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Abstract:
Visual Analytics (VA) has shown to be of significant importance for Supply Chain (SC) analytics. However, SC partners still have challenges incorporating it into their data-driven decision-making activities. A conceptual framework for the development and deployment of a VA system provides an abstract, platform-independent model for the whole process of VA, covering requirement specification, data collection and pre-processing, visualization recommendation, visualization specification and implementation, and evaluations. In this paper, we propose such a framework based on three main aspects: 1) Business view, 2) Asset view, and 3) Technology view. Each of these views covers a set of steps to facilitate the development and maintenance of the system in its context. The framework follows a consistent process structure that comprises activities, tasks, and people. The final output of the whole process is the VA as a deliverable. This facilitates the alignment of VA activities with business processes and decision-making activities. We presented the framework's applicability using an actual usage scenario and left the implementation of the system for future work.

Keywords:
visual analytics; supply chain analytics; conceptual framework; business intelligence.

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1. Introduction

Visual Analytics (VA) capability has shown to be of paramount importance for Supply Chain (SC) analytics. Nevertheless, SC stakeholders yet struggle to integrate it into their data-driven decision-making activities [1], [2]. In order to exploit the VA capability, there should be an alignment in a top-down approach from business strategies and their inferring business processes and issues, all the way down to decision goals and analytical tasks [3]. On the other hand, SC partners need to collaborate and share information throughout the chain to gain mutual benefits and leverage their data assets [4]. However, data sharing imposes numerous challenges, such as information leakage [5]. To mitigate such challenges, it is imperative to have a data governance framework in a consensus of various partners, without which data would not be utilized as an asset [6]. In general, many factors should be considered to have a well-established VA system. For instance, a VA system requires a human-in-the-loop process model to streamline human interaction with various stages of the process [6].

The study of developing VA into SC decision support systems is comprised of various aspects belonging to different disciplines. Within the information system community, several studies have explored the connection between user requirements and visualization practices [7], [8]. However, SC requirements are not explored significantly. At the same time, the Business Intelligence (BI) community is studying the mapping of business processes to specific analytical activities, but without identifying visualization best practices [9]. In general, business processes are considered but not supply chain-specific processes. VA community addressed many visualization aspects, such as automation, recommendation, and interaction [10]–[12]. Nevertheless, they are often generic, and decision areas that link the VA system with business decision goals are not identified rigorously. On the other hand, data governance has neither been explored regarding SC stakeholders' data challenges nor been explicitly considered for VA system requirements [13], [14]. Finally, although the SC community recognized VA as one of the SC data analytic capabilities, it is not discussed sufficiently [15].

In computer sciences, conceptual frameworks are the constellation of concepts, assumptions, expectations, processes, and methodologies that support the development and deployment of a technology in an application domain [16]. Therefore, conceptual frameworks can be used to understand a real-world phenomenon and to provide a roadmap toward streamlining the integration of a technology into its corresponding application domain. In SC VA, a conceptual framework can be used to understand the interlinked concepts from SC decision-making, data governance, VA requirements, and their relationships. It can also outline target decision areas, data sources, data sharing requirements, human agents, and required VA attributes. As a result, an alignment between VA practices and business strategies in a value chain can be achieved. In addition, a coalition between SC stakeholders can be formed for data and analytics development and sharing.

In this study, a conceptual framework is proposed for the development of a SC VA covering three main aspects of the system at a macro level: 1) VA-assisted SC decision-making process to align VA with business strategies, 2) data governance strategies to identify and share required data, and 3) VA system development process to streamline SC VA developments. The proposed framework specifies a SC VA system's development process and the inputs, outputs, activities, and involved human agents for each step at a micro-level. The framework facilitates the process of identifying SC decision areas that the VA can support and their alignment with decision goals and business strategies. Moreover, it helps recognize the required data sources and sheds light on data sharing requirements. Finally, it streamlines the SC tailored VA system development process. Indeed, the study results assist SC stakeholders in identifying pitfalls in strategic planning for their VA activities and providing plans to mitigate them. The main contribution of this study is as follows:

- Proposing a conceptual framework for developing SC VA systems.
- Presenting a multi-view representation of the SC VA development.
- Presenting a meta-model for creating SC VA models.
- Providing an overview of existing approaches for VA integration based on the related works.
- Identifying aspects of VA development in SC practices and providing future research directions.

The rest of this paper is structured as follows: In section 2, we present a background of the study covering related works and concepts. Section 3 presents the method for conceptualizing VA development in SC practices. Section 4 provides the proposed framework and explains its different parts and processes. Section 6 highlights the study's findings by discussing its essential aspects. Finally, section 6 wraps up the paper with a conclusion and prospective future works.

2. Background & related works

2.1 Business-driven analytics

Business-driven analytics studies investigate the process of aligning analytical activities in organizations with their business goals and strategies [17]. Previous studies looked at it as a requirement engineering problem from software engineering practice to understand the business goals for which data analytic activities are to be formalized. In this regard, Lavelle et al. [7] proposed a requirement model based on a technique so-called goal-oriented modeling. The model is based on the "i*" modeling framework [18] and traverses the decision-making hierarchy from business processes and strategies to analytical types, decision goals, and information goals. The authors assumed that knowing the business process can be a starting point to determine the scope and objective of the analysis. At the same time, an effective analytical activity requires a more precise analytical goal, such as exploring multi-dimensionality or identifying patterns.

In another effort toward analytical requirement elicitation, Nalchigar and Yu [9] presented a conceptual modeling framework for developing data analytic processes based on business objectives. As part of their framework, they have proposed design catalogs for analytics design. In order to align business issues with the analytical activities, a number of business questions have been categorized based on the possible analytical technique to address them accordingly. In general, design catalogs facilitate the analytical process, especially if it is defined in the context of a specific business domain. Likewise, Golfarelli and Rizzi [19] proposed a design catalog for different visualization types based on a visualization system's six aspects: goal, interaction, user, data dimensionality, cardinality, and type. The goal aspect provides the generic analytical goals, such as composition, order, cluster, etc. A domain-specific goal definition, in our case, SC goals, streamlines the identification of decision goals and eventually results in a better alignment of analytical activity with business processes.

In summary, information system research groups explored business-driven analytics and visualization as a requirement engineering problem. However, the focus on SC requirement analysis and their connection with VA needs more research.

2.2 Supply Chain data governance

SC activities are data-rich, and the information flow within the partners is essential to circulate the desired data for various decision-making activities. However, this raises data control, information security, and data quality challenges. Therefore, there is a need to define data integration and usage policies, data exchange standards, interaction, and collaboration procedures, as well as service level and data sharing agreements [6]. Data governance deals with the control and management of data [20]. It orchestrates data principles, quality, access, lifecycle, and metadata [21]. Apart from the governance of data between partners, the management of data integrity and quality should be handled by each stakeholder to align the business needs with the data and information needs [6]. In this regard, Teruel et al. [22] proposed a modeling language for collaborative BI to foster business-process-oriented decision-making activity, preventing information loss and poor analytical results. Despite several previous works related to data governance [13], [14], [23], SC consortium-specific data governance requires more research.

2.3 Visualization recommendation

During the last five decades, there have been various efforts toward automating visualization type selection and recommending the best visualization type to the user [10], [19], [24]–[29]. In general, the approaches taken by these studies can be categorized into three main types: 1) Task-oriented, 2) Data-oriented, and 3) User-oriented. Task-oriented approaches either focus on the type of analytical tasks, such as descriptive, prescriptive, diagnostic, and predictive analytics, or focus on the specific goal of the user, such as comparison, clustering, and trend analysis. Data-oriented approaches, instead, either rely on the data characteristics, such as dimensionality, cardinality, and data types, or focus on the statistical properties of the data, such as normality of distribution, uniformity of distribution, outliers, and correlation. Finally, user-oriented approaches are mainly based on the user's interaction with the system.

Basically, visualization recommendations are in two ways; 1) providing a ranked list of visuals to users in a faceted view, facilitating the selection of the most desired visuals, and 2) analyzing the interaction between the user and the system, such as zooming and filtering, identifying a meaningful pattern in users’ interaction with the system and recommend the best visualization based on previous real-world, observed activities. More recently, Golfarelli and Rizzi [19] proposed a mixed approach by taking into account a combination of these coordinates, such as goal, dimensionality, cardinality, and interaction. However, to the best of our knowledge, previous studies did not consider the SC domain-specific decision areas to recommend corresponding visualizations.

2.4 Supply Chain Visual Analytics

Previous attempts towards conceptualizing VA mainly covered the VA system itself [30] rather than focusing on a specific application area, such as SC analytics. Several studies emphasized the importance of visualization for SC analytics; nevertheless, to the best of our knowledge, there have not been any studies providing a comprehensive SC VA framework. However, conceptual frameworks' use to communicate information systems models has shown to be promising [31]. In this context, Nalchigar and Yu [9] used a conceptual modeling framework to develop an advanced business analytics platform. In our study, we extend this work firstly by replacing the analytic part with a VA module and secondly by focusing on SC specific business activities in the business part. Furthermore, we explore SC stakeholders' required data sharing and governance.

In Wongsuphasawat et al. [32], the authors explored the effects of analysis goals and context on Exploratory Data Analysis (EDA). The authors identified challenges that analysts face during EDA. Two main exploration goals have been mentioned: 1) Profiling: the act of understanding the data and assessing its quality, and 2) Discovery: the attempt to capture insights from the data. The authors discussed that although the EDA literature's primary focus has been discovery, analysts are more involved with profiling activity. Authors in this study added a new phase to what Kandel et al. [33] provided regarding the analysis phases, called the exploration phase. Exploration involves identifying the possibilities within the data by directly playing with the data examining values, statistical analysis, and visualization. This is also a recognized activity in another study by Alspaugh et al. [34]. The authors distinguished between exploratory analysis and directed analysis, emphasizing that exploratory analysis, as compared to directed analysis, does not pursue a clear goal to answer a specific question. Instead, it tries to obtain hidden insights underlying the data. Three main challenges identified during the exploration phase were the time-consuming, unknown goal, and biased outcome. The main point is that almost all of their interview participants said they are using some kind of visualization in their exploration stage, and not only for reporting. Therefore, a proper requirement analysis based on business processes and goals to identify the corresponding decision goals is an essential step in VA activity. The analytical reasoning from SC VA requires a scientific foundation based on theories, models, and evaluations [35].

3. Methodology

This paper proposes a conceptual framework for developing and deploying a VA system applicable to SC stakeholders. The framework provides an abstract platform-independent model for the whole process of VA development. The research methodology is represented in Figure 1.

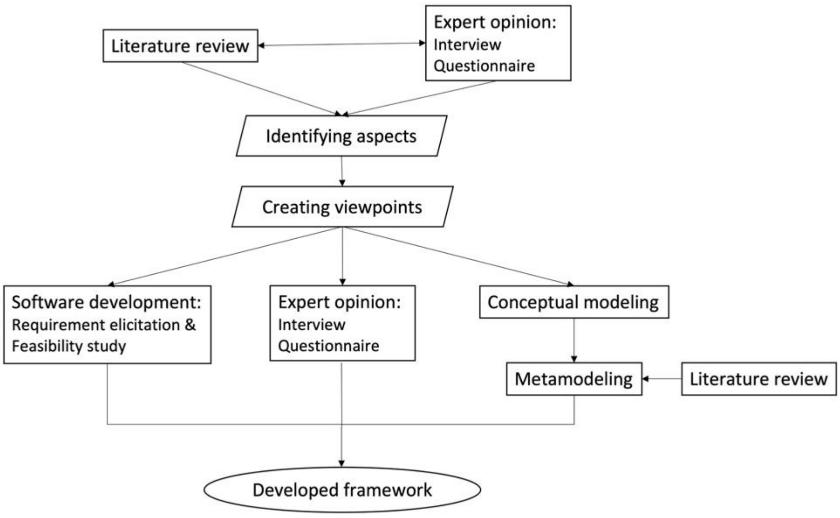

Fig. 1. Research Methodology

3.1 Qualitative approach

The methodology to develop the framework begins with a combination of literature review and expert opinions, from which three aspects as a basis for the development of the framework were identified: 1) goal-oriented data analytics, 2) data governance, and 3) domain-specific VA development. Based on these aspects and adapted from Nalchigar and Yu [3], we created three viewpoints to include the process steps related to different stakeholders and to elicit requirements and specifications of different stages of the process.

Therefore, our representation of the SC VA framework comprises three views as the main pillars of the framework, namely, 1) Business view, 2) Asset view, and 3) Technology view. Each of these views covers a set of steps in its context to facilitate the development and maintenance process. The software development process introduced by Sommerville in [36] was used for the business requirement elicitation and feasibility study in the business view. Furthermore, collecting domain expert opinions (SC director, data platform engineers, and visual analytic developers), both by means of interviews and questionnaires, led to the formulation of the asset view. The interview and questionnaire aimed to determine the following:

1. What are the data analysis tasks they perform?
2. What are the current tools they use?
3. What type of data is used?
4. How are the data collected and stored?
5. What are the results of the analysis being used?
6. What are the gaps in current data analysis and visualization practices?
7. What are the requirements?

The participants for the interview and the questionnaire need to be among the following: 1) Solution developers as enablers of data analysis and visualization, 2) Data analysts as providers of data analysis and visualization, and 3) Decision-makers as users of data analysis and visualization. However, it is not feasible to find many such actors as the participants, given there are not many visual analytics solution developers within our reach. Therefore, we only used questionaries and interviews as a tool to communicate with the most suitable and well-informed contacts we had. This can be identified as a mixed purposive and convenience sampling technique [37]. In this regard. we provided the questionnaire to an IT company providing such solutions to SC actors and conducted semi-structured interviews with the SC director of a Norwegian food producer using these solutions as both data analysts and decision-makers. The questions for the questionnaire and the interview was developed based on the guidelines provided by King et al. [38]. Adapted from the guideline we carry out four main tasks as follows:

1. Framing the research question.
2. Choosing the type of data collection (interview/questionnaire).
3. Defining the sample and recruiting participants.
4. Developing an interview guide.

The guide for the interview and the questionnaire is formulated based on a set of questions and answers presented in Table 1. The complete guide along with the questions are presented in Appendix A. Consequently, one of the authors recorded and transcribed the interview. We then used descriptive coding for both the interview transcripts and the open-ended questionnaire. From the coded data we identified the most relevant information to our problem domain and made conclusions.

Table 1. Questions and answers to create the interview guide.

Questions	Answers
Upon what do we base our guide?	▪ Personal experiences
	▪ Other’s experiences
How comprehensive should we be in covering topics relevant to the research area?	▪ Enough comprehensive to cover key aspects of the aims of the study
	▪ Narratives for particular cases
What types of questions should we ask?	▪ Experience questions
	▪ Opinion questions
	▪ Knowledge questions
	▪ Information questions
How to format questions?	▪ Open-ended Question format

3.2 Conceptual modeling and metamodeling

Conceptual modeling [31] suggests using models within each viewpoint as an abstraction technique to consider a specific set of concepts within the system [39]. Within conceptual modeling, meta-models [40] facilitate the generalization of the framework to fit different SC stakeholders’ scenarios. Meta-models provide the capability of dynamic stakeholder extensions and the interchange of model concepts to the framework [41]. Using meta-models, we can tailor the visualization models for different stakeholders both externally across the SC partners and internally across each organization’s departments. For example, the framework can be used to develop visualization models for the marketing department of a manufacturing company as well as the operation department of a warehouse company.

During the model-building process, we need a language as a medium for representing concepts. We used Domain-Specific Modeling Language (DSML) to build a platform-independent approach for VA and Unified Modeling Language (UML) notations to create our meta-model for the technology view.

Simultaneously, we used the findings of our previous systematic literature review study Khakpour et al. [1] as a catalog to create the meta-model. We also created a usage scenario by collaborating with a manufacturing company from a food SC. The usage scenario describes a real-world example of the envisioned usage of the framework. Hence, we conducted interviews with participants from the company to identify their goals and integrate their existing VA activities into the proposed framework.

3.3 Hybrid agile-waterfall approach

Inspired by the manifesto for agile software development [42], the framework design follows a hybrid agile-waterfall approach to benefit most from the two methodologies [43]. A waterfall strategy is used to design the overall procedure of the framework, reflecting the ultimate goal of the framework regarding requirement abstraction. Essentially, waterfall models are suitable when requirements are stable in nature [44]. However, once the requirements concerning business goals and data are identified, agility is needed in the visualization development process concerning decision goals. Therefore, we proposed the visualization design based on an agile strategy. An initial visualization model will be developed and go through a feedback loop with the user(s) before it proceeds with implementation. In this way, the analysts are in continuous communication with the consumers of the analysis, and the final visualization dashboard will be delivered with a better alignment with the decision goals.

4. Supply Chain Visual Analytics conceptual framework

The overall representation of the framework is shown in Figure 2. In the following section, we also explain each layer and its steps.

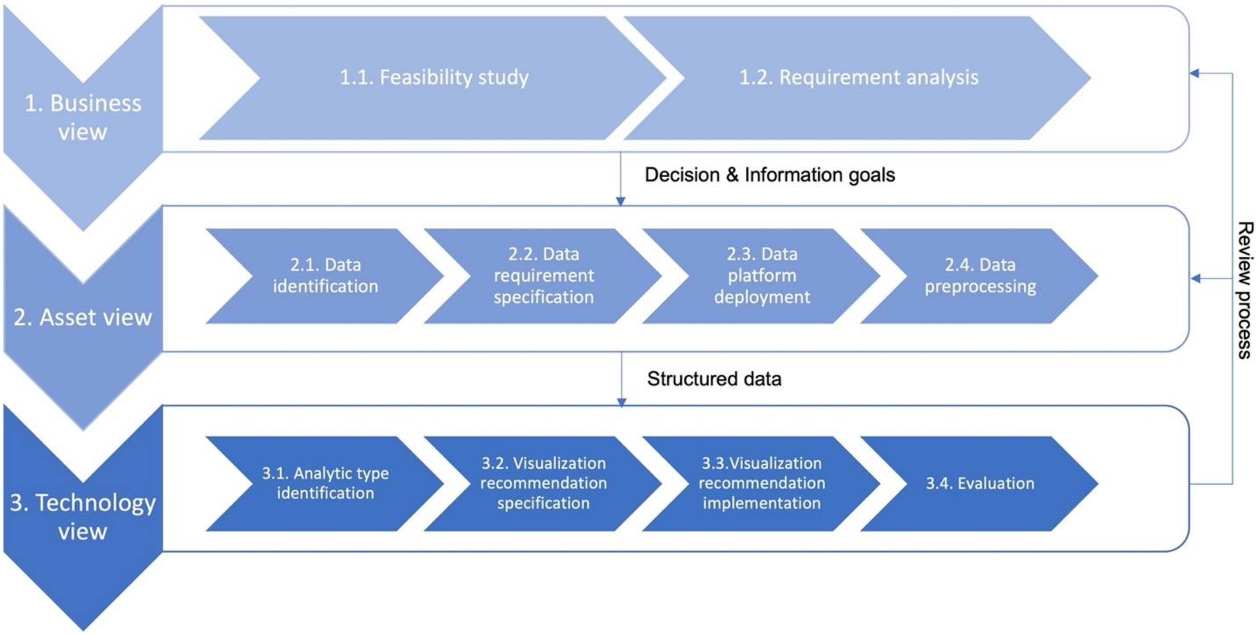

Fig. 2. The proposed framework

4.1 Business view

We start with the business view, where the business requirements should be identified and analyzed from the stakeholders' point of view. "Requirements are usually understood as stating what a system is supposed to do, as opposed to how it should do it. However, understanding the organizational context and rationales (the "Whys") that lead up to systems requirements can be just as important for the ongoing success of the system" [45].

Firstly, it is required to investigate how feasible the development and deployment of a VA system into a certain business area is for different objectives. For example, a visualization system may be feasible in the marketing section of a company, rather than in the manufacturing section, given that the company is more marketing oriented. The feasibility study also justifies the need for investment both in terms of infrastructure and human resources. To identify the requirements, we need to identify 1) Users of the system and 2) Business processes.

The feasibility of a proposed system should be considered from both business and technical stakeholders' points of view. However, depending on the size of a business, corresponding roles may overlap. For example, in a medium-scale company, a SC director may also carry out data science tasks. Therefore, various stakeholders' involvement is not described explicitly. Instead, we tried to focus on the required objectives and outcomes of the feasibility study. The feasibility study begins by interviewing the company's executive directors to understand the business objectives and strategies and to identify if the deployment of a VA system will align with the business requirements. At this point, the input to the feasibility study is business domain knowledge, business requirements, and current resources and operations of the organization, and the output will be an assessment of the extent to which a VA system should be implemented. The feasibility study is, in fact, part of the requirement analysis step where interviews with the system stakeholders, such as business directors, analysts, and decision-makers, help to understand the requirement of a prospective VA system.

Moreover, to formulate a useful VA task, it is required to identify decision goals that the VA intends to support [29]. Decision goals can be identified from business processes and issues. At the same time, information goals need to be recognized, being the desired information that stakeholders seek to analyze [8], both of which can be identified from understanding the business processes and goals. Finally, requirement analysis is also concerned with understanding the skill level of users to design the VA system accordingly. Later on, required skills can be taught to users through training and workshops. In this regard, corresponding tasks include (i) defining the system requirements based on business strategies, (ii) identifying business processes that VA may support, (iii) understanding the business issues and defining decision and information goals, (iv) identifying target user skillsets, and (v) planning user development strategies.

4.2 Asset view

Asset view deals with the company's data assets, including identifying the available data sources, data requirement specification, required data platform description, and data pre-processing. This stage gathers and prepares the required data for analytical activities. Data identification deals with information sharing throughout the SC partners. Corresponding tasks are a collaboration with multiple partners to identify the available data and streamline the process of sharing the data. SC partners are increasingly required to share both third-party data and their collected data to optimize and improve SC operations [46]. This includes sharing collected data that can contribute to the development of analytical activities from various sources, such as freely provided data, observed data, derived data, and inferred data [47]. In this regard, various partners should be informed of the mutual benefits of cooperative analytical activities. On the other hand, the data governance aspects such as data quality assurance, security, and privacy should be handled with the help of data engineers and security experts under the asset view of the framework. Abraham et al. [6] describe these activities as part of the governance mechanisms to retain control over organizational data.

Then, the decision and information goals identified in the earlier stage should be mapped to the available data sources. This process would be the result of the collaboration of data scientists having acquaintance with the data needs and SC directors having the authority to negotiate with their peers among SC partners. It may be required to define new data collection procedures to gather required data from new sources. Here, data scientists describe the metadata for all the available data and provide a plan for future metadata definitions. Additionally, data scientists collaborate with data engineers to perform the required activities related to the pre-processing of the data, including data integration, cleaning, transformation, and data characterization. Kandel et al. [33] describe the data preparation process as four high-level tasks: data acquisition, wrangling, modeling, and profiling. The authors identified data integration from various data sources and visualizing data at scale as the main challenges of the data analytics process. Eventually, the identified, pre-processed structured data will be available and ready to be analyzed in the VA phase of the framework.

4.3 Technology view

The goal of the technology view is to identify the required analytical goal and create a formal visualization specification language to facilitate the process of creating a goal-oriented VA output. The first task is identifying the analytic type based on the decision goals identified in the requirement analysis phase. Analytics type can either be descriptive, diagnostics, prescriptive, or predictive. Corresponding actors in this process are data analysts and data scientists. The second task is to automate the process of converting an analytical goal into a visualization specification, which is mainly done by VA solution providers who build VA tools. For this purpose, a domain-specific modeling technique can be used to satisfy the goal-oriented visualization development [48]. In this regard, integrating the SC decision domain categorization from Khakpour et al. [1] provides a means to create a decision goal-based model. Based on this study, corresponding domain decision goals can be the identification of sales strategies, sales management, collaborative forecasting, network integration and visibility, production and distribution planning, demand management, SC network design, and transportation and operation management. This kind of taxonomy of decision areas helps further to identify corresponding visualization tactics and required data types. In this view, we created a meta-model based on the catalog presented by Khakpour et al. [1]. The meta-model is created using the graphical modeling of Eclipse Modeling Framework (EFC) as a tool. Figure 3 depicts the simplified version of the meta-model. The description of the model is as follows:

1. A dashboard is a superclass that can contain multiple visualizations.
2. Each visualization is a separate entity that pursues one-to-many VA goals and supports zero-to-many decision areas. It also explores the corresponding data source.
3. Each decision area has on- to-many corresponding data sources.
4. Each VA goal is achieved through one-to-many visualization tactics that use one-to-many visualization techniques.
5. Each visualization technique is associated with one-to-many analytics types.

Further on, the visualization expert will generate a visualization specification that provides a detailed description of the visualization presentation and the dashboard. This is where a DSML will be generated to implement the visualization specification defined. Then, the DSML will translate into a visualization dashboard using a code generator, such as Vega-Lite visualization grammar. Vega-Lite is a high-level visualization grammar that uses JSON format to translate visualization specifications into interactive visualization designs [49]. Vega-Lite is an example of a tool that enables the implementation of visualization designs from the visualization specifications. Finally, the developed visualization dashboard goes through another review process with the involvement of stakeholders from previous views to ensure alignment with decision goals and data requirements.

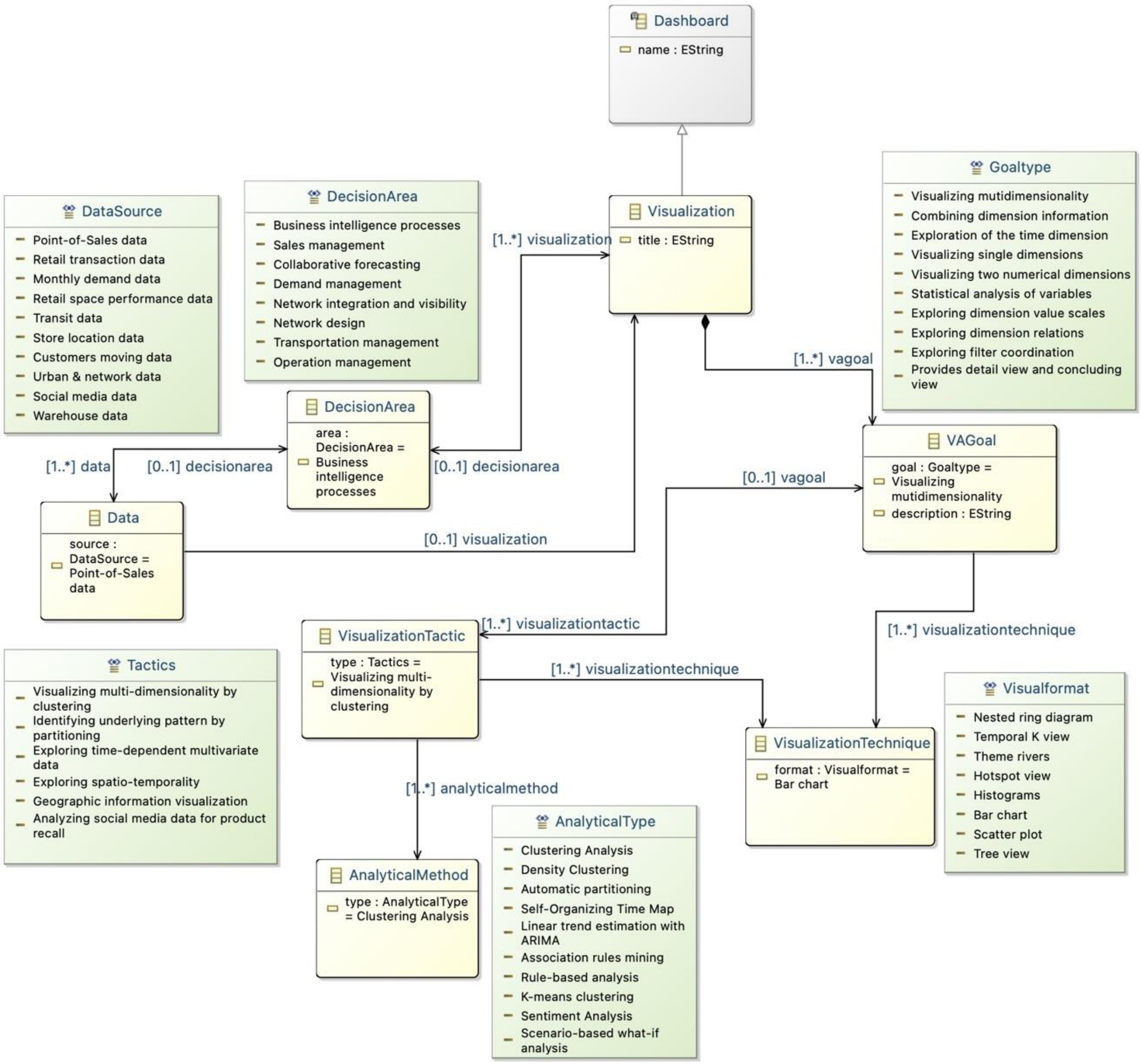

Fig. 3. SC VA meta-model

5. Usage scenario

The usage scenario here describes a real-world example of how to use the proposed framework. We consider the case of a manufacturing company (XYZ, anonymized name) that produces different types of confectionaries, nuts, and dried fruits. They collect and store data from various sources, both internally from their operations and externally from their SC partners. XYZ intends to exploit the potential of its data assets and improve its processes and decision-making activities with VA. Currently, the company does not have any VA system in place, and managers use some of the commercial out-of-the-box visualization tools. This makes the VA activities inefficient and loosely coupled with companies' business processes and goals. Figure 4 shows the instantiation of the framework for this example.

Fig. 4. Instantiation of the framework for the example

5.1 *Business view*

The first step is to check the feasibility of implementing a VA system in the company's current operations (1.1. in Fig. 4). In this regard, we interviewed the SC director of the company as the person who is in charge of creating strategic plans for future developments of the business processes. During the interview, he stated that although the existing out-of-the-box VA systems are not feasible for their size of company and operations, they are optimistic about the future development of such technologies for their operations, as he described:

"*We are a small company, so many existing solutions are not so relevant for us. As IT technology becomes cheaper relative to costs and gains, the benefit ratio changes in time so we can prepare for future solutions like point of sales data. We should run at a point where these are available. 90% of our demand is covered by point-of-sales data. So, we can have a better forecast. Finally, log all the data and visualize to see what is going on.*"

At the same time, XYZ presents challenges in collaborating with their warehouse partner (1.2. in Fig. 4). They acknowledged that the amount of work at the warehouse is highly correlated with the sales forecast. For instance, they can predict the workload at the warehouse if they know what type of products they sell more (either single products or mixed products). In this scenario, they inform the warehouse partner about the number of people the warehouse needs in the following months, which is crucial for the warehouse's profit making. Based on the feasibility study, defined as part of the framework, the company needs to answer at least two main questions regarding the feasibility of deploying a custom-made VA system: 1) Will the system contribute to the overall objective of the company? And 2) What are the current approaches, and how can the system be integrated into existing systems?

Within the business view part of the framework, we identified that a VA system could contribute to the overall objective of the company by 1) Collaborating with the warehouse partner by forecasting the main drivers for the amount of work at the warehouse and 2) The root-cause analysis of the events within historical data. Both aspects contribute to improving the decision-support activities of the company. We also identified that currently, the SC director collects the data from the warehouse partner manually, although he mentioned it is also possible to fetch the data through an Application Programming Interface (API) from the Warehouse Management System (WMS) to the company's BI system. In this regard, the framework can assist with creating the required data ingestion pipeline as part of its asset view. Therefore, answering both questions lead to accepting the feasibility of deploying a VA system for this purpose. At the same time, the company's business requirements regarding the decision goals and information goals are recognized.

5.2 Asset view

XYZ gets invoices from the warehouse partner every month reflecting its services as part of a management report (2.1. in Fig 4). The final amount of the invoice is calculated based on the number of pallets stored and the number of cartoons that enter and leave the warehouse, so-called key payment indicators. The main key payment indicators affecting the invoices are based on two primary warehousing factors: 1) How much of the warehouse is being used, called storage, measured by the average number of pallets going into the warehouse in a month. 2) Handling cost: measured as transactions, basically the number of pallets going into the warehouse calculated by the WMS and the number of pallets going out of the warehouse plus the number of cartoons being picked. That is the second biggest key payment indicator contributing to the cost of warehousing. The corresponding data goes back in time to 2014. This is where visualization of the data can help demonstrate and compare the workload at the warehouse in different months and identify significant historical changes that are not due to typical annual seasonality.

The information goals here are to identify whether there are significant changes in the monthly warehouse transactions or not, and if so, what the reasons behind these changes are. The company also has some raw materials, finished goods, and trading goods in the warehouse. Consequently, the changes in transactions can either be due to changes in raw materials, changes in production plans that are making much larger production batches or buying more trading goods. The decision goals would be to optimize how many people the warehouse needs daily, how much power time, and how many extra people and temporary workers they need.

The next step is to map the decision and information goals with the required data. In this regard, the main activity is facilitating the data-sharing process with the warehousing partner. From the interviews, we found that the warehouse managers are aware of the mutual benefits of the resulting VA since they did previous pilot test cases and are willing to share their data instantly. This data is present in their WMS, and the company's data engineers can create an ingestion pipeline to collect the data using an API to the existing BI system, where the visualization can be created. This is the data identification step within the asset view of the framework. This follows the data requirement specification step, where the main activity is to ensure the data governance of the shared data (2.2. in Fig. 4). A data-sharing agreement with the warehouse partner should be made to determine the data-sharing policies within the partnership. This is where data integrity and quality management will be handled to align the business needs with the data and information needs.

Currently, the required data is not in the company’s BI system. Although it is possible to fetch it from their ERP system periodically, it will be more beneficial to fetch the data from the WMS of their warehouse partner in real-time. This activity is related to the data platform development step of the asset view (2.3. in Fig. 4). The data collection pipeline should facilitate the ingestion of the warehouse data in real-time into the BI storage system for further processing. The extracted data is unstructured and needs to be pre-processed to foster the desired analysis (2.4. in Fig. 4). Pre-processing requires data scientists to perform data acquisition, wrangling, modeling, and profiling. During the data acquisition, data should be located within the BI system. During the data wrangling process, other available data may be ingested and integrated into the analysis, such as inventory data from the ERP system. Then, within the data profiling activity, the quality of the data should be verified by identifying possible errors in the data or any missing data points. Finally, data modeling involves feature selection and feature engineering processes to create final structured data ready for VA.

5.3 Technology view

This layer of the framework deals with the analytical part of the system deployment. Firstly, based on the decision goals, the desired analytical type should be defined (3.1. in Fig. 4). Given the current decision goals, the corresponding analytical type would be predictive analytics which attempts to visualize the amount of work in the warehouse in the following months. This is also descriptive analytics that will show the reason behind historical changes in warehouse transactions. In this regard, a domain-specific visualization model should be created based on the data specification and analytical goals identified (3.2 in Fig. 4). Based on the meta-model created in section 3, the following visualization model was created for this example (Fig. 5).

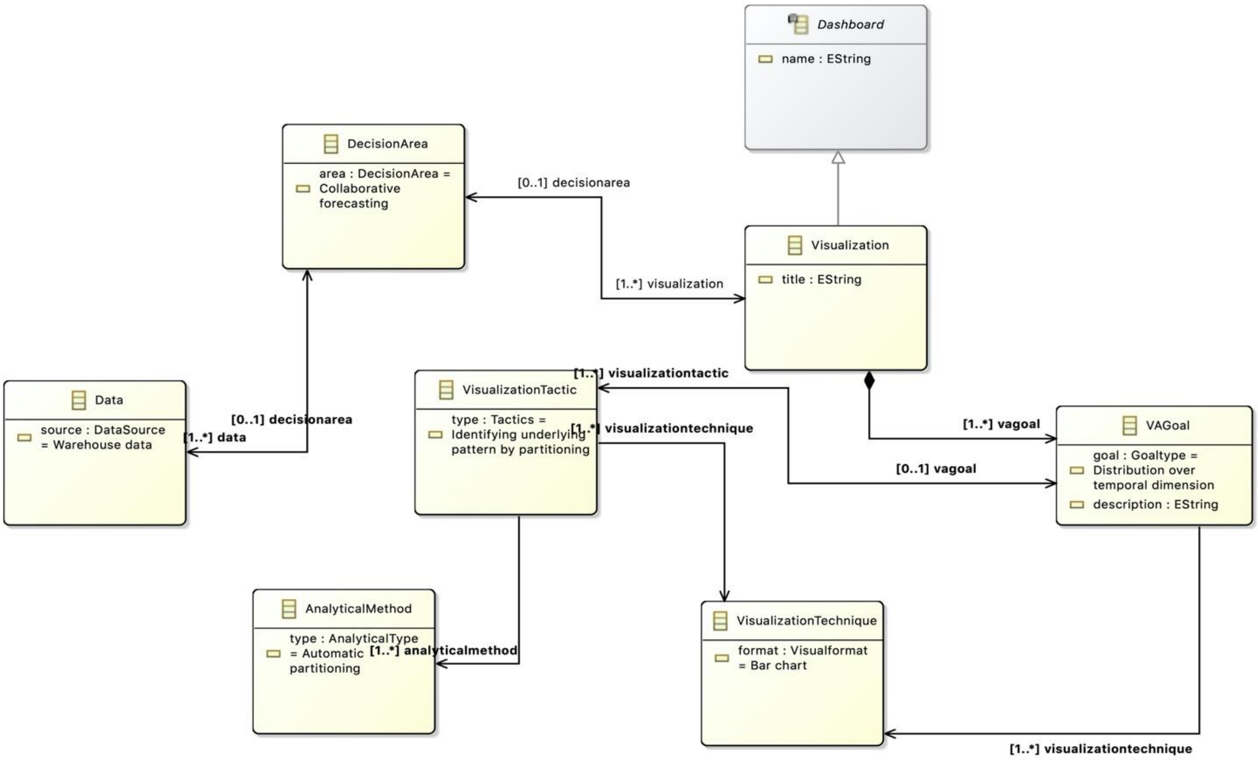

Fig. 5. Visualization model for the example

Following the creation of the visualization model, the DSML will be used to implement the visualization model into a dashboard (3.3. in Fig. 4). Vázquez-Ingelmo et al. [40] presented a DSML to implement visualization in different application scenarios. This can be adopted for the SC application area. This process will create a visualization dashboard which will be presented to the user for a final round of review. The users will interact with the dashboard and have the opportunity to get design alternatives. It is also possible to modify the requirements and repeat the process (Fig. 3).

6. Conclusion and future work

In conclusion, we first attempt to explicitly clarify three significant issues that we considered in this study:

1) How is VA preferable to statistics for data analytics?

2) What are the challenges of integrating VA into SC business activities?

3) What are the benefits of using domain-specific modeling techniques, specifically DSML, UML, and code generation, to address those challenges?

Regarding the first question, we argued that the vast amount of data generated and collected within SC activities need some form of exploratory analysis to identify hidden insights underlying the data. Statistical analysis often has a clear goal to answer a specific question, is time-consuming, and is biased with presumptions. On the contrary, VA provides unbiased data exploratory analysis by visualizing different contexts of the data and letting the analyst discover the unknowns. To answer the second question, we refer to the three main challenges: 1) There is a misalignment between VA activities with business processes and decision-making activities, 2) There is a need to locate and consolidate data from different sources, and 3) Selecting and using the best VA approach is a difficult task and needs particular expertise.

To address these challenges, we proposed a conceptual framework to provide an abstract platform-independent approach for the development and deployment of VA in SC application areas, which relates to the third question. We identified that a goal-oriented VA, based on a domain-specific modeling framework, can streamline the process of VA development. However, there is a gap between the visualization experts who build VA tools and the domain experts who use the tools for their analytic activities.

Furthermore, VA tools do not support the entire pipeline of decision-making, which is identifying the business goals and decisions and deciding on the visualization task and suitable visualization design. A solution is to program VA. However, not all domain experts and visualization users can write programs. On the other hand, not all visualization experts that can develop customized visualization using programming understand the domain aspects. Therefore, domain-specific modelling techniques such as DSML, UML, and code generation can be used to define the visualization tasks using modelling and domain concepts and fill the gaps between VA and domain experts. In this regard, based on conceptual modeling and metamodeling, we created a hybrid agile-waterfall representation for the framework covering three main levels of the process.

Firstly, to align the VA with the business goals, having a goal-oriented VA, we need to elicit the analytical requirement from the respective stakeholders. This is the main aim of the business view part of the platform. Every step is related to certain actors that help perform the tasks and achieve the goals. For example, one of the main participants in SC practices is the SC director, who is usually in charge of developing productivity, quality, and efficiency of operations. They analyze existing performance data and produce forecasts to develop better strategic plans. They typically take reports from analysts and report to top-level managers. Therefore, they are the main actors in the requirement analysis step of the framework. This process starts with a feasibility study by considering the business strategies and goals and producing the decision and information goals as output.

Later on, the asset view deals with data collection and integration. The data then needs to be gathered and collected in a data platform to streamline the process of data pre-processing. The primary data pre-processing challenges identified are data integration from various sources to visualize data at scale. This stage's main actors are data engineers dealing with data integration, cleaning, transformation, and data characterization. Moreover, the data governance aspects of the data integration should be handled with the help of security experts, where data quality assurance, security, and privacy are the main aspects to consider.

Finally, we define the VA specification and analytic type. Based on this, an implementation of the VA will be carried out. We presented the VA specification as a modeling activity, where a domain-specific modeling technique will be used to align the decision goals and VA outcomes. Eventually, a visualization meta-model was created. To demonstrate the application of the framework, we presented a usage scenario based on a real scenario of a confectionary manufacturing company. Such a scenario shows that the proposed framework achieves its intended goal.

In future work, we plan to implement the framework in a set of organizations to evaluate its applicability and identify possible improvements more broadly. In this regard, we may need to extend the meta-model as the centerpiece of the process to be more comprehensive in the case of SC activities but also calibrate the model to adapt it to the actual needs of organizations. The future work also includes the development of a DSML for our particular application domain, SC VA, which also requires the integration of a code generator and testing it in a real application scenario.

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Appendix A. Road Towards Interview and questionnaire guide

Steps	Questions	Answers
1	What is the aim of the project?	▪ Exploring and integrating VA in supply chain activities.
2	What are the project research questions?	▪ What are the available and required data for VA in supply chain? ▪ How the VA techniques can be used in supply chain activities?
3	What is the aim of the sub-project?	▪ Understanding the current practices and requirements.
4	What are the sub-project research questions?	▪ How are the current VA practices are conducted? ▪ What are the requirements for future VA practices?
5	What is the aim of the study?	▪ What are the current VA practices? ▪ What are the challenges?
6	What are the research questions for the study?	▪ What are the data analysis tasks they perform? ▪ What are the current tools they use? ▪ What type of data is used? ▪ How are the data collected and stored? ▪ What are the results of the analysis being used? ▪ What are the gaps in current VA practices? ▪ What are the requirements?
7	What are the priori and/or posteriori to look for?	▪ What is the current VA framework and what would be the desired VA framework?
8	What are the constructs of either the priori or the posteriori?	▪ Available types of Data. ▪ Current data collection techniques. ▪ Current data Storage means. ▪ Any VA tasks. ▪ Any VA tools.

9	What is the guideline?	▪ Available Data? ▪ Desired Data? ▪ Data Collection? ▪ Data Storage? ▪ VA Tasks? ▪ VA Tools? ▪ VA Gaps? ▪ VA Requirements?
10	What are the Questions?	▪ Regarding the data collection strategies (if possible, walk us through an example). ▪ What are the data collection tools you are using? ▪ What are the data warehousing tools you are using? ▪ Do you use any ETL/ELT architecture? If yes, which technologies do you use? ▪ How do you connect the data from existing systems such as SAP ERP to a BI system? ▪ Regarding the data analytics strategies (if possible, walk us through an example). ▪ How do you identify data analytics tasks? ▪ Which analytical techniques do you use? And how do you choose them? ▪ How to locate the required data? What are the main data sources? ▪ Regarding visualization strategies (if possible, walk us through an example). ▪ What are the visualization tasks you perform? ▪ Which visualization tools do you use? Do you see any shortcomings? ▪ How do you integrate visualization practices into your activities? ▪ What are the challenges in visualization tasks using current tools? ▪ Supply chain analytics. ▪ What type of data platform technologies do you use? For example, regarding data warehouse, data hub, and real-time components. ▪ What are the key challenges you face in using data analytics platforms and any prospective plans to handle them? ▪ Do you have any specific analytical teams in the company? How are they communicating with other sections?

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