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Visual Analytics for Decision Support: A Supply Chain Perspective

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ABSTRACT Supply chain (SC) activities generate huge amount of data that can be used in decision making processes. However, proper data analytics techniques are required to combine, organize, and analyze data from different sources and produce required insights available for decision makers. These techniques promote analytical reasoning of the events and patterns hidden in the data using visualizations, so-called Visual Analytics (VA). Although there is a large number of VA systems to facilitate the process of analysis and decision making, there is a lack of an adequate overview of what already exists in this area for SC management. To address that need, we conducted a systematic literature review to analyze the state of the art in SC VA systems. Particularly, we focus on use cases, the type of the decisions that a VA system intended to support, the type of visualizations employed, the type of analytics used, and the data that has been used for analysis. The goal of this study is to provide SC and VA researchers with an overview of the works carried out in the field of SC VA, helping them to observe latest trends and to recognize existing gaps that need further investigation. Consequently, a mapping between decisions of various SC business processes and their reciprocal visualization techniques and tactics have been provided. Adding to that, VA applications and use cases in SC are identified based on the SC Operation Reference (SCOR) model and underlying decision areas are recognized.

INDEX TERMS Decision support, information visualization, value chain analysis, visual analytics, visualization techniques and methodologies.

I. INTRODUCTION

The massive and heterogenous amount of data produced by Supply Chain (SC) actors raises the need for developing data analytics solutions to support decision making activities [1]. Visual Analytics (VA) plays a key role in analyzing the vast amount of data collected by different SC actors as the result of their day-to-day supply network operations, taking from suppliers and manufacturers to warehouses, logistics and retailers.

Many analytical approaches have been proposed to support decision making for SC processes and activities [2], [3]. These studies are mainly focused on the big data capabilities of companies. There, VA is defined as "the science of analytical reasoning facilitated by interactive interfaces" [4]. The study presented in [2] included data visualization as part of their proposed architecture for SC analytics; in this paper, authors emphasized the role of VA in making effective decisions, however, the corresponding decisions regarding different SC processes are not identified. In our study, we aim to identify each of the decisions related to a particular SC business activity supported by VA. The authors in [3] conducted a systematic literature review (SLR) regarding SC analytic systems. They have focused on big data capabilities of such systems, and despite the recognition of data visualization as one of the main capabilities, it is not investigated in-depth. In this study, we identify the state of the art in the visualization techniques and tactics that have been used in SC analytics.

Authors in [3] provided insights regarding data visualization and SC activities, and some of the specific visualization techniques have been mentioned. However, the connection between different visualization techniques and tactics and SC business needs have not been addressed comprehensively. Tactics are approaches addressing an analytical goal with the human in the loop, such as, visualizing multi-dimensionality

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by clustering, or providing multiple concurrent workspaces to analysts. In contrast, techniques are the types of visual elements, such as, histograms, bar charts, scatter plots, and so on. Therefore, in this study, we reviewed the literature with a special focus on the identification of various visualization tactics and visualization techniques. Moreover, the authors of the study presented in [5] analyzed the challenges and opportunities of using VA in organizations, and outlined the collection, preparing and understanding of the data as the main challenges of data analysis that can be addressed with the help of VA. In this context, they have investigated companies from different industries. In our study, we focus on the SC activities, to specifically formulate the benefits of each of the VA tactics according to their use in the corresponding SC process. On the other hand, the study in [6] presented a literature review underlining the need for big data analytics in SC management, and the necessity for visualization is highlighted in the process of data discovery from different SC activities. We also investigate into literature on the use of data visualization, but in particular we look into identifying the analytical capabilities of visualization in SC processes.

Furthermore, the authors of the study [7] explored the big data technologies adopted in different industrial sectors. They found that VA is the most used technology with an adoption rate of 40% within different sectors, especially in retail industry as part of the SC networks. In general, VA can be used for three different types of analysis in SC processes: 1) descriptive analysis, by providing the ability to identify the problems from visual presentation of bottlenecks, 2) predictive analysis, by visualizing the prospective future events, and 3) prescriptive analysis, by providing the what-if scenarios [8].

Therefore, we have identified following five gaps that are supposed to be addressed by our study:

1. The lack of identifying specific SC business decisions that can be supported by VA.
2. The lack of exploring various analytical capabilities of SC VA systems.
3. The lack of identifying the state of the art in visualization techniques and tactics.
4. The lack of clear mapping between business decisions addressed by a specific visualization tactics and the visualization techniques that have been used for that purpose.
5. The focus of the previous studies has not been mainly on SC VA.

In general, majority of the previous studies are either focusing on the application of VA in other topics [9]–[11] or even if it is considered from a SC perspective, it is mainly focused on VA itself [12] and the SC related activity has been mostly used only as a case study for the proposed VA, making it difficult to identify all SC specific VA studies from the literature.

Additionally, given the interdisciplinarity of the topic that involves Human-Computer Interaction, Information Systems, and SC Management, it requires a systematic approach to identify previous works published from different channels. Although there is an increasing body of works exploring the application of VA in SC, to the best of our knowledge, there is not a comprehensive study characterizing the SC processes and decisions that can be supported with VA.

Hence, the rationale for this study is twofold: First, the necessity to identify the specific SC decisions that can be supported with the help of VA, and second, the need to consolidate the customization that is required for the specific needs of the corresponding domain decision. Therefore, the requirements that need to be addressed by the relevant discipline research community get highlighted. Moreover, VA practitioners will find a clear and precise interpretation of research around VA for SC activities, and eventually, all the particularities of the potential VA system can be easily identified and implemented.

Therefore, in this study, we investigate the literature to identify previous attempts concerning the application of VA in different SC related activities, and we provide a holistic overview of VA techniques and data that are being used to support decisions associated with different SC processes. Consequently, both SC and VA researchers and practitioners can benefit from this study towards enhancing SC decision support systems.

The rest of this paper is structured as follows: First, the backgrounds of the study are presented in Section II along with some of the related works that emphasized more on the need for this study. Then, the research methodology is introduced in Section III along with research questions that are the main constructs of this study. Section IV-A and IV-B provide the findings of the study in detail. Then, we synthesize our findings in section V suggesting some potential future research directions.

II. THEORETICAL BACKGROUNDS AND RELATED WORK

A. SUPPLY CHAIN ANALYTICS

The statement provided by Forrester about management dates back to 1958, but it still holds true especially in the scope of SC management. ''Management is on the verge of a major breakthrough in understanding how industrial company success depends on the interactions between the flows of information, materials, money, manpower, and capital equipment.'' [13]. Forrester emphasized the impact of information flow on company success. In recent years, companies realized the importance of collaborating with their SC partners in developing the information flow throughout the SC in order to compete with other SCs [14].

On the other hand, companies involved in SC activities are facing the collection of an enormous amount of data as the result of their day-to-day operations. However, given the heterogeneity and high volume of the data, the interpretation and analysis of such data remains a challenging task [15]. These data are the backbone of many decision making activities towards the companies short and long term strategies [16]. In this scenario, the impact of business analytics on the SC management performance has shown to be notable [1]. In simple words, SC analytics focuses on information and analytical tools to make decisions that better match supply and demand [17].

B. VISUAL ANALYTICS

VA is defined as ''the formation of abstract visual metaphors in combination with a human information discourse (interaction) that enables detection of the expected and discovery of the unexpected within massive, dynamically changing information spaces'' [18]. VA contributes in the process of analyzing heterogeneous data spaces by providing insight and knowledge generation ability for decision support systems [19]. While the advantages of VA have been investigated in many fields in the last decade, its application in SC networks has not been analyzed rigorously. VA provides decision makers the ability to combine their knowledge and expertise with the computer analytical capabilities in an interactive manner to gain more flexible, fit to the purpose, and reliable insights from the complex systems such as a SC network [20].

The increasing amount of data intensifies the desire to make data-driven decisions. In this respect, data analytics has been identified as a subfield of decision science and information systems [21]. In general, there has been an increasing body of work exploring the advantages of data analytics for industries and in specific for the SC players. In this context, VA has shown promising results with respect to providing the analytical capabilities to firms. The authors of the study [22], proposed a VA system that analyzes the structural aspects of the SC network to identify risks and provides what-if analysis to predict future events. The application of VA in different use cases of the SC processes is also studied by various authors. For example, the study in [23] presented the application of VA for retail space management, or the study in [24] that showed the use of VA for production performance improvement.

Literature also investigated the viability of different visualization techniques in the context of SC processes. In this regard, in [25], authors proposed the presentation of sales data in a labelled tree structure to facilitate the interpretation of the hierarchical multi-dimension data. The study in [26] focused on the temporal characteristics of sales data that used charts and maps along with some specific design consideration in order to maximize the potential of the VA system. Although many studies are available with regards to providing VA proposals related to SC processes, to the best of our knowledge, there have not been any literature reviews analyzing those studies while focusing on the following four important aspects: uses cases of VA in SC, types of VA used in SC, types of decisions supported, and the type of data used. Therefore, this study provides a comprehensive literature review that aims to shed light into the aforementioned aspects and to identify previous research gaps and future research opportunities.

C. SC OPERATION REFERENCE MODEL

The results of this study are classified according to the Supply Chain Operation Reference (SCOR) model developed by the Association for Supply Chain Management (ASCM) [27]. ASCM is a non-profit international organization that aims at informing companies around the world to optimize different aspects of their SC. SCOR is a reference model that describes the businesses activities related to meeting the demands of the customers in a SC environment. This model was previously used by researchers to ground SC analytics studies based upon to enhance the mapping of the concepts and SC activities [6], [17], [28]. The SCOR reference model is based on three underlying aspects: business processes, metrics and best practices and technology, linking them into a unified structure [29]. ASCM defines business processes as activities that are performed to meet predefined outcomes that a SC must execute to fulfill the requirements of its customers [29]. These processes are then divided into 6 major categories corresponding to different SC phases: plan, source, make, deliver, return and enable.

The plan processes are defined as the activities related to planning for operating the SC. These activities include identifying requirements, understanding the state of the resources, balancing requirements and resources, and planning the actions to fulfill the requirements based on the resources. Source processes are defined as the activities in connection with the ordering, delivery, receipt and transfer of raw material or services. These activities mainly include the placement of purchase orders, planning deliveries and receiving, and validating and storing orders. The make processes are activities associated with the actual conversion of the raw material to the finished products. These activities include but are not limited to, repair, recycling, refurbishment, and manufacturing of the products and services. The deliver processes are defined as activities that lead to the creation, maintenance and fulfillment of customer orders. The most significant activities in this category include receiving, packing, shipping and invoicing the orders. The return processes are activities linked with the reverse flow of the product. These activities include identifying the goods that need to be returned, shipping and receiving the returned items, and the processes for the disposal of the returned products if required. Finally, the enable processes are defined as activities that contribute to the overall management of the SC. These activities include the managing and regulating the SC rules, data, resources, facilities and the network in general.

III. RESEARCH METHODOLOGY

SLRs have been successfully used in many secondary studies to determine the state of the art in various areas of computer science [30]–[32]. In this study, we have employed the general guidelines for SLRs proposed by Kitchenham and Charters [33]. In general, systematic reviews are defined as a means of identifying, assessing and interpreting all available research relevant to a particular research question, or topic area.

By means of a SLR, an appropriate overview of the state of the art is formulated in order to determine the gaps in existing literature and opportunities for future research. Indeed, if the outcomes of a systematic review are formulated in the form of a string of beads created from the literature, the corresponding research direction will be outlined. In this context, we carried out the following steps: 1) Recognizing the need for study, 2) Outlining the review protocol, 3) Identifying the primary studies, 4) Assessing the quality of the identified studies, and 5) Performing data extraction. Consequently, many significant dimensions about different aspects of the field of study will be provided, opening the doors to the future innovations and evolutions.

A. RESEARCH QUESTIONS

Given the scope of this study we have formulated two main research questions (RQ) and they are further parsed into multiple sub questions as follows:

RQ1. *How has VA been used to support the SC activities?*

RQ1.1. What are the use cases of VA related to the SC activities?

RQ1.2. Which decision areas of the SC activities are supported by VA?

RQ1.3. How have the SC data been used for visualization?

RQ2. *Which VA techniques or tactics have been used in SC?*

RQ2.1. What type of data visualizations have been used?

RQ2.2. What type of data analytics have been used in the SC VA?

The answer to the first research question is intended to identify VA use cases that support decision making processes by enhancing the information retrieval from the data collected in different stages of SC decision phases, that is, strategy, planning, and operation. Therefore, we have further broke the question down into the mentioned sub questions. By answering these two questions the first two gaps mentioned earlier in introduction will be addressed.

By answering the second research question, we aim to identify 1) visualization types suitable for particular analytical goals in each of the SC activities, i.e., visualization techniques, and 2) analytical reasoning by analysts involving in the process of analysis, i.e., tactics. Therefore, we can further break the question down into the sub questions. These questions contribute towards covering the gaps number 3 to 5 mentioned earlier.

B. SEARCH STRATEGY

This literature review follows a systematic approach to identify the related previous studies and to select relevant papers for the review process. In this regard, we first needed to conduct multiple rounds of explorations using various keywords in the main research database of Google Scholar. Later, by interpreting the number of search results and consulting with some of the domain researchers we have identified 5 main publication databases to consider as our resources, namely, IEEE Xplore, ACM Digital Library, ScienceDirect, SpringerLink, and Wiley Online Library. Then, by conducting an initial search process, we have reached to a conclusion about the final search string and a number of specific publication channels, provided in next section, in order to dig deep into literature systematically.

TABLE 1. Search string terms.

Operator	Aspects	Keywords
AND	Visual Analytics	"Visual Analytics"
AND	Supply Chain	"Supply Chain" OR "Logistics" OR "Producer" OR "Warehousing" OR "Wholesaler" OR "Retail" OR "Consumer"
AND	Decision-making	"Decision"

1) SEARCH STRING

A search string is used to fetch the related articles from each of the databases. The search string is formulated in such a way that the results include studies that are related to three aspects of the research: 1) Visual Analytics, 2) SC processes, and 3) Decision-making. The preliminary scanning of the databases for each of the aspects leaded to generation of the search string presented in Table. 1, where a Boolean AND is used to connect the terms from different aspects.

2) SEARCH RESOURCES

The publication channels have been selected based on two criteria: First, they have a special focus on the computer science fields, second, they publish peer-reviewed journals, books, and conference proceedings, whereas the level of quality is assured by the publishers.

We then selected the articles in an iterative manner. In the first round of the process, we went through all the article titles, abstracts, and keywords of 1554 search results to either include or exclude the article into our review based on a set of predefined inclusion and exclusion criteria as follows:

- The study must be related to SC activities.
- The study must employ a VA technique.
- The language of the study must be English.
- The study must be peer-reviewed.
- The study must be accessible as a full text article.

Consequently, we selected 49 articles and in the second round, we went through the full text of each of them in order to verify the relevance to the research questions, as well as the appropriateness of the article. later, we assessed their quality based on a set of questions corresponding to three aspects of the quality as follows: 1) Selection and measurement bias, 2) Validity of the paper, and 3) Generalizability. Eventually,

TABLE 2. Number of papers retrieved in each round of the review.

Database	First Round	Second Round	Third Round
IEEExplore	493	20	10
ScienceDirect	395	13	4
ACM Digital Library	208	4	1
SpringerLink	265	8	5
Wiley Online Library	193	4	3
Total	**1554**	**49**	**23**

the final set of papers (23) is selected, after which a rigorous analysis of each article has been carried out to identify the answers to our research questions based on the contents provided.

In order to keep track of the findings and structuring the results, a data extraction form was developed. The form contains the data collected from each article about the general information and answers to the research questions. Table. 2 shows the number of papers retrieved in each round of the review along with the relevant databases used in the review process.

C. LIMITATIONS AND THREATS TO VALIDITY

Peterson and Gencel [34] provided a guideline to identify and prevent various threats to validity for research. We adapted this guideline to our study in order to outline and overcome the limitations and possible threats. According to Petersen and Gencel., similar to empirical studies, validity considerations are also applicable to SLR studies [34]. Similar to how other researchers considered and mitigated the potential threats to validity in their previous SLR studies [35]–[37], we also considered and mitigated threats to validity in our study. Petersen and Gencel categorized the threats to validity based on two main phases of research, i.e., 1) data collection, and 2) data analysis. These two phases are the main phases for a SLR where we collect the data regarding our research questions in each of the related works and then we analyze the collected data to provide an interpretation of findings and a research synthesis.

In this section, we present the threats to validy of this study and our approaches to minimize these threats. Based on Petersen and Gencel, we discuss four different threats to validity: 1) descriptive validity, 2) theoretical validity, 3) generalizability, and 4) interpretive validity. In what follows we briefly describe each category of the threats.

1) DESCRIPTIVE VALIDITY

Descriptive validity is to make sure that observations are carried out objectively and they are described accurately. Regarding which, we need to pay careful attention to the way in which we collect our data from each of the articles in order not to miss any important data and to mitigate bias. Systematic reviews' findings are mainly based on the collected data from the previous studies and not to be biasly positive or negative about the studies is crucial. In order to assure this, we used extraction forms to identify all the relevant information from each of the selected studies. In addition, a checklist for inclusion and exclusion criteria is developed to prevent any biases in the selection process of the papers. However, the limitation of databases regarding the possible number of search terms and filtration features for the search results may impose the possibility of missing some of the relevant studies.

2) THEORETICAL VALIDITY

Theoretical validity is to identify the confusing aspects of the study and to make sure that we seize what we aim to seize. That is, to make sure the data we collect from each of the studies are correctly answering our research questions, therefore the reliability of the answers to each of the research questions are not subjected to any threats. This is rather an important check, normally there is an overwhelming number of studies that can be referred to in a SLR, however, the quality of all those studies may not be acceptable [38], and may impose threats to the reliability of answers to our research question. This, therefore, can be addressed by a proper quality assurance procedure of each of the studies.

Given that we have conducted a quality check on each of the selected papers, we assessed the quality of each study based on the common research method and techniques only, and we beware of evaluating papers based on their technical methods that can lead to missing some important aspect of a particular study.

3) GENERALIZABILITY

Generalizability deals with the extent to which the study is generalizable either internally, within the corresponding community, or externally, across other communities. In the context of a systematic review, it refers to the extent to which the results of the review can be used by various disciplines. In this study, the results can be used by both the VA community and the SC management community. As mentioned earlier, given the multidisciplinary nature of the topic, i.e., human-computer interaction, information system, and SC management, we tried to establish a link between different fields by dividing the main research questions to sub questions comprising of different aspects relevant for each of the disciplines. Therefore, we made sure to formulate our research questions, and consequently, categorize our findings in such a way that all the disciplines can gain from the results of this study. This also leads to the clarity and a broader understanding of the topic from different perspectives.

4) INTERPRETIVE VALIDITY

Interpretive validity is to confirm that the inferences of the study are interpreted correctly and objectively. Which is another important aspect to consider while conducting a systematic review study, since the result of such studies are basically based on the interpretations from previous related

TABLE 3. Classification of the collected data from the selected studies based on the research questions.

Key	Ref.	SCOR	RQ1				RQ2	
			Supporting Decision	Decision area	Use Cases	Data	Visualization Type	Analytical Method
S1	[43]	Plan	Business decisions based on business circles	Business intelligence processes	Trends of Consumer demands, retail	Sales data	Map, Chart	Clustering Analysis
S2	[40]	Plan	Marketing decisions based on sales pattern	Sales management	VA of business Circles and products	Sales data	Nested ring diagram, Theme rivers map, Temporal K view, Hotspot view	Density Clustering
S3	[41]	Plan	Report of sales in stores, factors affecting profit, identifying bottlenecks that should be addressed	Sales management	Trends of Consumer demands, retail	Sales data	Charts in Dashboard	Manual Analysis
S4	[44]	Plan	Decisions on time-market targets	Collaborative forecasting	Trends of Consumer demands, retail	Water Usage and weather forecast	Interactive Dashboard of Charts	Interactive analysis
S5	[25]	Plan	Decisions on Sales strategy	Sales management	Trends of Consumer demands, retail	Sales data	Labelled trees	Manual Analysis
S6	[26]	Plan	Decisions on Sales strategy	Collaborative forecasting	(1) Product segmentation. (2) Temporal comparison. (3) Market segmentation.	Sales data	Charts, maps	Automatic partitioning
S7	[42]	Plan	Decisions on Business strategy	Demand management	Assessing how customer behavior varies over customers' degree of greenness.	Loyalty card and transaction data	Feature plans	Self-Organizing Time Map
S8	[46]	Plan	Model selection for demand forecasting	Collaborative forecasting	Demand forecasting	Monthly demand data	Circular design, bar chart, matrix view, and star plot.	Manual Analysis
S9	[47]	Plan	Decisions on growth and risks	Network integration and Visibility	Market analysis by total sales, trends, and growth rate	Point-of-Sales data	Pixel-based visualization, line graphs, stacked bar graphs, and choropleth maps	Linear trend estimation, ARIMA
S10	[24]	Make	Production time and product attributes	Production and distribution planning	Milk Production improvement	Test record data	Scatter plots, Density plots, Timeline views	Manual Analysis
S11	[51]	Deliver	Decisions on Sales strategy	Demand management	Sale strategy identification	Online Sale data	Multiple panels of charts, graphs and feature plane	Association rules
S12	[52]	Deliver	Decisions on Pricing	Sales management	Location based pricing based on sales channel	Historical sales transaction data (offline and online)	Charts, feature patterns and graphs	Manual Analysis
S13	[23]	Deliver	How and where specific retail products should be placed on retail shelves or displays	Sales management	Increase customer purchases in Retail	Retail data related to space performance.	Map, 3D view, charts	Manual Analysis
S14	[55]	Deliver	Shopping Analytics for purchasing decisions	Sales management	Improving Customer shopping experience in retail	Not Specified	Charts in Augmented Reality	Interactive analytics
S15	[49]	Deliver	Store location	Network design	Retail Store Location	Sales data, Transit data, store location data	Map view, multi-layer circular diagram	Manual Analysis
S16	[48]	Deliver	Sale strategies like location of the products, sale time of the products, advertisements	Sales management	Sales strategy support	POS data and customers moving history in the store	Map and Feature visualization	Manual Analysis
S17	[50]	Deliver	Detecting changes in customer behavior during a sales campaign.	Demand management	Customer behavior identification	Loyalty card system	Feature plans	Self-organizing maps
S18	[53]	Deliver	Supply chain Monitoring	Transportation management	Transportation Monitoring	RFID Tags Data	Map-based visualization interface	Rule-based analysis techniques
S19	[54]	Deliver	Finding an ideal warehouse location	Network design	Warehousing	Urban road network data, GPS trajectory data, warehouse and store data	Map view, matrix-based view, radar chart-based view	K-means clustering
S20	[56]	Return	Decision on product recall	Operations management	Product Monitoring	Social Media	Graph and Attribute p-charts	Sentiment Analysis
S21	[22]	Enable	Decisions to enhance the structural aspect of the Network	Network design	Supply chain Management	Supply network data	Chord diagram, Tree map layout, Matrix Layout, Substrate-based Layout	Scenario-based what-if analysis functionality
S22	[57]	Enable	Risk and bottleneck identification	Network integration and Visibility	Providing KPIs and visibility into supply network structure	Not Specified	A network-based representation of the global supply chain	Interactive Analysis
S23	[58]	Enable	Insights regarding the spatial distribution of innovations, flow of knowledge, cluster of innovations, and shared knowledge	Network integration and Visibility	Supply chain innovation management	Supply network nodes, edges and attributes	Geographic, Circus-based, Concentric, Force-directed, Matrix visualization	Interactive Analysis

works. In order to prevent any misinterpretation, the data collection procedure has been carried out in a systematic manner by identifying the exact answer to the RQs from each of the studies. The conclusion of the study is made based on the answers to the research questions.

IV. RESULTS AND ANALYSIS

Based on the research questions and the background of our study, we have used a data collection strategy to create a building block for presenting the results of the study. In this way, the interrelation between different studies can be identified based on their data and a conceptual framework can be developed from the analysis of these studies. To do so, the collected data from the results of the study are categorized based on the following dimensions to answer our research questions: the use cases of VA in the SC, the decisions a VA system aims at supporting, the data that is used for VA, the types of visualizations employed, and the type of analytics implemented. Moreover, these dimensions are categorized based on the SC business process they are involved in.

One of the aims of this review is to identify the decisions that are supported by a VA system. Therefore, we use the SCOR business process model, explained earlier, to recognize the underlying decisions that are related to a particular business process of the SC. Each of the process activities involves with some sort of decision making that can be enhanced with the help of VA. In this case, we scrutinized the selected studies in order to identify these decisions that are either supported by a proposed visualization system or have been the case studies presented in the literature. Thus, the identification of the SCOR process addressed by each of the studies helps linking the application of VA to each of the SC processes, which in turn answers the first RQ.

Table. 3 summarizes the classification of the collected data from each of the studies based on the RQs. Based on this table, in the next section, we present the VA applications, the decisions they support, and the data they use corresponding to each of the SCOR processes, providing the answer to the first RQ. In the latter section, we present the visualization and analytical methods employed in each category that delivers the answer to the second RQ.

A. VA APPLICATION AREAS, DECISIONS AND REQUIRED DATA

In what follows, we analyze related primary studies in detail with respect to the different business processes and activities they are involved in. In Figure 1 we provided a quantification of number of studies in the corresponding business processes

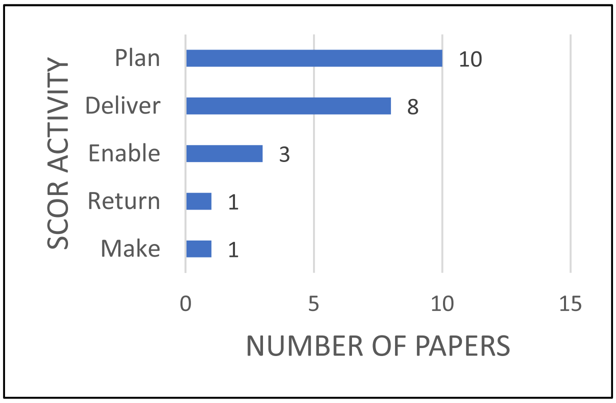

FIGURE 1. Quantification of studies in each of the SCOR activities.

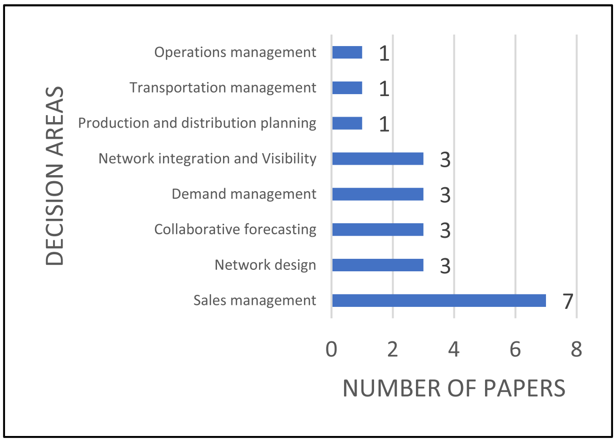

FIGURE 2. Categorization of papers across different decision areas provided by Wanke *et. al*.

of the SCOR model. In this section, we focus on the application areas that the proposed visualization system or the artefact in place has been used in, the decisions that are being supported, and the data that has been used for analysis. This section intends to answer the first RQ and its sub questions.

In the categorization of the decisions that VA systems are intended to support, we have also used the SC decision area categorization provided by Wanke *et al.* [39]. These authors provided the most relevant decision areas of the SC management based on the literature. On the other hand, the SCOR model activities are encompassing the SC processes' decisions and the presentation of our results based on this model provides a supplementary categorization for the decision areas. Therefore, the categorization of the decisions can be observed from two dimensions, first, the SCOR model activities, and second, the decision area categorization provided by Wanke *et al.* [39]. Figure 2 shows the categorization of the studies into different decision areas provided by Wanke *et al.*

1) PLAN PROCESSES

A set of 9 studies out of 23 papers presented in the literature are covering the use of VA systems in the plan process activities of the SC. These visualizations that mainly concern the planning of SC operations have been employed in various use cases, the most significant of which are sales and demand analysis [23], [40]–[42].

The authors of the study [43], proposed a VA system of market sales data of agricultural products. This system investigates the dynamic information on the business circles and identifies the trends in the consumer demand over a particular period. The identification of trends in consumer demands helps to achieve auxiliary market analysis and decision making. This is an activity that is useful for different stakeholders in the SC, taking from the manufacturers, to distributers, warehouse, and retail. This study uses the market sales data collected from different sources and in different formats, after which they have been collected and unified in a data pre-processing step that includes the removing of the incomplete data, missing value handling, and noise treatment. Therefore, data processing is an important task and given that data is collected from various heterogeneous sources, the process of data collection requires an underlying strategy and technology consideration that is not discussed in this study.

In a similar effort of sales data analysis, the same authors conducted another study presented in [40], supporting the same set of decisions with different visualization techniques in a different application domain. This time the focus is on the Fast-Moving Consumer goods (FMCG) industry and particularly, the sales information of a tobacco retailer. The analysis includes comparison of the sales volume and the percentage of different brands of cigarette in different business circles. The result of this analysis helps decision makers in production and retail to identify the consumer preferences and adjusting the next ordering round based on the location of the retail. Another analysis has been done towards assessment of the sales stability for a particular brand in a shopping district in order to adjust sales patterns. Furthermore, the analysis of the sales volume for various categories of products provides the ability to the retailers and manufacturers to select more efficient marketing strategies. In addition, identifying the consumers shopping habits may enable decision makers to consider the peak of the consumer purchases and adjust their marketing activities with respect to those timings. Although the sales data hold a lot of information about consumer shopping activities, there are many other sources of information such as seasonal events that can be considered in order to analyze sales patterns.

The study presented in [41], focused on VA techniques and developed a prototype to investigate the benefits of having multiple workspace capability in a VA system. The authors argued that having the ability to create multiple workspaces in a tab-based interface, provides users the ability to follow multiple analysis paths and pursue different hypothesis simultaneously. Regarding the decision support aspect of their work, they provided a user scenario of an analyst investigating the store sales data to create sales report of stores. It is based on the factors affecting the profit of each store and identifying the bottlenecks of the sales that should be addressed. However, this approach has not been tested in a real word scenario, and instead a sample dataset is used for evaluation of the systems.

The study presented in [44], provided a VA sensemaking framework that supports the prediction of water demand based on the historical demands and weather data. The framework is designed based on the engineering system design thinking, where frame and data components are defined as two main elements of the sensemaking process. A frame is the pattern recognition concept of data mining and is defined as the mental map of the situation to support the decision-making process. The framework considers visualization, models, insights and knowledge as frames. The analyst is supported by tools such as visualizations, data-mining, and statistical analysis to frame from the data and reframe further. This process is based on the definition of VA process provided by Keim *et al.* [45], that is, to analyze the data first (frame), demonstrate the importance (visualize), interact and filter, and analyze further (reframe).

The study presented in [26] is an attempt for market segmentation and demand trend forecasting, where clustering analysis is used to identify the patterns in data and mapping them with trends. Authors proposed a piecewise rank-one tensor decomposition method that slices the data into homogenous partitions for a comparison visualization. Using this method, a VA system is proposed for identifying the cross selling of different product groups in different times and locations, known as product segmentation. Furthermore, based on the geographical location of the sales, the comparison of sales over different products in different periods and market segments are carried out. Consequently, the spatio-temporal trend patterns of the regional sales data are analyzed, and the spatio-temporal events are identified in the data slices.

Identifying customer behaviors is another VA task that supports decision making in the plan business processes. In the study presented in [42], the quantification of the tendency of customers towards buying green products is discussed. This objective can be helpful both for the production and marketing planning, as well as for sustainability decision making. In this study, the demographic data of the customers are captured from the retail loyalty card program database along with their transactions in order to summarize customers purchasing behaviors. Upon this investigation, the level of the so-called customer greenness is identified based on their incomes.

Demand forecasting is one of the main challenges of the SC industries as their operations are highly correlated to the demand pattern of the consumers. However, demand forecasting models are facing the challenge of market uncertainty and data complexity. In this regard, the study presented in [46] focused on developing a VA system to demonstrate the performance of various models in order to support decision makers in selecting the best performing model for their demand forecasting activities. Both manufacturers and retailers can benefit from such models towards facilitating their model selection tasks. Authors of this study argued that a forecasting model that is developed based on the company sales data may be good only for some particular products and not reliable for some other products. Hence, in this study authors investigated the model selection based on a specific product selected by the analyst. Since many demand analysts and decision makers in manufacturing and retail companies are not familiar with the machine learning techniques, the approach of visualizing the model performances can help them to select the demand forecasting models with more confidence.

One of the aims of sales data analysis is to provide competitive intelligence [47]. Competitive intelligence is related to the ability to evaluate the growth, risk, and opportunities in connection with the market share. The authors of the study [47] proposed a visualization tool that demonstrates the total sales, trends and growth rate of the focal company in comparison to one of its competitors. Using the tool in a case study, an analysis of the market with the aim of stepping into the market with a new product is demonstrated. The analyst looked for the weaknesses of the leading competitor by looking at the visuals showing the current sales volume of the best and worst-selling products, the trends of the companies, and the rate of growth in different regions. In general, decision support systems require a risk analysis that can evaluate the implications of decision making. Analysts require some sort of risk demonstration using a what-if analysis setup to make more confident and reliable decisions.

2) MAKE PROCESSES

Make processes are mainly associated with manufacturing activities and efforts for optimizing productions. In this context, the study presented in [24] provided a VA system for optimizing the production of milk and maximizing the profit. This study investigated the analysis of animal test record data, specifically cows, in a dairy industry, to identify seasonal and monthly variations of milk productions. The authors evaluated the viability of the tool by means of experts' feedback. The overall user opinion about the system was positive. However, the level of interactivity with the system is low and it does not provide the ability to conduct predictive analysis.

3) DELIVER PROCESSES

The studies related to the delivery business process activities of SC are commonly around the approaches concerning the identification of the best sale strategy in retail stores. This application of VA can best serve retail industries to enhance their product deliveries to the hand of customers and improving customers purchasing experiences. Due to the dynamic market behavior, retailers should be able to dynamically adapt to the day-to-day changes of the consumers requirements. In this context, the authors of the study presented in [48], proposed a VA system for new sales strategy creation. This utilizes the combination of the Point-of Sales data and the data from the historical movement of customers in the store area. This system supports the decisions about the location of the products in store, sale time of the products, and advertisements, all of which are based on the customers moving and purchasing patterns. However, in this system, the interpretation of the visualized data is very much dependent on the analyst opinion and its validity is not identifiable at the analysis stage.

In a similar study related to the retail space management, the study presented in [23], developed an interactive visualization tool that supports retail stores in conducting analytical reasonings for the product locations in the store. In this study, the retail sales data and the store floor plan are used to visualize the amount of sales in each product category corresponding to their locations. The application of VA system in this scenario helps analysts to manage space allocation for the products in different periods based on seasonality and forecasts. It is also possible to investigate the bottlenecks and failed sales strategies and modify them accordingly. However, the sales performance of a particular product can be affected by multiple factors and it may not be addressed subsequently by the relocation of the product in the store.

Apart from the store space management, the location of the store is also an important factor towards the successful delivery of products. In this regard, the study presented in [49], developed a visual store location recommender system that makes use of the sales data, transit data, and store location data for identifying the attractiveness of a business district. In this study, a customer flow analysis is combined with the economic insights and expert knowledge to recognize the candidate location for a store maximizing profit. The analysis of transit data that includes the records of fare payment for public transportations is used to identify the customer flow in each district. This approach results in identifying locations as attractive business districts that are more in the business centers of the city.

With the same context of customers purchasing activity analysis from their flow in the stores, the customer purchasing behaviors have been analyzed as an another important factor to enhance the deliver business activity [50]. In [50], the customers' response to the sales campaigns is investigated using a VA system. The customers historical purchasing behavior is analyzed based on the customer loyalty card system data and is compared with their behavior during the sales campaign to identify their reaction to the campaigns. This helps decision makers to reorganize the campaigns based on their loyal customers purchasing behaviors, providing a dynamic sales strategy.

However, the customer behavior characteristics changes in different time periods and resolutions. Therefore, it is important to be able to characterize the customers with different granularity as per day or per month and also in different time periods such as daily or weekly. This is something that is explored in the study presented in [51]. The authors proposed a VA system for association rule mining in different granularities and time periods. They used sales data of an online retail to identify the relationships between product sales and sales strategies. However, the online and offline sale strategies should be different as they are having different means.

In general, retail industries are currently operating in both online and offline settings and identifying the right sales strategy for each of the setting is a significant challenge. The authors of the study presented in [52] used VA to optimize the profit regarding delivery in a food SC industry. In particular, VA is used to come up with the suggestion that in a dual channel SC setting, improving the logistic and operational activities together results in the increase of the profit in both the channels. They have utilized the historical transaction data of both online and offline sales to develop a location-based pricing model and later the VA is used to make suggestions for the respective decision makers by means of charts, feature patterns, and graphs.

As observed in [51], rule-based analysis technique is considered to be a noteworthy approach for SC data analysis. Another study that utilized this technique is presented in [53]. This study proposed the use of RFID tags to analyze the SC transportation events during the delivery activities. The proposed method can be used to detect and locate SC inefficiencies such as delays in shipments, inventory reduction, robbery, and out-of-stock cases. This study presented a visualization system that enables an analyst to identify inconsistencies in the SC along with a set of performance metrics such as dwell time, transportation time and product flow.

Transportation of goods is influenced by the traffic conditions of warehouse to retail routes in an extensive way. Indeed, a factor that can impact in the successful delivery of goods and products is the right placement of warehouse facilities. The study in [54] proposed a VA system towards enabling the comparison of different candidate locations for warehouses corresponding to a business district. The authors employed four types of data for such analysis: urban road network data, GPS trajectory data from a logistics company, warehouse data including information about warehouse characteristics, and business store data consisting of store locations and characteristics. The consideration of the traffic condition into the selection of the warehouse location responds to the uncertainties in delivery imposed by traffic.

The study presented in [55] corresponds to the shopping analytics tasks related to providing VA as part of customers' shopping experience. The authors of this study presented a user study scenario of shopping activity that provides users an analytical interaction capability. The combination of VA and augmented reality is called situated analytics. It provides the users with the ability to visualize the analysis of data about a physical object. Three different types of user interaction with the analysis have been introduced: filtering—the process of visualizing only objects of interest, finding—showing the exact object of interest to the users, and ranking—the process of sorting the objects of interest based on a particular criterion and visualizing the results. Additionally, a set of abstract information is provided to the user by means of bar charts. In general, immersive technologies such as augmented and virtual realities enable users to engage with the analysis of physical objects. This is an innovative approach for developing customers shopping experience.

4) RETURN PROCESSES

Return processes consist of activities related to identifying the product disruptions and acting on product recalls. In this scope, the study presented in [56] proposed a VA framework that detects possible product recalls by analyzing social media comments. The sentiment analysis investigates the negative comments that customers provide about a product and visualizes the output to demonstrate the necessary time to organize the recall. The proposed approach helps decision makers to monitor product consumptions and predict possible disruptions in order to reduce company's response time. Despite the importance of return processes, we identified only one study that supports the decisions connected to these activities.

5) ENABLE PROCESSES

Decisions about SC network management as a whole are considered as the enable business activity in the SC reference model. Some of these decisions are SC coordination, risk management, and the detection of SC inconsistencies. Towards supporting these decisions, related studies focused on understanding the structural aspects of the network. In this context, the authors of the study presented in [22] proposed an interactive VA system that is developed based upon data from a multi-echelon SC that consists of various SC day-to-day operation records of different SC stages, such as, procurements, manufacturing, distribution, and retail. These data included for instance average processing time in each stage, daily demand rate at each stage, and orders that each stage plans to satisfy. The study is a proper endeavor towards demonstrating the development process of a VA system for SC complexity analysis.

Indeed, understanding the structural aspects of the SC network lies under a broader field known as business ecosystem intelligence. The application of VA in this scope is explored in [57]. This study presented a representation of the global SC that helps SC managers to gain benefits from the visibility into their supply network structure and key performance indicators (KPIs). The proposed system offers three significant insights to SC decision makers: recognizing the dependency on a particular supplier known as SC breaking points, identifying SC bottlenecks, and distribution of SC risks. In general, these insights help decision makers to analyze the business ecosystem and gain more transparency and risk identification abilities.

SC managers are involved in organizing many aspects of their firm's relations with their SC partners. One of these aspects is the level of innovations employed in the SC processes. Innovation refers to the interaction between elements of process, technology and structure [58]. The VA system provides insights that support decision makers in the identification of knowledge and technology flow trends and patterns in the SC network. The authors of [58] investigated the development of a VA system for SC innovations. In this study, the development process involves design requirements, data preparation, visual representation, interaction, and iteration and refinement. Regarding data preparation, authors argued that the focus of the analysis determines which type of data should be collected. That is, if the focus is one firm, the data should include all direct and indirect partners of the firm, if the focus is on the product flow, supply relationships should be considered, and finally, if knowledge exchange is the focus of the analysis, the R&D relationships should be the main sources of data. Moreover, the attributes of each of the firms in the SC and their connections are another source of data that augments both the visualization and analytical potential of the system.

B. VA TECHNIQUES AND TACTICS

In this section, we present the visualization techniques and tactics used in different SC processes, as well as the analytical supports provided by the proposed VA systems. Overall, this section contributes to answer the second research question and its sub questions.

1) PLAN PROCESSES

Plan processes normally require the identification of sales trends and recognizing the amount of demands in various business circles. A practice known as market analysis. There is a range of visualization techniques used for this purpose, such as maps, charts, and temporal views. The study presented in [43], proposed an interactive visualization approach in which two types of Macro and Micro visualization of data are provided. The Macro display uses map visualizations to display the business circle analysis view that is achieved earlier with the help of clustering analysis over data and dividing the market data into different business circles. The map view provides the users with the ability to easily select a business circle on the map and conduct detailed multi-dimensional data analysis. On the other hand, the Micro display provides chart analysis of product sales data in each of the business circles. The pie charts for example, can be used to demonstrate and analyze the market share of each of the products in each business circle. The interaction level provided is to choose parameter setting for the cluster analysis, controls for the map displays, and personalized settings for the chart views. Although the clustering algorithm is a powerful tool for classification of market data, the optimization of this algorithm has not been considered. In addition, the level of interaction with the system lacks the possibility to conduct analysis in an iterative manner, which is the requirement for every powerful VA system.

The same authors conducted a similar study [40] with different visualization types in order to support other decision-making activities. That study proposed five different visualization types: Density-based clustering results map view, Nested ring diagram, Temporal K view, Theme Rivers map, and a Hotspot view. The use of the different visualization methods provides the ability to analyze the business districts from different angles. The choice of the visualization method is very much dependent on the number of the dimensions of the underlying data. As an instance, Nested ring diagrams combine and visualize multi dimensions of brand, categories sales, and percentages at the same visual representation. On the other hand, the Hotspot view is based on a two-dimensional Cartesian coordinate system that shows the frequency of hotspots that occur in a certain period. The type of the data dimension is another factor that affects the selection of the visualization method. For example, the Theme Rivers map is chosen because of the need for presentation of the time dimension. However, an analysis about the effectiveness of that approach is not provided.

In general, VA is an interactive iterative process in which analysts explore and analyze data in multiple rounds of questions and answers. However, in the conventional visualization systems such as those presented in [43] and [40], data visualization is done once and any modification to the data filtering or dimension selection alters the overall visuals and previous analysis paths will be lost. This issue is addressed in another study [41], where multiple concurrent workspaces are proposed as a solution for back tracking of previous analysis paths. In this way, users can see multiple outcomes of their work and analyze different aspects of the analysis at the same time. According to the authors, the four main design considerations of this VA system are: separate analysis paths, a shared context between different workspaces, the ability of the user to easily navigate between workspaces, and the ability to review, recall, and reuse previous steps and workflows. They have used histograms, charts, and scatterplots for different dimension preferences of the users.

In the previous section, we have seen the VA process as a sensemaking activity that was investigated in a water demand prediction case study [44]. In this study, JMP software from SAS Inc. and Tableau desktop were used for the VA process. Based on their proposed framework, they investigated the relationships between weather variables and water supply demands. To understand the correlation, data was prepared and transformed first, then visualization took place to understand the relationships between variables. An interactive visualization is provided for the analysis of top-level relationships. The analysis continued by correlation analysis, stepwise regression modeling and consequently the required insights and knowledge about the supply system is gained. The matching of the visualization framework and the visualization case study demonstrates a better understanding of the advantages of providing a conceptual framework for VA activities that are in line with system engineering tasks.

From another perspective, sales and demand data analysis are normally multi-dimensional historical data and the required VA system should preferably have the ability to support many dimensions. Another study [25] argued that sales data, as a typical component of On-Line Analytic Processing systems, consists of well-defined dimension hierarchies that divide dimensions into intervals. Authors then proposed an interface, a hierarchical labeled tree presentation of data that can be used for sales data exploratory analysis. In this type of tree visualization, the top-level node of the tree is a single node consisting of all the data points in a dimension, while the lowest level contains one node for each of the data points. Each dimension tree has multiple levels, representing different intervals of various dimensions. The three key design aspects of the proposed method are: dimension value scales, dimension relations, and filter coordination. Dimension scale is the presentation of attribute frequency in a visualization element. This study proposed the proportional tree scale that is a stacked bargram presentation, where the width of each bar shows the relative frequency of that data attribute. The analysis of different dimension relations is another important task that these authors proposed, the coloring of the bargrams itself to demonstrate the relations. Filter Coordination is also introduced to provide the ability of applying interactive filters to the visualization to restrict the presentation in other dimensions. In this manner, the user can select one of the categories in a dimension and gets the corresponding presentation of that category in other dimensions. This approach is to solve the issue of multi-dimensional data visualization, however, the user study conducted in this paper revealed that their visualization generates difficulties in reading data distribution and reading time trends, two of the important data analysis tasks related to the sales data.

In another effort regarding the multi-dimensional VA using tree views [26], authors proposed a VA system that mainly focus on partitioning or clustering data in order to identify underlying patterns. Such VA system should fulfill the following design requirements: presentation of hidden patterns on different dimensions, ability for comparison of different clusters of data, analysts should be able to visually identify if a pattern is reliable or not, the clustering task should be interactive, and finally, the iterative process of partitioning should be trackable by the analyst in order to refine and repartition. The combination of different charts and maps along with an automatic partitioning algorithm provide the ability to satisfy previously mentioned design requirements.

In general, clustering of data is a method that helps identifying hidden patterns in data. However, the authors of the study presented in [42], decided to use a Self-Organizing Time map (SOTM) to identify the different degrees of the so called customers greenness, instead of general partitioning of customers into groups of green and non-green. The SOTM algorithm indeed, is another method to analyze the multi-dimensional data by viewing the data from a single variable point-of-view. This study presented the results using colored feature planes. In this visualization method a dimension is presented upon differing degrees of the target variable with the help of stacked colored circles, being the level of greenness in this case.

Analyzing multi-dimensional data by viewing the data from a single variable point-of-view helps the analysts to capture the hidden uncertainties related to different data points in a specific dimension. In this context, the study presented in [46], provided five components in their visualization system for demand forecasting model selection: an overview of the analysis, a similarity view that allows users to select clusters of data manually, an item view which displays analysis specific to a particular data item, a detail view that demonstrates more information related to the analysis of that specific data item, and a concluding view that helps analysts to come to some sort of a conclusion at the end of their analysis. These different views are provided in a dashboard with a mixture of different graph-based glyph designs.

These dashboards are commonly known as multiple coordinated views. Demonstrating the data in different views, provides the ability to the user to consider different aspects of the data. As we already mentioned, Keim *et al.* [45] described the first step of VA as analysis and then visualizing the analysis. However, [47] argues that visualization of the whole data in a single view without prior analytics in turn can provide a great ability for analysts to get an overall insight about the data, especially in the case of sales data. Therefore, authors of this study proposed a pixel-based visualization that shows each datapoint as a pixel in a matrix. Although this technique shows good outcomes as a response to the issue of scalability, in cases when sales data consists of various trends occurring in multiple durations can be extremely large to demonstrate in a single view. That is where an interactive filtration feature permits focusing on a subset of data at a time, making analysis feasible.

2) MAKE PROCESSES

Regarding the make process of the reference model, the authors of the study presented in [24] utilized various visualization techniques to provide a VA system for milk production optimization. This study integrated visualization techniques that are particularly useful for time-dependent multivariate data. Three visuals are implemented to satisfy the requirements of the application. First, a scatter plot is used to show milk attributes (fat, protein values…). In this way, the dependency of attributes to the production time can be identified. Second visual is a mix of a line charts and histograms to show the density of the data and enables the user to verify the data quality. In this way, the value of produced milk in each day as well as the relation of the quantity of the produced milk and milk attributes are shown. Finally, a multiple timeline view is used to demonstrate the overall production performance. Although multiple views are developed in order to provide analysis, the system lacks interactive analytic capabilities.

3) DELIVER PROCESSES

Multi-dimensionality of the data in the SC, such as the spatio-temporality, requires the combination of other visualization techniques to obtain required results. In this vein, the study presented in [23], developed a visualization framework that provides 3D graphics, parallel coordinates, choropleth map, scatter, ternary and some other visualization elements to provide a layered component based visualization toolkit. The proposed framework is used to develop a retail store management visualization system that provides interactive 3D views to store managers along with the spatio-temporal data analysis. Regarding the store space management activity, the tool should have some set of design requirements such as: space and time awareness, large-scale data views, ability to manage multiple views, interactivity of the system, and facility to steer the high-dimensional and multivariate data. The 3D view of the store space provides the store managers that are not data analysts the ability to interact with the system and understand the insights from the massive amount of sales data more efficiently.

With the same approach of combining the map view and statistical analysis view, the authors of the study presented in [49] used the subway map to provide a geographic information visualization. Given that the study investigated the customers flow to identify an attractive location for retail store, different degrees of color in the map demonstrate the level of attractiveness in different areas. The VA system proposed in this study also provides statistical analysis view using a multi-layer circular diagram that stacks different levels of information on top of each other in a circular design. Moreover, a heat map provides the recommendations for the store location and a bar chart presentation of different factors that affect the attractiveness of each location in a comparison view. The authors provided a dashboard that consists of different views in order to satisfy different design requirements that are fulfilling the objectives of the application.

Another visual analysis of the customer behaviors is carried out in [50]. In this case, a self-organizing map (SOM) is used to first cluster the customers based on their purchasing habits. Then, the customers' behavior migration pattern is visualized using a feature plan representation. SOM converts the high-dimensional data into two dimensions and helps the presentation of clusters visually. This study mentioned the motivations of using SOM over alternative methods as the link between the dimension reduction and clustering activity, the grid structure of the visualizations, ability to handle missing data and outliers, and computational efficiency.

In general SOM is a visualization technique that is used to identify the multivariate temporal patterns in data. It is, in fact, detecting similar data records that are close to each other. With a similar objective, association rule mining is to discover time-dependent association rules by finding the relationships between data records. The study provided in [51] explored the VA design for association rule mining. They have defined five design requirements for such a system: the support for temporal pattern analysis, ability to do the task of rule mining based on an item view, possibility to analyze the rules visually, clear demonstration of the relationship between data and the rules, and the ability to save and compare rules in their course of analysis. So, this study provided a multi view dashboard that consists of multiple panels of charts, graphs and feature planes to provide the design requirements as desired.

The rule-based analysis is also explored in [53] by a map-based visualization method. It demonstrates the aggregation of the product flow throughout the SC and visualizes the problematic areas by identifying the potential business issues. The system also provides the ability to the users to analyze the data manually by filtering capabilities and performance metrics. These authors use different rule-based analysis to detect some of the SC inconsistencies such as Velocity, Dwell-Time, and Life-Cycle inconsistencies.

Map-based visualization methods have been used by many studies [23], [48], [49], [53], [54] to analyze various spatial parameters such as the location of the facilities and the flow of the products. In [54] authors use a radar chart-based to demonstrate the comparison between different candidate warehouse locations. Providing the ability to compare different visuals gives the analysts a great ability to contrast relevant information and differences in a precise way.

4) RETURN PROCESSES

Regarding the return processes, in [56] authors used graphs and control attribute p-charts visualizations to provide users the ability to identify product disruptions. In this method, first, sentiment analysis is used to classify customers' feedbacks and comments as either negative or positive, then, VA is provided. Three different visuals are provided for exploring these sentiments. A graph demonstrates the daily net score which is the daily transition of customers' sentiments about a product along with a timeline of events showing the product announcements to understand user's reaction. This view provides a general idea about user's reaction to a product rather than showing the number of negative or positive comments. Therefore, a second visual is provided with the help of a heatmap that presents the distribution of the comments by showing their score and day. Finally, an attribute p-chart is used to show the variation in negative comments per day. Although the proposed framework provides a good means of analyzing social media data for a product disruption identification, it does not provide the ability to interact with the data and conduct predictive analysis.

5) ENABLE PROCESSES

Given that enable processes are connected with the management of the SC network as a whole, the visualization techniques used should provide a holistic view of the SC network so that decision makers and analysts can get insight about working condition of different nodes of the network. The authors of the study presented in [22] utilized a supply network view called Force-directed layout to distinguish between different clusters and modules. The authors visualized the structure of a network with a set of connected nodes. Nodes demonstrate the different stages of the network and edges are the connection between the stages. This type of visualization facilitates the identification of the primary sources at the heart of the network that are acting as the lifeline of the SC. Moreover, the system made use of one version of the circular layout called chord diagram. This view provides a comprehensive summary of the overall flows between different types of the activities in network. Three other views integrated in the system are Tree map layout, Matrix layout, and Substrate-based layout to highlight node compositions, visualizing edges, and network structure, respectively. The authors also provide a what-if analysis capability covering both descriptive and predictive analysis tasks. The what-if analysis is based on scenario-based techniques rather than the advanced machine learning based methods. The scenario-based analysis provides sensitivity analysis on each node that can be used in different scenarios such as monitoring the impact of a sale campaign on the network performance. However, the study covers only cost and demand sensitivity analysis and other high-level analytics such as the impact of various uncertainties, e.g., a disease outbreak, are left open for future studies.

In a similar effort to determine the structural aspects of the supply network, in [57], authors used the force-directed layout to provide insight into complex interdependencies and to facilitate determining the suppliers at SC breaking point. This study used a circular concentric layout to demonstrate risk distribution in the network. In this visualization method, suppliers are shown with colored dots. The size of the dots represents the importance of each supplier and the color represents the level of the risk as being either medium or high. The connection between different entities in the network are also shown using colored lines. The authors explored using of different visualization techniques, but the proposed tool lacks the power of interactivity and some of the required analytical capabilities such as predictive analytics.

As mentioned before, one of the implications of structural aspect analysis is the ability to analyze the propagation of innovation in the supply network. In this scenario, given that the data for the innovation circulation in the network is spatio-temporal, the corresponding visualization should have the ability to present such multi-dimensionality. Consequently, in [58], authors proposed the utilization of five types of visualization as follows: Geographic visualization for Insights regarding the spatial distribution of innovations, Circos-based visualization for identifying the concentration of the knowledge, Concentric visualization for flow of knowledge, Force-directed visualization to cluster innovations, and Matrix visualization for shared knowledge landscape presentation. Thus, different visuals to the user along with an enough set of interactions, such as selecting, filtering, and navigation, provide users the ability to conduct reliable analysis.

In order to sum up our interpretation of previous studies, we provided a mapping from each of the tactics taken for tackling a particular analytical goal to the visualizations techniques that have been implemented. In Table 4, we present the techniques used towards implementing each of the tactics along with the analytical goals and their advantages or applications. In fact, Table 4 presents the state of the art in deploying each of the tactics with the help of the corresponding visualization techniques tailored for an analytical goal. However, only 20 studies out of 23 primary studies found deployed a particular tactic. In a nutshell, we found 15 different tactics towards achieving 39 analytical goals with the help of 45 different visualization techniques. Moreover,

TABLE 4. Summary of visualization tactics and techniques used for different analytical goals.

#	Ref.	Visualization Tactics	Visualization Techniques	Analytical goals	Applications / Advantages
1	[40], [43]	Visualizing multi-dimensionality by clustering	Nested ring diagram	Visualizes multi-dimensions at the same visual representation	Provides ability to look at the analysis from multiple angles
			Temporal K view	Combining dimension information	Useful to identify abnormalities in multi-dimensional data
			Theme rivers	Exploration of the time dimension	Useful to explore trends based on variations in time dimension
			Hotspot view	Frequency of hotspots that occur in a certain period.	Provides ability to present the variations in the proportion of discrete, non-numeric field values within the data
	[41]	Providing multiple concurrent workspaces to back track previous analysis paths	Histograms	Used for visualizing single dimensions	Provides separate analysis paths, a shared context between different workspaces, the ability of the user to easily navigate between workspaces, and the ability to review, recall, and reuse previous steps and workflows
			Bar chart	Used for visualizing one dimension is categorical and the second numerical	
			Scatter plot	Used for visualizing two numerical dimensions	
3	[44]	Finding relationship between variables by correlation analysis and stepwise regression	Mix of different visual formats in a Tableau dashboard	Statistical analysis of variables	Identifying interdependencies of variables helps rapid design of a proof-of-concept design of decision-making system
4	[25]	Exploring each dimension by dividing dimensions into intervals	Hierarchical labeled tree of Stacked bargram	Exploring dimension value scales	Provides relative frequency of a data attribute along with their relation
			Coloring of the bargrams	Exploring dimension relations	
			User can select one of the categories in a dimension and gets the corresponding presentation of that category in other dimensions	Exploring filter coordination	Restricting the presentation to one dimension
5	[26]	Identifying underlying pattern by partitioning	Tree view	Comparing the patterns across different subsets of data	Presentation of hidden patterns on different dimensions
			Bar chart	Distribution over temporal dimension	Emphasizing on individual values
			Line chart	Distribution over temporal while performing	Better than bar chart on trend detection
			Bubble map	To show a thematic map	Provides ability for comparison of different clusters of data
			Flow map	Shows origin-destination data which describe spatial movements	Trackable by the analyst in order to refine and repartition
6	[42], [46], [47]	Viewing the data from a single variable point-of-view by Self-Organizing Time Map (SOTM), and Machine Learning methods	Colored feature planes	A dimension is presented upon differing degrees of the target variable	Identify the different degrees of a variable, instead of general partitioning of data into similar groups
			Ranked list of models	Overview of the analysis	Multiple coordinated views help capturing the hidden uncertainties and provides the ability to the user to consider different aspects of the data
			Scatter plot	Similarity view showing similar historical data	
			Bar chart-based and circular glyph design	Item view showing model performance on each item	
			Bar and line charts	Provides detail view and concluding view	
			Pixel-based visualization showing each datapoint as a pixel in a matrix	Provide an overall insight about the data	Shows good outcomes as a response to the issue of scalability
7	[24]	Exploring time-dependent multivariate data	Colored scatter plot	Dependency of an attribute to time	Supports multivariate data analysis by showing three dimensions at the same time
			Mix of a line charts and histograms	Density of the data	Enables the analysts to verify the data quality indirectly
			Multiple timeline view	To analyze the temporal effects by showing two timelines simultaneously	Distinguishes cyclic data patterns and showing variations in different time periods
8	[23], [58]	Exploring spatio-temporality	3D graphics	A layered component-based visualization toolkit provides space and time awareness, large-scale data views, ability to manage multiple views, interactivity of the system, and facility to steer the high-dimensional and multivariate data	Provides the users that are not data analysts the ability to interact with the system and understand the insights from the massive amount of sales data more efficiently
			Parallel coordinates		
			Choropleth map		
			Scatter plot		
			Ternary		
			Geographic visualization	To analyze the propagation of innovation and knowledge in the supply network	Provides Insights regarding the spatial distribution of innovations
			Circus-based visualization		Ability to identify the concentration of the knowledge
			Force-directed visualization		Presenting the flow of knowledge
			Concentric visualization		Ability to cluster innovations
			Matrix layout		Provides shared knowledge landscape presentation
9	[49], [54]	Geographic information visualization	Multi-layer circular diagram	Combining the map view and statistical analysis presents different factors that affects the target variable over a geographical location	Ability to stack different levels of information on top of each other
			Heatmap		Provides comparison view
			Bar chart		
			Radar chart-based	Comparison between different candidate elements	Providing the ability to compare different visuals gives the analysts a great ability to compare the

TABLE 4. *(Continued.)* **Summary of visualization tactics and techniques used for different analytical goals.**

10	[50]	Dimensionality reduction by self-organizing map (SOM)	Feature plan representation	Converts the high-dimensional data into two dimensions and helps the presentation of clusters visually	Provides ability to handle missing data, outliers, and computational efficiency
11	[51]	Finding relationships between data records by association rule mining	Multi view dashboard that consists of multiple panels of charts, graphs and feature plans	To discover time-dependent association rules	Support for temporal pattern analysis, ability to do the task of rule mining based on an item view, possibility to analyze the rules visually, clear demonstration of the relationship between data and the rules, and the ability to save and compare rules in their course of analysis
12	[53]	Detecting inconsistencies by association rule mining	Map-based visualization	Aggregation of the product flow throughout the supply chain and visualizes the problematic areas by identifying the potential business issues	Provides users with the ability to analyze the data manually by filtering capabilities and performance metrics
13	[56]	Analyzing social media data for product recall	Timeline	Sentiment analysis	Provide the analysts the ability to identify product disruptions
			Heatmap		
			Control attribute p-charts		
14	[22]	What-if analysis based on scenario-based techniques	Force-directed visualization	To distinguish between different clusters and modules as well as the presentation of the whole network as nodes and edges	Provides a holistic view of the supply chain network so that decision makers and analysts can get insight about working condition of different nodes of the network.
			Chord diagram	Comprehensive summary of the overall flows between different types of the activities in network	
			Tree map layout	To highlight node compositions	
			Matrix layout	To visualize edges	
			Substrate-based layout	To show network structure	
15	[57]	Determining the structural aspects of the supply chain network	Force-directed visualization	Demonstrate risk distribution in the network.	Provides insight into complex interdependencies and facilitates determining the suppliers at supply chain breaking point.
			Circular concentric layout		

from the table, it is also possible to identify the application or the advantages of each of the tactics paired with their corresponding techniques to address a possible analytical goal. We hope this summary serves as a guide for taking SC VA steps further in research and development.

V. DISCUSSION AND CONCLUSION

The overall procedure of this study, from formulating to research questions to identified context for grounding the results, is illustrated in Figure 3.

A. OVERVIEW

In this study, we have conducted a SLR to identify, evaluate and interpret previous related works regarding the use of VA for SC processes and decision making. In this review, we have scrutinized the literature and classified the findings based on a SC reference model provided by the ASCM. We have then mapped our findings towards identifying the use cases of VA systems in SC, the decisions they intend to support, the type of visualizations employed, the type of analytics used, and the data that is being used for analysis. Finally, in order to answer the first research question and its sub-questions, we have categorized the studies found in literature based SCOR model activities, as well as the decision areas categorization provided in the literature. Based on the literature, we have identified 8 different decision areas that have been previously addressed by VA systems, namely, sales management, network design, collaborative forecasting, demand management, network integration and visibility, production management and distribution planning, transportation management, and operation management (Table. 3). These decision areas can be used to identify the SC requirements for developing respective VA systems.

Furthermore, in order to answer the second research question, a mapping between visualization tactics towards achieving specific analytical goals regarding SC business processes and the reciprocal visualization techniques has been provided. Adding to that, applications, uses cases, and advantages of tactics and techniques pairs are identified.

Therefore, both VA researchers and developers can benefit from the state-of-the-art VA systems, including the data they utilized and the decisions and use cases they intended to address. We also analyzed the literature to identify latest trends in visualization techniques and tactics that have been utilized for some specific analytical goals in SC. We believe, this study highlights the significant aspects that VA researchers and developers need, in order to outline a customized VA system for a particular SC.

Overall structure of the results of this review are towards answering the main RQs on how VA is being used in SC activities and which VA techniques and tactics should be used for SC related activities.

B. RQ1: HOW HAS VA BEEN USED TO SUPPORT THE SC ACTIVITIES?

Considering the RQ1, we have found that 10 studies are focused on the plan business processes. *Plan processes* mainly used sales and demand data to identify trends on consumer demands. However, the relationships between sales

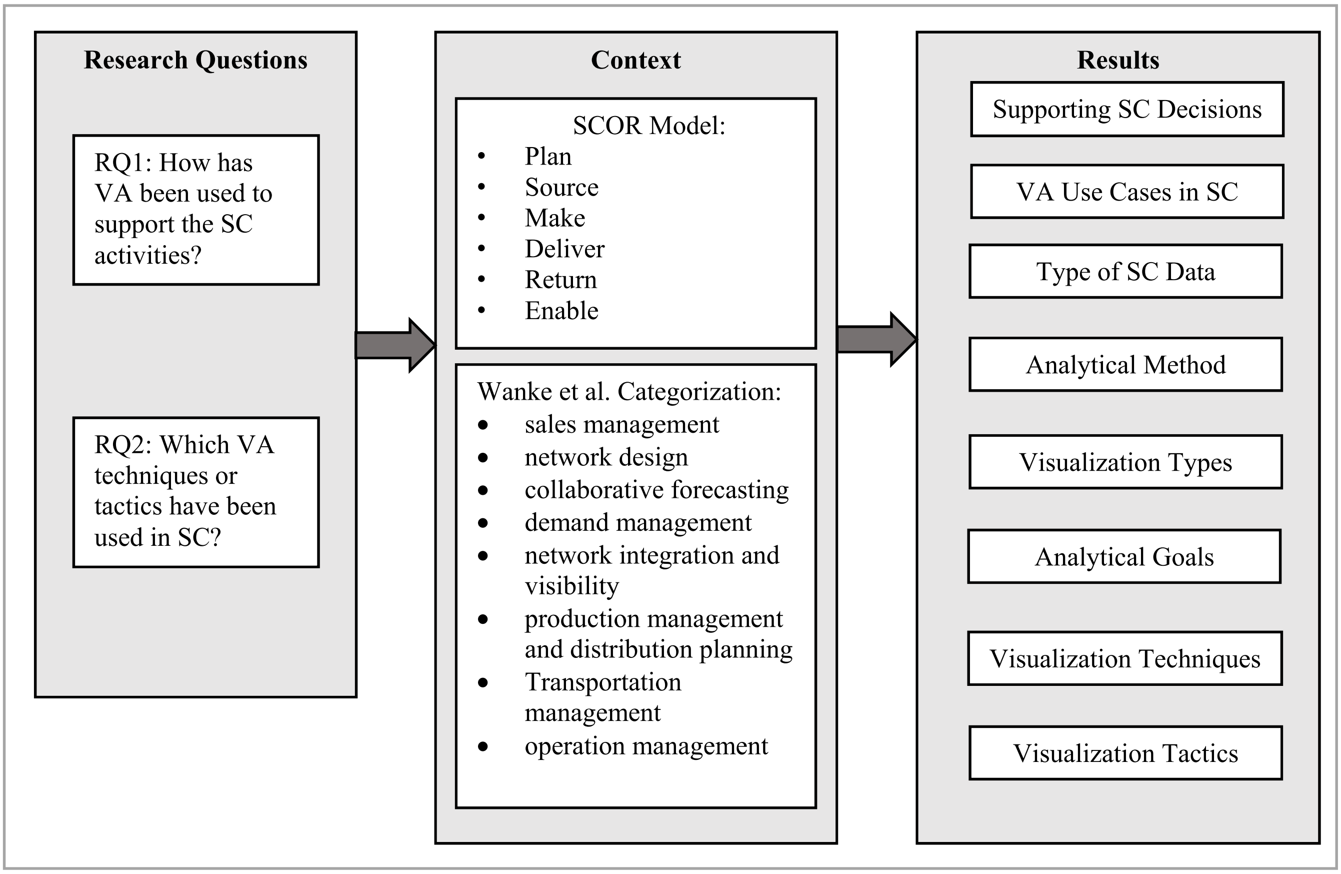

FIGURE 3. Research framework.

and demand and the current operations of the company or the external variables, e.g., the uncertainties that can impact the sales, are not considered extensively. Likewise, given that sales and demand patterns are influenced by many factors, the VA system should either have an ability to be scaled with external data or the use of such data should be integrated into the system. In this regard, one of the primary studies included consumers' demographic data into the system to analyze customers purchasing behavior.

Plan processes mostly include sales management and collaborative forecasting, three studies for each. After which demand management have two studies following with business intelligence processes and network integration and visibility decision areas with one paper for each.

In general, market and sales pattern analysis can help decision makers to identify factors affecting the sales and conduct comparison inspection on different product sales against different timings and periods. Moreover, we found that although *source* and *make processes* are important parts of the SC activities involved in procurement and preparation of raw materials and the actual production of goods, there have not been many studies to address those aspects. Production activities are developing a lot of data consisting of product attributes in different parts of the manufacturing line. Such data can be used as a basis for VA and improve the company's production potentials. Furthermore, delivering the products to customers is an important part of the SC activities that involves almost every partner in the chain. A notable percentage of the studies, i.e., 35% (10/23), inspected the identification of sales strategies regarding the location of the stores, the location of the products in the store, the timings for offering products to customers, and analyzing the reactions of the customers to sales campaigns, all of which are parts of the *delivery process*. As high as 45% (4/9) of the papers within the delivery processes are also mainly address the sales management decision area. *Return processes* are also an important part of the SC covering the product disruption identification and recall. It is becoming more viable with the help of social media data by fetching consumers' opinion about products. In this situation, the on-time prediction of disruptions can prevent future losses, the visualization of trends in consumers' sentiments both spatially and temporally assists with identifying the disruptions and acting for recall. In this regard, operation management has been identified to be the target decision area.

Finally, the *enable processes* concerning the management of the SC as a whole have been addressed mainly by analyzing the structural aspects of the supply network. In general, network design, and network integration and visibility have been identified as the decisions areas within which analysis have been carried out. This type of analytics can provide several benefits to SC managers. In this regard, VA helps a rapid detection of risks and SC disruptions and, at the same time, inspecting the bottlenecks of the chain by identifying the sole dependency on a particular actor in the chain in order to react accordingly. However, the problem of information flow within SC partners and the lack of required data form the overall SC operations, act as big barriers towards integrating such systems to the decision-making processes. We believe, the development of information flow within SC partners can enhance the overall SC intelligence that can benefit all the partners.

C. RQ2: WHICH VA TECHNIQUES OR TACTICS HAVE BEEN USED IN SC?

Concerning the RQ2, we identified 15 visualization tactics as the main approaches to address several particular analytical goals within the SC business processes. These tactics provide the way analysts decide to intervene towards some application areas. Accordingly, for each of the goals, a specific visualization technique with its characteristics is required to implement the visualization tactic under consideration. Table 4 provides the list of all identified tactics and techniques. Adding to that, the application or advantages of the each of the pairs are also recognized. The difference between application and advantages is where the application of a particular tactic and technique pair necessarily does not provide the proof for any advantages but have been used for a specific application in SC.

Moreover, many visualization techniques have been identified. Majority of the works are using dashboards that include different visuals of charts and maps to provide some sort of analysis capability to the analysts. However, the gap here is the level of interaction of the analysts with the system. In fact, significant boosters for a VA system are in the abilities of analyst to interact with the system and the options they get in logging the interactions for further reviews and comparisons. On the other hand, given that most of the data used are sales data and spatio-temporality is one of the main characteristics of such data, the visualization technique should have the ability to provide the analysis of different attributes against the time and location. In this manner, map-based visualization and time-line views provide space and time dependent views for the pattern extraction support. The gap here is the identification and visualization of the links between the space and time dimensions that comprises of changes in space dimension according to the time, leading to a significant analysis capability. In general, the choice of a given visualization technique mainly depends on the analytical goals that is supposed to be achieved. As an instance, theme rivers are used to explore time dimensions, histograms are used for visualizing a single dimension, or tree views are used to compare the patterns across different subsets of data.

The main focus of the data analytic capabilities is the clustering analysis of data, namely, density clustering and self-organizing maps. Here, the application of other machine learning methods, such as classification and regression analysis, remained unexplored that can provide more advanced analytical capabilities to a VA system. The main analytical capability is left to the interaction of the analysts with the visuals with the help of filtering and selecting the subsets of data in order to identify hidden patterns on different dimensions of data.

D. FUTURE WORK

For future research a number of directions can be mentioned. First, the application of VA in supporting of *source* and *make processes* of the SC may be explored, such as cost modeling of different sources and production scheduling. Second, visualizing the impact of external variables on different SC operations such the effect of weather forecast on sales may be investigated more extensively. Third, we suggest improving the interaction level of the visualization systems in order to gain more advantage of the human in the loop of analytics. Finally, the application of different machine learning methods based on different analysis tasks and providing the users with the ability of choosing the underlying machine learning method for analysis may be studied in future research. We hope this review could highlight the previous efforts in connection with the use of VA in SC and shed light into future research opportunities.

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