within the data. In the age of the information explosion, it has developed into a potent tool for individuals to evaluate and manage data (Yang et al., 2018). Interaction-based temporal visualization techniques, such as scatter maps and heat maps, can add information to each point when you click your mouse, in addition to using one point's shape or color to represent numerous qualities. However, according to Wang et al. (2017), spatial, temporal data visualization is a potent tool that can transform data into a visual framework and make the essential information simple for a human to understand. It could be utilized in all phases of emergency management and help geographical analysis and decision-making. According to Persson (2020), there are numerous visual representations for the depiction of spatiotemporal data, and the most popular ones are the most universally understood. The choropleth map can be used in many contexts and is simple for beginners to grasp. It provides a clear understanding of the material and is relatively logical and clear. There are numerous applications for basic 2D trajectory maps. Suppose the issue is posed from the perspective of the user. In that case, it turns out that the most common visual representations are simple, intuitive visualizations that most people can quickly understand.

According to Andrienko et al. (2003), the advantages that various tools of the temporal data visualization technique offer for decision-makers can be demonstrated by the features of each device. However, this visualization deals with information concerning actual occurrences, such as spatial objects going through existential changes, information representing changes in the spatial characteristics of things, particularly places, and time variable values of these aspects. Shaito et al. (2023) found that different techniques are used in spatial data visualization: choropleth maps; heat maps; dot maps; hexagonal binning; bubble maps; and cartogram maps. The most common spatial visualization technique was a heat map, which identifies relationships between data points and generalizes trends. According to Divyashree & Thomas (2016), Maps of any kind, including 2D, 3D, and others, can be used to visualize spatiotemporal data. The primary mapping technique is cartography. Using GIS, it is also possible to view the data by layering various map types on top of one another. There are several popular data visualization approaches, but it is essential to choose which ones to use based on the application's needs.

Geographic or spatial data visualization is one of the DV techniques. Wada et al. (2022) stated that many map-based visualization applications for decision-making had been proposed with the rapid growth of information technology and geographic information science. These applications are used in various contexts to generate insights into vitality concerning data nature. Geographic visualization, as defined by Nöllenburg (2006), is the use of visual geospatial displays to explore data and, through that exploration, generate hypotheses, develop problem-solving strategies, and construct knowledge. Geographic visualization is significant because it makes exploring, analyzing, synthesizing, and presenting data simple and effective. Hedley (2003) discovered that various perceptual and task-based activities for users of geographic visualizations appear to benefit from augmented reality interfaces over desktop interfaces. The internal representation measures that were used (video analysis, sketch and verbal protocol analysis, timed and untimed perceptual and judgment tasks, survey responses, interview responses, forced choice, and recall tasks) suggested that when geographic visualizations were used, people developed more thorough and detailed internal representations than when desktop interfaces were used. Silva et al. (2020) emphasized the significance of geographic visualization, pointing out that it differs from other strategies that include simple statistical summaries, such as mean and variance, which can produce ambiguities and conceal significant data patterns. The design space is significantly constrained by this technique, which relies on (for example, choropleth maps) that use the location (and perhaps the color) visual channel to portray the geographical context. Meruga (2019) argues that geographic visualization is crucial for decision-makers since it offers information on location and industry. More facts can be added to the decision-making process by adding dashboards with other data, such as demographics, asset value evolution, market statistics, employment markets, crime rates, taxes, etc. Conclusions are more exciting and correct when there are more data variables. Which, in turn, leads to the development of plans and tactics that assure the survival and prosperity of organizations.

Hierarchical visualization is considered to be the most effective type. However, a genemultidimensionalonal aggregation pyramid (MAP) model was chosen by Guan et al. (2020) and is based on the 2D Tile Pyramid and the Spatiotemporal Cube, two well-known graphics concepts. The suggested MAP model can enable simultaneous hierarchical aggregation of time, location, and characteristics, as well as the eventual transformation of the aggregates into discrete key-value pairs for scalable storage and effective retrieval. According to Mansmann et al. (2007), hierarchical layouts are the best types of data visualization because they naturally demonstrate the step-by-step breakdown of aggregate values. By exhibiting examples from diverse domains and the visualization methodologies effective for completing particular analysis tasks, this tool can serve a variety of application situations. Wang et al. (2021) also identified the advantages of hierarchical visualization due to its capacity to simultaneously explore global features and specific characteristics, provide in-depth insights into potential features, and adaptively present multi-scale clusters with lower coefficients of variation. According to Müller et al. (2017), hierarchical visualization has various scientific and commercial applications. Treemap, icicle plot, and node-link are a few of the related techniques that have been created and improved over the past few decades. However, treemap only outperforms the chance level for one straightforward task and draws visual attention more effectively to pertinent features. According to Zheng & Sadlo (2021), hierarchical visualizations are thought to be an effective tool that decision-makers could use. It provides a brief explanation of the external environment's actual state and challenges. It has many methods, such as the sunburst chart, the icicle plot, the circular treemap, and the bubble treemap. A qualitative examination of 18 hierarchical visualization techniques described in the literature was carried out by Paes Gusmo et al. (2016). The utilization of the dynamic elements provided by the funnel plot graph made it the most effective tool since it allowed for greater visual exploration, better and quicker interpretation of the pertinent data, and, finally, further data exploration through analysis, which improved user cognition. According to Schulz et al. (2011), there are numerous varieties of hierarchal visualization, including Contour Maps, Bubblemaps, Grid Treemaps, Context Treemaps, Treemaps with Textures and Bump Mapping, Filled Unbursts, and Hybrid Sunburst/Treemap (essentially a 2-sided Icicle Plot). However, to achieve the most significant results, it must combine various layout strategies; otherwise, parametrizing a layout based on a subtree's width/depth would produce distinctive visuals that, on their own, are illustrative of the hierarchy they represent.

Network data visualization is another technique, which addresses how to display and present big data in both the exploratory and discovery processes, and link analysis, which addresses how to communicate and demonstrate the intelligent data produced from these processes, are two typical deep models with two use cases that are included in network data visualization, according to Zhao et al. (2019). utilizing a variety of visualization methods, including lexical link analysis, Tableau, and D3. Decision-makers can quickly employ these visuals to obtain greater sense-making and decision-making by turning them into interpretable and explicable deep models. Ulrik et al. (2006) state that the network data visualization technique has many potentials and supports the decision-making process in many aspects, which include documentation of the data's origins and characteristics, the steadfast enforcement of appropriate comparisons, the quantitative expression of cause-and-effect mechanisms, the recognition of the inherently multivariate nature of analytical problems, and the examination and evaluation of alternative explanations. According to Schulz & Schumann (2006), network representations can be classified as explicit or implicit or based on how much of their node structure is predetermined. However, the specific top-to-bottom ordering of trees, tapped mainly by tree visualization approaches to develop an appropriate layout, must be present in network data visualization. However, it is typical in many application areas to steer the network's edges and impose an ordering on it. According to McGuffin (2012), network visualization visually displays linked or networked data. It belongs to the broad topic of data visualization and is also known as graph visualization or connection analysis. Several benefits of network visualization can change the game for teams operating in various industries, including Gain insights more quickly, comprehending data intuitively, being flexible and dynamic, communicating ideas efficiently, and improving the decision-making process. Composite View, an open-source Python-based tool that interfaces with Cytoscape Dash to enable interactive user editing of visible data and associated derived composite scores, is one of the most crucial types for network data visualization, according to Allegri et al. (2022). To lessen information overload, composite scores are defined representations of smaller groups of conceptually comparable data that, when combined, yield a single value. The user can modify the interactive visual results using filtering tools like sliders for node value and edge weight and choices for manipulating the graph (e.g., node color and layout spread).

The effect of data visualization on decision-making:

Data-driven decision-making (D3M) has been highlighted as a practice that adds value to business decision-making. D3M leverages data to produce evidence-based information for end-user decision-making through improved analytics and related information management systems (Cao, 2010). The framework offers six cognitive processes that help the decision-maker choose after gathering data from data visualization techniques, as shown in Figure (8) (Moore, 2017). Data must first be collected; therefore, the decision-maker chooses which data from which sources are pertinent. After that, it must be structured or classified to make sense of the data. This procedure converts data into information from which meaning can be deduced. The decision-maker can then start the analytical processes, checking the accuracy of the initial hypothesis (Chowdhury, 2010). The analysis findings will now be summarized. A specific problem could have many different situations and dimensions depending on the information in the overview. The decision-maker must synthesize or combine information, prioritize knowledge, and frequently use judgment based on prior experiences to develop an understanding (Siemens, 2014).

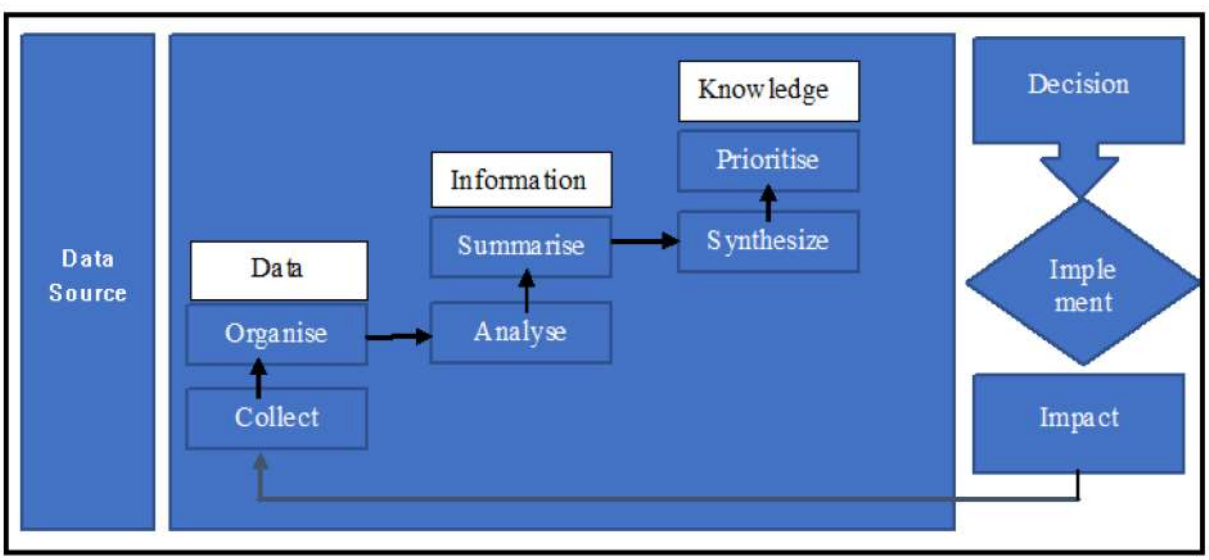

Figure (8)

Data-driven decision-making (D3M) framework

Park et al. (2021) stated that data visualization technologies have the potential to help public health professionals make decisions. Visualization benefits decision-making by increasing the amount of information supplied and minimizing the cognitive and intellectual cost of interpreting information. Data visualization affects attitude, perception, and decision-making compared to controls. Mediating factors such as perceived trustworthiness and quality, domain-specific expertise, basic ideas shared by social groupings, and political opinions were used to explain these correlations. Alharthi & Gutub A. (2017) found that data visualization is a very effective way to take advantage of big data and help decision-makers to optimize services, especially in Hajj services. It allows decision-makers appropriately act in each governmental and private agency to the best possible affecting all operations steps, such as planning, implementation, modification, and evaluation. However, Eberhard (2021) concluded that information visualization has complex moderating and mediating effects essential to comprehending visualizations' total power. These impacts range from decision quality and speed to confidence and attitudes. Since managerial decision-making frequently relies on big, unstructured data sets that are computer-centered, dynamic, and require consistent interpretation under time constraints, it is particularly well-positioned to benefit from compelling visualizations.

Rokhayati et al. (2019) found that information visualization or information presented in tables or graphs consisting of concise illustrations can improve decision-making quality and efficiency by enabling quicker and more accurate comprehension and management of data without experiencing information overload or a lack of information. The way information is presented and how decisions are made. Investor confidence in the decision is influenced by how simple the material is to understand. According to Piri et al. (2020), data visualization using tailored dashboards aids university decision-makers in spotting trends, advantages, and disadvantages. Additionally, information that has been visually represented might assist users in making decisions and gaining new perspectives. Academic managers can compare their performance in national and international rankings in addition to improving their performance, productivity, decision-making, and service quality.

Data analysis and visualization are becoming increasingly important to financial performance management, according to Khatri & Gupta (2022), who said that business and finance managers rely on them to measure performance indicators and suggest a budget, forecasting, and planning applications. Visualization can speed up the performance management process and improve the standard of decisions made throughout the organization. According to Cassenti et al. (2019), data visualization can enhance the accuracy of law enforcement decisions compared to raw data. Sen & Boe (1991) found that data visualization has a positive effect on decisions making process; the accuracy of decisions is increased when using data visualization techniques. Meanwhile, Falschlunger et al. (2015) stated that data visualization's effect on decision quality could be achieved by enhancing the accuracy of the decision. Correll & Gleicher (2014) found that confidence in decision-making could be achieved and enhanced by using information visualization techniques.

Data visualization supports decision-making in conceptual design, according to the findings of Xin et al. (2018). demonstrating a prototype made up of four methods for concisely and comprehensibly visualizing multidimensional data, showing how "hidden" information and patterns have a significant impact on supporting decision-making, particularly concerning fuel consumption strategies and related decisions. According to Almilia et al. (2019), the visualization effect in decision-making only has an impact when decision-makers are given assignments that are not overly difficult. The level of precision, confidence, and calibration are all indicators of how the complexity of the work affects decision-making. Utami and Nahartyo (2016) investigated the usefulness of group support systems (GSS) and the influence of data visualization techniques in reducing information ambiguity in audit judgments. They demonstrated that the more ambiguous a set of supplied data is, the less accurate the audit decision will be. They also discovered that GSS-based interactive reviews could improve audit decision accuracy and quality.

Eppler & Platts (2009) found that data visualization techniques positively affect the strategic planning process, which prompts the achievement of quality and effective strategic decisions. Data visualization techniques positively impact decision-making, especially in the following dimensions: accuracy; memorability; statistical reasoning; and judgment, which in turn enhance the quality of decision-making, according to Bancilhon et al. (2019). While Khatri & Gupta (2022) state that organizations should consider how they can match visualization technologies and practices to user requirements, train users and give them the skills and expertise necessary to work on such tools and techniques. Users need data visualization for various decision-making and analytics activities, including reporting, scorecards, operational alerting, and data discovery and analysis. Allahabad (2018) The value of data visualization enhances the power of communication between all organization members; it also discovers the realities in the outside market, the strength and weaknesses in both internal and external environments, which in turn provide the decision maker a solid base for reaching a precise and quality decision by choosing the best of identified alternatives.

Canonico et al. (2022) discovered that information visualization and accompanying tools facilitate knowledge translation and knowledge sharing, hence assisting decision-making. Knowledge visualization is viewed as both a collaborative and interactive process and a systematic strategy in which various actors translate their expertise, share a framework, and build common ground to improve decision-making quality. According to Benn et al. (1994), data visualization promotes critical problem-solving and quality decision-making processes: differentiating a problem from its symptoms and choosing and carrying out a course of action. The creation of graphs and the facilitation of organized mental processes are the initial goals of visualization. While according to Almilia & Anas Hartika (2022), task complexity has a more significant impact on nonprofessional investors' investing decisions than information visualization. The amount of accuracy, trust, and calibration in amateur investors' decision-making can be decreased by highly complicated tasks requiring high levels of visualization of the information. This is because a nonprofessional investor is more concerned with the difficulty of the tasks. Therefore even a high degree of information visualization is ineffective when making investment decisions.

However, and according to the previously mentioned literature, the study took into account five techniques of data visualization techniques which are: (temporal, geographic or spatial, hierarchical, network, multidimensional) because it has a positive effect on the quality of decision-making in many fields, so the current study hypothesized that the following data visualization techniques (temporal, geographic or spatial, hierarchical, network, multidimensional)positively affect the quality of decision making at pharmaceutical companies at Jordan.

Decision-making process:

Company management in the twenty-first century is quite challenging and intricate. Since management decisions frequently determine the firm's and its employees' future, a thorough investigation of the decision-making process is required. However, a manager's choice is influenced by various variables, including the manager's knowledge, experience, and capacity for comprehending the process and objective variables. Professional managers will be conscious of their responsibility for their judgments; it should be noted (Khakheli & Morchiladze, 2015).

The concept of decision-making pulls from various fields, including management, psychology, economics, and mathematical modeling. It comes down to weighing the pros and cons of many options and selecting the best one. The theory presents three methods of decision-making: intuitive-emotional, political-behavioral, and rational-analytical (Ilori & Irefin, 1997). To better understand how people make decisions when faced with danger, decision-making scholars have mainly followed two lines of inquiry. The first presupposes that people make well-informed decisions that can be quantitatively represented based on weighted and ordered probability functions. The second suggests that people frequently use heuristics in their intuition (Padilla et al., 2018).

The study of locating and selecting alternatives by the decision maker's values and preferences is known as decision-making. Making a choice implies that there are other options to take into account. In this situation, we want to identify as many options as possible and select the option that best aligns with our goals, objectives, desires, values, and other factors (Davidaviien et al., 2020). The ability to decide between possibilities after weighing two or more is known as decision-making (Brown et al., 2011). The most crucial elements of the decision-making idea identified in literary formulations are preference and choice.

Decision-making, in the words of Vroom & Yetton (1974), is a social process. They created five decision-making philosophies, which managers can use in each challenging circumstance.

The decision-making style considers the decider's personality. It is based on how he acts, such as whether he involves a group in the decision-making process or makes the decision alone. The following styles are mentioned in the literature: emotional, intuitive, collaborative, rational, and cognitive (Negulescu, 2014). The three steps of the decision-making process, according to Chestnut (2013), are identification, creating decision components, and implementation. Alternatively, according to Doyle (2012), the decision-making process entails five primary phases, namely the identification of the decision to be made, the examination of the options, the gathering of information, the decision-making process, and the implementation of the decision. Litherland (2013) asserted that seven steps in the decision-making process are frequently used by most managers, starting with the definition of the problem, followed by the identification and restriction of the factors, the development of potential solutions, the analysis of the alternatives, the selection of the best option, the implementation of the decision, and the establishment of a control and evaluation system. These claims are demonstrated in the following Figure (9). While according to Bizer et al. (2012), there are several processes in gathering data, starting with data collection and ending with decision-making. In this procedure, six steps must be considered: data collection, data storage, data searching, data sharing, data analysis, and data visualization.

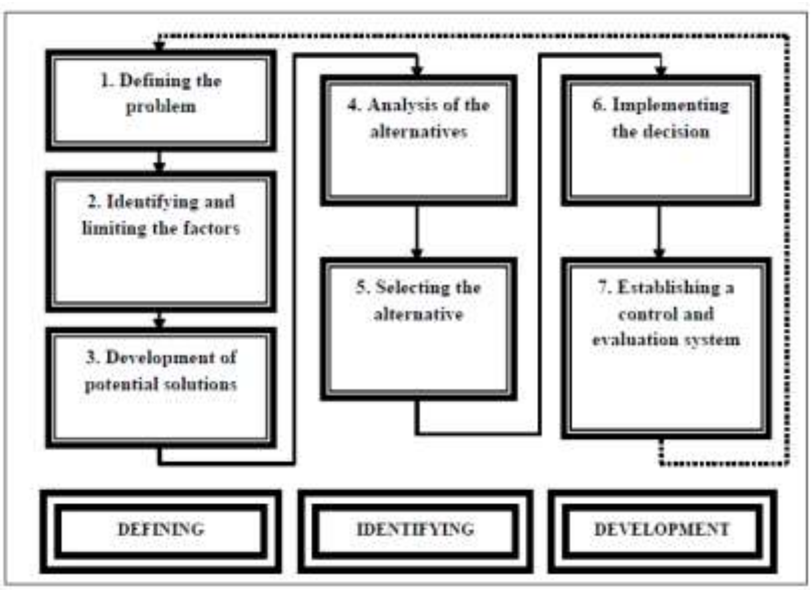

Figure (9)

Seven processes of decision making

Diverse researchers in different fields have examined the quality of decision-making dimensions. According to Oriana Negulescua & Doval (2014), the effectiveness and timeliness of decision-making are the primary factors in determining whether a board succeeds or fails. For effective decision-making, it is essential to identify goals, offer alternatives for resolving issues, and analyze and balance competing interests and values. Because of this, risk analysis must distinguish between potential solutions. The accuracy and confidence of the decision are the most critical indicators of a manager's performance, claim Kozio-Nadolna & Beyer (2021). The fact that decisions are made at every level of management and affect both the top management and every employee in the company must be underlined.

According to Chung and Monroe (2001), task complexity is a crucial consideration in decision-making because it impacts the degree of accuracy, degree of confidence, and calibration level, which are the characteristics of decision-making quality. Almilia & Anas (2022) similarly concluded that data visualization approaches are helpful in decision-making, particularly when decision-makers are given straightforward tasks. The results also showed that decision-making quality, as determined by the degree of accuracy, degree of confidence, and degree of calibration, is influenced by the complexity of the assignment. A dual-process theory of decision-making with visuals receives strong direct and indirect support from a review of empirical investigations of decision-making with static two-dimensional representations that Padilla et al. (2018) conducted. Fast, simple, and computationally light decisions were deemed higher quality than longer, more thought-out, and labor-intensive decisions that used visuals. According to DeLone & McLean (1992), the suitability of decision-making is influenced by data quality and variety, accuracy, timeliness, completeness, consistency, relevance, and timeliness. Finally, Negulescua & Dovaal (2014) claimed that it is possible to identify elements that directly affect decision-making. The most important factors influencing choice effect are typically personal decision-making behavior, group limits on it, and member interaction behavior. These variables are summarized in the following Figure (10).

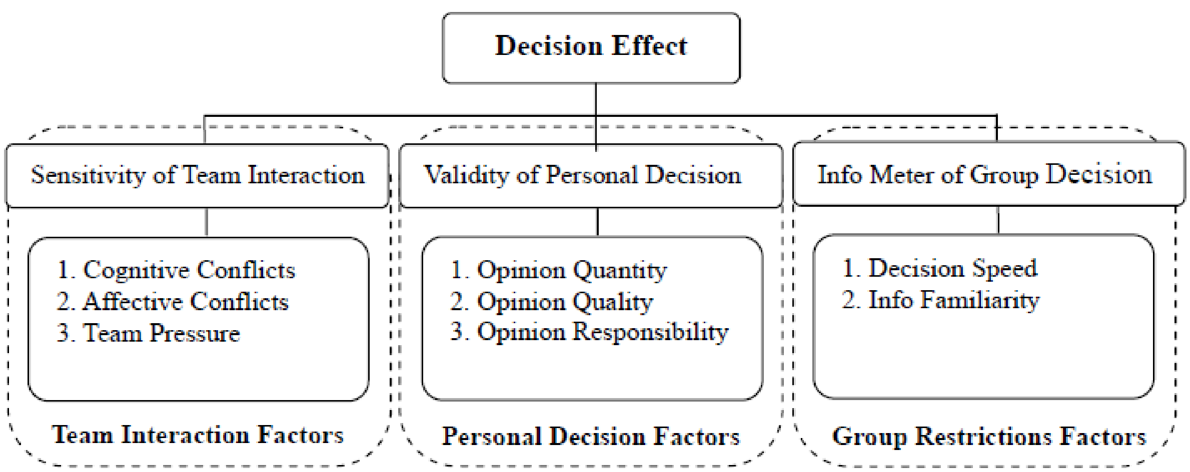

figure (10)

Decision quality influencing factors

In this study, the researcher has measured the quality of decision-making by three dimensions: the level of accuracy, confidence, and calibration. It has been hypothesized that data visualization techniques positively affect each of them.

The study framework and hypotheses:

Figure (11) describes the variables included in this investigation. The factors include the independent variable, data visualization techniques, and the dependent variable, the quality of decision-making. Data visualization techniques were measured by many variables derived from previous literature, which are (**temporal, geographic or spatial, hierarchical, network, and multidimensional**), ex. For temporal visualization (TabinHasan et al., 2013; Wang et al., 2017; Persson, 2020; Divyashree & Thomas, 2016). For geographic visualization (Wada et al., 2022;

Nöllenburg, 2006; Silva et al., 2020; Meruga, 2019). For hierarchical visualization (Guan et al., 2020; Mansmann et al., 2007; Wang et al., 2021; Müller et al., 2017; Zheng & Sadlo, 2021; Gusmo et al., 2016). For network visualization (Zhao et al., 2019; Ulrik et al., 2006; Schulz & Schumann, 2006; McGuffin, 2012; Allegri et al., 2022). For multidimensional visualization (Kaushik & Naithani, 2016; Shneiderman, 1996; Schottler et al., (2021; Stalph & Heravi, 2021). At the same time, the dependent variable, which is the quality of decision-making sub-variables (level of accuracy, level of confidence, and level of calibration), were derived from previous literature ex. (Negulescua & Doval, 2014; Kozio-Nadolna & Beyer, 2021; Chung & Monroe, 2001; Almilia & Anas, 2022; Padilla et al., 2018; DeLone & McLean, 1992).

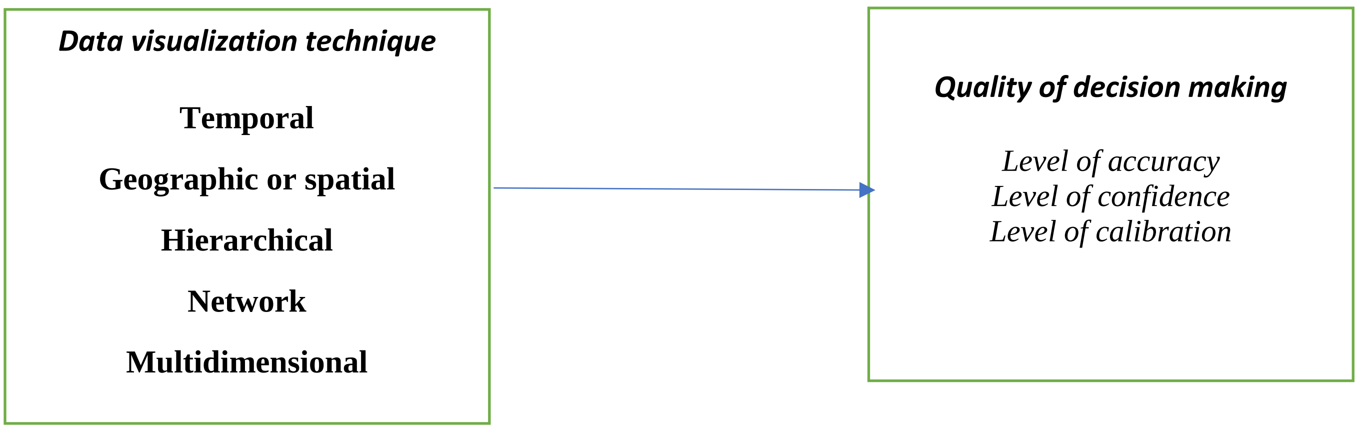

Figure (11)

Research Model

Hypotheses development:

As illustrated in Figure (1), a total of three hypotheses were proposed based on the relationships between three constructs as described in the previous literature; data visualization techniques are considered to have a positive and robust effect on the quality of decision-making, according to that the study hypothesized the following hypotheses:

(H01): There is no statistically significant effect (a ≤ 0.05) of data visualization techniques (temporal, geographic or spatial, hierarchical, network, multidimensional) on the quality of decision (level of accuracy, level of confidence, level of calibration) at the Jordanian pharmaceutical companies listed on the Amman Stock Exchange.

(H02): There is no statistically significant effect (a≤ 0.05) of data visualization techniques (temporal, geographic or spatial, hierarchical, network, multidimensional) on the decision level of accuracy at the Jordanian pharmaceutical companies listed on the Amman Stock Exchange.

(H03): There is no statistically significant effect (a≤ 0.05) of data visualization techniques (temporal, geographic or spatial, hierarchical, network, multidimensional) on the decision level of confidence at the Jordanian pharmaceutical companies listed on the Amman Stock Exchange.

(H04): There is no statistically significant effect (a≤ 0.05) of data visualization techniques (temporal, geographic or spatial, hierarchical, network, multidimensional) on the decision level of calibration at the Jordanian pharmaceutical companies listed on the Amman Stock Exchange.

Study Methodology:

This section includes a description of the methodology and procedures used by the researcher in the study, as well as an introduction to the study community and its sample, a presentation of the functional and demographic characteristics of the study sample, the study tool, building procedures, and validity and reliability, in addition to the description and statistical treatments that were used in analyzing study data, and drawing conclusions. The researcher used the "quantitative descriptive analytical approach" to collect and analyze data to answer the study's questions and verify its hypotheses. A field survey was conducted at Jordanian pharmaceutical companies, and data were collected from community members at all administrative levels. Then the researcher analyzed the data and information gathered using appropriate statistical methods to come up with the results and recommendations to show the impact of data visualization on the quality of decision-making.

To carry out this research, a three-phase plan was implemented: research design, data collection, and lastly, data analysis and discussion of findings. Starting with a general understanding of the investigated topic, which is the impact of data visualization on the quality of decision-making at Jordanian pharmaceutical companies. A questionnaire-based quantitative approach was employed to collect data from study respondents. The questionnaire instrument was divided into three parts: first, demographic information; second, the data visualization techniques dimensions; third, the quality of decision-making dimension. All questionnaire questions were developed according to previous literature, and the answers were based upon the Likert scale in which strong agreement=1 to strong disagreement=5. The literature was used to derive the items for each factor, modifying this research's specific setting. The researchers ensured that the questionnaire was simple for participants to read, comprehend, and complete appropriately. Data were analyzed using the Statistical Package for Social Sciences (SPSS). In addition to the reliability and validity tests, multiple regression analyses were carried out. The results were based on accepting or rejecting the hypotheses and addressing the issue of research.

Study Sample:

One of Jordan's most vibrant businesses is the pharmaceutical sector. In 1962, the first pharmaceutical company was founded. Three more companies were established in the 1970s, and three more entered the market in the 1980s. The establishment of nine companies during the 1990s led to remarkable growth in the sector. This growth was directly related to the Gulf War's flow of capital from the Gulf states and the Jordanian government's adoption of several investment-related laws and procedures to promote and facilitate foreign investment in Jordan (Amman Chamber of Industry). The study sample consists of (3) pharmaceutical companies listed in the ASE with a capital of 48 million JOD out of 14 companies with a wealth of 187 million JOD. The study excluded the Jordanian pharmaceutical companies not listed in ASE because of the difficulty of data received and the absence of certified data collection for scientific research. The study sample was only (3) companies listed in ASE, which are:

(Dar Al-Dawa for Development and Investment, Al-Hayat Pharmaceutical Industries, Philadelphia Pharmaceutical Industry), and the selection of pharmaceutical companies as a community for the study came due to the importance of this sector and the increasing risks it is exposed to in light of global competition and economic openness. The members of the study community consisted of all department managers and workers in the various departments of the companies, the study sample in the multiple branches amounted to (1663) male and female workers from different administrative levels, according to the statistics of the human resources departments in the study sample companies. Due to the large size of the study community, the researcher chose a random sample Represented by (450) male and female workers from different administrative levels as a sample for the study (Sekaran, 2016), where the researcher distributed (450) questionnaires to the study sample (420) questionnaires were retrieved, of which (93.3%) are valid for analysis, as shown in Table (2).

company name	Total distributed questionnaire	Total recovered questionnaire
Dar Al-Dawa for Development and Investment	236	222
Al-Hayat Pharmaceutical Industries	121	115
Philadelphia Pharmaceutical Industry	93	83
Total	450	420
Percentage	100%	93.3 %

Table (2)
Study sample

Validity and Reliability Tests

Validity is defined by Smith (1991, p106) as "The degree to which the researcher has measured what he has set out to measure." All extracted components have a value greater than 0.5, which is acceptable (Santhi el at., 2001). While reliability test Cronbach's Alpha to indicate the reliability of the data, Cronbach's Alpha must be between 0.7 and 0.99 (Gliem and Gliem 2003). Table () shows that the values of internal consistency stability coefficients according to the Cronbach alpha method for the paragraphs on the dimensions of visualization of the data ranged between (85.50-94.00), while the Cronbach alpha stability coefficient on the sections of the tool as a whole reached (89.66). It also shows that the values of internal consistency stability coefficients according to the Cronbach alpha method for items on the dimensions of the decision quality tool ranged (from 89.70-80.60), and the stability coefficient of Cronbach alpha for the items of the device as a whole was (0.86). The reliability coefficient of Cronbach alpha for the tool items was (88.28), and these values are considered suitable for the current study, which is the case here. The exceptionally high Cronbach's alpha for all the structures is likely due to the objects' extraordinarily high internal consistency, which could explain their extremely high Cronbach's alpha (Weerakkody et al. 2016).

Factor	Cronbach's Alpha	Number of Items
Temporal data visualization	91.40	5
Geographical or spatial data visualization	85.50	5
Hierarchical data visualization	94.00	5
Network data visualization	87.70	5
Multidimensional data visualization	89.70	5
Independent variable average	**89.66**	25
Accuracy	80.60	5
Confidence	89.70	5
Calibration	87.70	6
Dependent variable average	**86**	16
Overall Value	**88.28**	41

Table (3)
Reliability testing

Data analysis and Results:

Demographic Analysis:

The following Table (4) presents the descriptive statistics and the description of the demographic and functional characteristics of the study population, which are represented by the variable of gender, age, job title, years of experience, and educational qualification. Therefore, the frequencies and percentages of all variables were extracted as follows:

Demographic Object	***The valid items***	***number***	***Percent %***
Gender	male	233	55.5
	female	187	44.4
Age	30-less than 30	91	21.7
	30- less than 40	142	33.8
	40- less than 50	125	29.8
	50 and more	62	14.8
Education level	Diploma	52	12.4
	Bachelor	169	40.2
	Masters	136	32.4
	PhD	63	15.0
Job experience	Less than five years	43	10.2
	5- less than ten years	180	42.9
	10- less than 15 years	117	27.9
	15- less than 20 years	65	15.5
	More than 20 years	15	3.6

Table (4)

Demographic Analysis

The results show that the most significant percentage of the study sample members are from the category of males, as they constitute (55.5%) of the total size of the study sample, and then came the type of females, as they constitute (44.4%) of the full scope of the study sample. We also note that the percentages were relatively close. With an increase of about (10%) in favor of males, this percentage is logical, as males tend to work in the productive sectors, unlike the services sector, for example, to which the female category tends more than males. The study also found that the most significant percentage of the study sample individuals are from the age group (30-less than 40) years, with a ratio of (33.8%), and the lowest was for the age group (50) years and over, with a rate of (14.8%). This indicates that this category has complete understanding and perception as it has the vastest practical experience. This category is characterized by the ability to make administrative decisions and sufficient skills commensurate with their practical knowledge based on experience and accumulated learning. The study also found that the most significant percentage of the study sample holds a bachelor's degree, as they constitute almost half of the study sample, at a rate of (40.2%) of the total size of the study sample, and in the last place came holders of an intermediate diploma, as they constitute (12.4%) of the total size of the study sample. Here we notice a high level of educational attainment among individuals. The study sample is due to the increased interest in education in Jordan. The percentage of holders of professional certificates reached (20.5%) of the sample. The study also found that the highest rate of the study sample is concentrated in the experience category (from 5 years to less than ten years), as they constitute (42.9%) of the total size of the study sample. Finally, came to the category of experience (more than 20 years), which constitutes (3.6%) of the total size of the study sample, and is an indication that the experience of the study sample is excellent and sufficient To carry out the work entrusted to them, as it gives them an additional positive advantage that enables them to deal with accounting matters related to their work in a very professional manner.

Descriptive statistics results for the study variables

This part includes a presentation of the results of descriptive statistics analysis, represented by arithmetic means and standard deviations, to clarify the level of agreement of the study sample members on the items of each of the independent variables (data visualization), the dependent variable (quality of decision making). The following Table (5) illustrates these results.

Demographic Object	***The valid items***	***Athematic averages***	***Standard deviations***
Independent Variable (Data visualization techniques)	Temporal data visualization	**3.29**	**1.15**
	Geographical or spatial data visualization	**3.11**	**1.22**
	Hierarchical data visualization	**3.01**	**1.18**
	Network data visualization	**2.84**	**1.16**
	Multidimensional data visualization	**3.03**	**1.18**
	Average	**3.06**	**1.18**
Dependent Variable (Quality of decision making)	Accuracy	**3.24**	**1.20**
	Confidence	**3.44**	**1.19**
	Calibration	**3.15**	**1.16**
	Average	**3.28**	**1.18**

Table (5)
Descriptive statistics results

Table () shows that the responses of the study sample on the dimensions of the independent variable (data visualization) as a whole came in a (medium) degree, with an arithmetic mean (3.06) and a standard deviation (1.18). In first place came the dimension of "temporal data visualization" with an evaluation score (of average), with an arithmetic mean (of 3.29), followed by the measurement of "geographical or spatial data visualization" with an evaluation score (of medium). Arithmetic means (3.11), and the "multidimensional data visualization" dimension came in third place with an evaluation score (average), with an arithmetic mean (3.03), w. In contrast,e "hierarchical data visualization" dimension came in fourth place with an evaluation score (Average), with an arithmetic mean (of 3.01), and in last place came to the "network data visualization" dimension with an evaluation score (average), with an arithmetic standard (2.84). These results indicate the extent of interest in the dimensions of data visualization in the Jordanian pharmaceutical companies, through which future directions are identified and for building strategic and marketing plans and enhancing the quality of decisions in these companies.

Table () also shows that the responses of the study sample to the dimensions of the dependent variable (decision quality) as a whole came with a (medium) score, with an arithmetic mean (3.28) and a standard deviation (18.1). In first place came the "level of confidence" dimension with an evaluation score (of medium), with an arithmetic mean (of 3.44) followed by the "level of accuracy" dimension with a (medium) evaluation score with an arithmetic mean (of 3.24). In contrast, the third and final rank came after the "level of calibration" with an evaluation score (average) with an arithmetic mean (3.15). These results indicate the extent of concern for the quality of decisions in the Jordanian pharmaceutical companies; the study sample makes decisions after sufficient analysis of the data and information available, analyzing the situation and the problem they face, and choosing the most accurate and confident, and calibrated decision.

Hypothesis Testing:

To verify the level of linear overlap between the dimensions of the independent variable (data visualization) and the absence of a problem in the internal correlations of the variables, this was done by using the Variance Inflation Factor (VIF) test, the allowable variance (tolerance). Table (6) summarize these values:

Independent variables dimensions	**Collinearity Statistics**	
	VIF	**Tolerance**
Temporal data visualization	**6.017**	**0.156**
Geographical or spatial data visualization	**7.067**	**0.145**
Hierarchical data visualization	**7.543**	**0.143**
Network data visualization	**6.675**	**0.165**
Multidimensional data visualization	**6.123**	**0.154**

Table (6)

Results of the linear overlap test between the dimensions of the independent variable (data visualization)

Table () shows that the variance inflation coefficient (VIF) for the dimensions of the independent variable data visualization (time, geographic, spatial, hierarchical, network, and multidimensional) ranged between (6.017-7.543), and all values were more significant than (1) and less than (10), and as it is shown that the tolerance values ranged between (0.143-0.165), and all of these values were greater than (≤0.05 α), which indicates that there is no high correlation and therefore the absence of A problem with the linear correlation between the dimensions of the independent variable in the current study (Bian, 2011).

To test the first hypothesis, the multiple regression coefficients were used using the method of entering the predicted variables (Enter) to detect the existence of a statistically significant effect between data visualization techniques and the quality of the decision as a whole variable in the Jordanian pharmaceutical companies listed on the Amman Stock Exchange. Accordingly, the values of the multiple linear regression coefficients and their squares were extracted, the amount of interpretation of the change in those coefficients, and Table No. (27) shows that. In addition to the above, ANOVA values were extracted to test this effect and the relationship between the study variables, as shown in Table (). Results indicated that the value of the correlation coefficient between the independent variable (data visualization) with its dimensions and the dependent variable (decision quality) as a total variable combined amounted to (R = 0.758). This indicates that there is a strong and positive correlation between the variables. It also shows the value of the coefficient of determination (R2 = 0.574), which means that data visualization techniques explained (57.4%) of the total variation in the quality of the decision, while other factors explain the rest. The result of the (F) value was (185.639) with a level of significance (0.000), which indicates the suitability of the model for the regression test, and that The relationship between the two variables (independent and dependent) follows the linear model. This value is considered a function at the significance level (α≤0.05). This means that there is a statistically significant effect (a ≤ 0.05) of data visualization techniques (temporal, geographic or spatial, hierarchical, network, multidimensional) on the quality of decision (level of accuracy, level of confidence, level of calibration) at the Jordanian pharmaceutical companies listed on the Amman Stock Exchange.

Model	**R**	**R2**	**Moderate R2**	**standard error of estimation**	**F value**	**sig**
1	**.758[a]**	**.574**	**.571**	**.367**	185.639	.000[a]
2	**.846[a]**	**.716**	**.714**	**.443**	347.610	.000[a]
3	**.770[a]**	**.593**	**.590**	**.510**	202.043	.000[a]
4	**.518[a]**	**.268**	**.263**	**.630**	50.839	.000[a]

To test the second hypothesis, the multiple regression coefficients were used to enter the predicted variables (Enter) to detect a statistically significant effect between data visualization techniques and the decision level of accuracy. In addition to the above, ANOVA values were extracted to test this effect and the relationship between the study variables, as shown in Table (). Results indicated that the value of the correlation coefficient between the independent variable (data visualization) with its dimensions and (decision level of accuracy) was ($R = 0.846$). This indicates that there is a strong and positive correlation between the variables. It also shows that the value of the coefficient of determination ($R2 = 0.716$), that is, the data visualization techniques explained (71.6%) of the total variation in decision level of accuracy.

In contrast, the rest is explained by other factors. The value of the (F) test calculated for the model was (347.610) at the level of significance (0.000), which indicates the suitability of the model for the regression test, and that the relationship between the two variables (independent and dependent) follows the linear model. This value is considered a function at a significance level ($\alpha \leq 0.05$). This means that there is a statistically significant effect ($a \leq 0.05$) of data visualization techniques (temporal, geographic or spatial, hierarchical, network, multidimensional) on the decision level of accuracy at the Jordanian pharmaceutical companies listed on the Amman Stock Exchange.

To test the third hypothesis, the multiple regression coefficients were used to enter the predicted variables (Enter) to detect a statistically significant effect between data visualization techniques and the decision level of confidence. In addition to the above, ANOVA values were extracted to test this effect and the relationship between the study variables, as shown in Table (). Results indicated that the value of the correlation coefficient between the independent variable (data visualization) with its dimensions and (decision level of confidence) was ($R = 0.770$). This indicates that there is a strong and positive correlation between the variables. It also shows that the value of the coefficient of determination ($R2 = 0.593$), that is, the data visualization techniques explained (59.3 %) of the total variation in decision level of confidence.

In contrast, the rest is explained by other factors. The value of the (F) test calculated for the model was (202.043) at the level of significance (0.000), which indicates the suitability of the model for the regression test, and that the relationship between the two variables (independent and dependent) follows the linear model. This value is considered a function at the level of significance ($\alpha \leq 0.05$), which means that There is a statistically significant effect ($a \leq 0.05$) of data visualization techniques (temporal, geographic or spatial, hierarchical, network, multidimensional) on the decision level of confidence at the Jordanian pharmaceutical companies listed on the Amman Stock Exchange.

To test the fourth hypothesis, the multiple regression coefficients were used to enter the predicted variables (Enter) to detect a statistically significant effect between data visualization techniques and the decision level of calibration. In addition to the above, ANOVA values were extracted to test this effect and the relationship between the study variables, as shown in Table (). Results indicated that the value of the correlation coefficient between the independent variable (data visualization) with its dimensions and (decision level of calibration) was ($R = 0.518$). This indicates that there is a strong and positive correlation between the variables. It also shows that the value of the coefficient of determination ($R2 = 0.268$), that is, the data visualization techniques explained (26.8 %) of the total variation in decision level of confidence.

In contrast, the rest is explained by other factors. The value of the (F) test calculated for the model was (50.839) at the level of significance (0.000), which indicates the suitability of the model for the regression test, and that the relationship between the two variables (independent and dependent) follows the linear model. This value is considered a function at the level of significance ($\alpha \leq 0.05$), which means that There is a statistically significant effect ($a \leq 0.05$) of data visualization techniques (temporal, geographic or spatial, hierarchical, network, multidimensional) on the decision level of calibration at the Jordanian pharmaceutical companies listed on the Amman Stock Exchange.

The values of the standard and non-standard regression coefficients were also extracted for the predictor variables, in addition to the test (t) values and the statistical significance. Table () shows these values for all hypotheses. The calculated t-test values for H1 were sequentially (4.185, 3.005, 8.303, 4,220, 7.234), with a significant level of (, 000, 003, 000, 002, 000) respectively, which confirm the positive relationship and effect between the study variables. T values results of H2 were sequentially (9.157, 1.419, 10.790, 5.534, 8,148), with a significant level of (8,148). .001, .000, .157, .002, .000) respectively. And based on the decision rule related to t, which stipulates the rejection of the null hypothesis if the value of the significance of t is less than (0.05). Accordingly, the null hypothesis for each (**temporal, hierarchical, network, multidimensional**) was rejected, meaning that there is a statistically significant effect for them on the decision level of accuracy. In contrast, the null hypothesis was accepted for the dimension (geographical or spatial data visualization), where the value of the (t) test indicated no statistically significant effect on the decision level of accuracy.

T values results of H3 were sequentially (10.775, 0.925, 4.670, 5,512, 6,435), with a significant level of (.000, .000, .355, .000, .001, .000) respectively. And based on the decision rule related to t, which stipulates the rejection of the null hypothesis if the value of the significance of t is less than (0.05). Accordingly, the null hypothesis for each (**temporal, hierarchical, network, multidimensional**) was rejected, meaning that they have a statistically significant effect on the decision level of confidence. In contrast, the null hypothesis was accepted for the dimension (geographical or spatial data visualization), where the value of the (t) test indicated no statistically significant effect on the decision level of confidence. T values results of H4 were sequentially (0.737, 2.090, 5.049, 7,123, 8,654), with a significant level of (.462 423, .000, .000, .000) respectively. And based on the decision rule related to t, which stipulates the rejection of the null hypothesis if the value of the significance of t is less than (0.05). Accordingly, the null hypothesis for each (**temporal, hierarchical, network, multidimensional**) was rejected, meaning there is a statistically significant effect for them at the decision level of calibration. In contrast, the null hypothesis was accepted for the two dimensions (temporal, geographical, or spatial), where the value of the (t) test indicated no statistically significant effect on the decision level of calibration.

Model	**T value H1**	**Sig value H1**	**T value H2**	**Sig value H2**	**T value H3**	**Sig value H3**	**T value H4**	**Sig value H4**
Temporal data visualization	4.185	.000	9.157	.000	10.775	.000	0.737	.462
Geographical or spatial data visualization	3.005	.003	1.419	.157	0.925	.355	2.090	.423
Hierarchical data visualization	8.303	.000	10.790	.000	4.670	.000	5.049	.000
Network data visualization	4.220	.002	5.534	.002	5.512	.001	7.123	.000
Multidimensional data visualization	7.234	.000	8.148	.000	6.435	.000	8.654	.000
Constant	21.349	.000	3.327	.001	6.290	.000	16.230	.000

Discussion:

The study found that there is a moderate application of data visualization techniques. The first came temporal data visualization; then geographical or spatial data visualization; multidimensional data visualization; hierarchical data visualization; and networked data visualization sequentially.

These results indicate the extent of interest in the dimensions of data visualization in the Jordanian pharmaceutical companies, through which future directions are identified and for building strategic and marketing plans and enhancing the quality of decisions in these companies. At the same time, the quality of decision-making was moderate at Jordanian pharmaceutical companies, which indicates that decisions are taken after adequate analysis of the data and information available to the decision maker, analysis of the situation and the problem it faces, and selection of the best alternatives.

Results also indicated that Jordanian pharmaceutical companies have tools related to temporal data visualization, such as (Scatter Plots, Line graphs, Time series sequences, and Polar Area Diagrams) related to buying, selling, customers, competitors, or other variables, which helps in determining the starting and ending points, and the development that occurred during the period; displaying Changes that occur continuously over a certain period. The geographical or spatial data visualization tools such as (Flow Map, Heat Maps, Density Map, …etc.) also exist at these companies that help in analyzing and representing data related to information records of customers, competitors, suppliers, and branches, in addition to their geographical locations, and data that have geographical implications, whether related to places of sale, purchase, or distribution and branch sales locally and globally, among other variables. In addition, these companies are keen to invest in developing and modernizing these systems.

Jordanian pharmaceutical companies also have special flexible hierarchical data visualization tools such as (Ring Charts, Tree Diagrams, Sunburst Diagrams, …etc.) which help in visualizing different and homogeneous data, whether geographical, spatial, temporal, or other information, as these systems depend on the representation and visualization of data based on a hierarchical tree structure, where each branch of the hierarchy represents several records related to the hierarchy and branching from the origin to the different departments. It also helps extract data and link it with time to identify the relationship between spatial, temporal, and geographical data. Network data visualizations tools such as (Matrix Charts, Word Clouds, Node-link Diagrams, Alluvial Diagrams, …etc.) also exist at these companies, which deal with homogeneous data, whether geographical, spatial, temporal, or other information. These tools have the power to access different data of different types, sizes, and homogeneity to extract figures that show the nature of the relationship (one-to-many relationship) and the influence between these variables, not to mention that these systems are characterized by flexibility and ease of use in terms of saving, extracting, processing, analyzing, and visualizing data graphically.

Jordanian pharmaceutical companies also have special flexible, multidimensional data visualization tools such as (Matrix Charts, Word Venn Diagrams, Pie Charts, Stacked Bar Graphs, …etc.) which deal with visualizing complex data that need to be represented in two dimensions or more or other words consisting of two or more variables. These tools are used to solve organizational problems and enhance the lack of organizational performance, in addition to defining the strategic plan of the company and strengthening the competitive advantage, as these systems are characterized by flexibility and ease of use in terms of saving, extracting, processing, analyzing and visualizing data. Graphically.

Results also indicated that data visualization techniques have a positive effect on the level of decision accuracy at Jordanian pharmaceutical companies, and this is evident through the availability of sufficient experience necessary for successful decision-making by all employees, especially at the higher levels, whereby the analysis of available data from visual imaging systems for data is used to diagnose the problem or situation on accurate scientific and objective bases, and to obtain the most significant number of the best alternatives in the right time. Straightforward way before making the decision, the most critical possible amount of accurate data and impartial and timely information are obtained, reflecting the accuracy of the decision taken by them.

Results also indicated that data visualization techniques have a positive effect on the level of confidence, and this is evident through the planning and evaluation of the consequences of important decisions by workers at various administrative levels, where the decision is taken after obtaining sufficient, sure and reliable information, the results of the decision are determined in advance, and the effects of the internal and external environment are also taken into account, so decision-makers could have the ability to make the best and accurate plans and strategies to deal with them. Decision-making confidence is guaranteed through the availability of sufficient knowledge and information about the circumstances surrounding the decision-making process in an environment of uncertainty. Previous predictive information is provided that helps predict the outcome of the decision.

Results also indicated that data visualization techniques have a positive effect on the level of decision calibration, and this is evident through the workers at various administrative levels developing a detailed plan for the implementation of important decisions, taking into account many criteria related to comparison and analysis of alternatives depending on the information available to them, with the presence and availability of appropriate information for decision-making. The decision is taken after calculating the expected value for this decision, and among these criteria (the criterion of optimism, the standard of pessimism, the measure of remorse, the criterion of rationality, and the criterion of realism), where the workers have the necessary experience and competence, which ensures the calibration of decisions in the Jordanian pharmaceutical companies.

Conclusion:

Data visualization has become ubiquitous in our daily professional and private lives, even more so with the advent of accessible and powerful computer graphics. However, the impact that visualizations have on human cognition and, ultimately, decisions stills remains unclear to a large extent. The evidence from this review generally suggests the positive effects of data visualization techniques on the quality of decision-making. However, an understanding of data visualization techniques specific to pharmaceutical companies' decision-makers still lacks. There is little guidance to understand parameters judging the quality of decision-making measurement. A visualization study involving pharmaceutical companies' decision-makers from the beginning of the design process could aid in developing practical visualization tools and interventions that accurately depict real-world problems and support the needs of these companies' leaders to make appropriate, accurate decisions. F

The study findings stress the need for data visualization to support the quality of decisions via the availability of accurate data, along with concise on-demand explanations of the data analysis process. The study also provided each visualization technique with special tools for novel visualization designs, including flexible data input and collaboration mechanisms, interrogation, scenario-based analysis, and aids for trade-off overview analysis.

Based on the results of the study, the researcher recommends the need for managers in pharmaceutical companies to invest in developing and updating geographical or spatial and network data visualization tools, especially those related to places of sale, purchase or distribution, and branch sales locally and globally, to enhance the quality of marketing decisions in them, because of their influential role in clarifying the network relationships between many variables, which In turn, it contributes to enhancing the level of accuracy, confidence, and standardization of the various decisions in these companies. The study also recommends the need for decision-makers in pharmaceutical companies to obtain as much accurate data as possible, impartial and timely information that helps diagnose the problem or situation on exact scientific and objective bases, to enhance the accuracy of their decisions. Finally, the study recommends conducting future studies on the survey in sectors other than pharmaceutical companies, in addition to testing the effect of data visualization on other variables such as strategic agility, competitive advantage, or others.

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