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Big Data Analytics and Decision-making

Master's thesis in Computer Science
Supervisor: Patrick Mikalef
June 2022

Master's thesis

NTNU
Norwegian University of Science and Technology
Faculty of Information Technology and Electrical Engineering
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Kunnskap for en bedre verden

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Abstract

The use of Big Data Analytics (BDA) is increasing as a response to the ever-growing amount of available data and has been found to assist its user's in gaining an understanding of business processes to support decision-making. Data visualizations are used as a tool to present the results of the analytic process in a way that enables human processing abilities and improves understandability. An increasing number of businesses are relying on data visualization for extracting information to use in decision-making, and dashboards have grown in popularity in the Business-to-Business (B2B) field in recent years. This study aims to create a deeper understanding of how BDA and data visualizations affect the decision-making process, by investigating the effect of information qualities of dashboards in a B2B context on decision quality. More specifically, this study examines the effect of four information qualities (completeness, format, accuracy, and currency), on information satisfaction and decision-making quality, through the mediation of three subjective measures of task performance: perceived ease of task completion, perceived usefulness, and perceived task complexity. Based on existing literature, a research model consisting of 16 hypotheses has been developed. A survey with two questionnaires based on four scenarios with decision-tasks and associated dashboards was used to evaluate the research model, and the records of 76 respondents were analyzed using partial least squares structural equation modeling (PLS-SEM). The results of this study empirically support several of the proposed hypotheses, and the key findings of this research are: (1) information format positively affects both perceived ease of task completion and perceived usefulness, (2) information completeness positively affects all three perceptions of task performance, (3) perceived ease of use and perceived usefulness is found to positively affect information satisfaction, and (4) perceived ease of use and information satisfaction is found to have a positive impact on decision-making quality.

Sammendrag

Bruken av stordataanalyse (BDA) øker som et svar på den stadig økende mengden tilgjengelig data, og har vist seg å hjelpe brukerne med å skape en forståelse av forretningsprosesser for å støtte beslutningstaking. Datavisualisering brukes som et verktøy for å presentere resultatene av den analytiske prosessen på en måte som muliggjør menneskelig prosesseringsevne og forbedrer forståelighet. Et økende antall virksomheter avhenger av datavisualisering for å hente informasjon til beslutningstaking, og datavisualiseringstypen *dashboard* har vokst i popularitet blant bedrift-til-bedrift (B2B) firmaer de siste årene. Denne studien har som mål å skape en dypere forståelse av hvordan BDA og datavisualisering påvirker beslutningstaking, ved å se på effekten informasjonskvaliteten i dashboards i en B2B kontekst har på beslutningskvaliteten. Mer spesifikt undersøker denne studien hvilken effekt fire informasjonskvaliteter (fullstendighet, format, nøyaktighet og aktualitet) har på informasjonstilfredshet og beslutningstakingskvalitet, via hvordan brukeren opplever oppgavefullføringen, nytten og oppgavekompleksiteten. Basert på eksisterende litteratur er det utviklet en forskningsmodell bestående av 16 hypoteser. En undersøkelse med to spørreskjemaer basert på fire scenario med tilhørende beslutningsoppgaver og dashboard ble benyttet for å evaluere forskningsmodellen. Svarene til 76 deltakere ble analysert ved bruk av analyse-metoden *partial least squares structural equation modeling* (PLS-SEM). Resultatene av denne studien gir empirisk støtte for flere av de foreslåtte hypotesene, og de viktigste funnene i denne forskningen er: (1) informasjonsformat har en positiv påvirkning på både hvor enkelt brukeren oppfatter det å løse oppgaven og opplevd nytte, (2) informasjonsfullstendighet har en positiv påvirkning på alle tre oppfatninger av oppgaveutførelse, (3) informasjonstilfredsheten påvirkes positivt av hvor enkelt brukeren opplever oppgavegjennomføringen og opplevd nytte, og (4) opplevd enkelhet av oppgavegjennomføring og informasjonstilfredshet har en positiv innvirkning på beslutningskvaliteten.

Preface

This thesis is written as a part of the course TDT4900 - Computer Science, Master's Thesis at the Norwegian University of Science and Technology during the spring of 2022. The thesis builds upon the work conducted as a part of the course TDT4501 - Computer Science, Specialization Project. I want to give a special thanks to my supervisor, Patrick Mikalef, for providing excellent support through the entire process and valuable advice. I also want to thank the computer science students and the Ph.D. candidates who provided useful and valued feedback during usability testing and pre-testing of the survey.

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Acronyms

AVE Average Variance Extracted. 29

B2B Business-to-Business. i, 1, 3, 5, 18, 28, 36, 38–41

B2C Business-to-Consumer. 1, 5

BDA Big Data Analytics. i, ii, 1, 3–5, 8–10, 36–38, 41

CA Cronbach Alpha. 29, 39

CR Composite Reliability. 29, 39

HTMT Heterotrait–Monotrait ratio. 29

IS Information System. 6–8

KMS Knowledge Management System. 12

MTurk Amazon Mechanical Turk. 24

NSD Norwegian Center for Research Data. 26

PLS-SEM partial least squares structural equation modeling. i, 2, 28, 29, 41

ROI return on investment. 20

SLR systematic literature review. 2, 33, 35, 38, 41

TAM Technology Acceptance Model. 35, 37

CHAPTER 1

Introduction

1.1 Motivation

The world has stepped into the era of "Big data", with an ever-increasing amount of data (Cui 2019). To cope with this increase, a rising number of businesses are employing BDA to gain a competitive edge (Mikalef, Pappas et al. 2018) and assist humans in making decisions with real-world repercussions (Phillips-Wren and Jain 2006). Historically B2B companies have been slower than Business-to-Consumer (B2C) to adapt and deploy commercial analytics (Ji-fan Ren et al. 2017). However, modern B2B companies are starting to expect the same level of analytics in their platforms (Ji-fan Ren et al. 2017). B2B companies that manage to effectively employ analytics to improve performance in marketing and sales are 1.5 times more likely to achieve above-average growth rates and experience a five percent higher return on sales (Davis, Warren et al. 2021).

It is challenging to extract information in a way the human mind can understand, and data visualization plays an essential part in the data discovery process (Chawla et al. 2018) by transforming abstract data into visual elements. Keim et al. (2006) emphasized the importance of combining analytics and visualizations to effectively access complex data sets and extend the cognitive abilities of humans. Data visualization provides a comprehensive overview of enormous data sets and makes it easier for data scientists to grasp the outcomes of data analytics (Qin et al. 2020). Data visualization aids decision-making by increasing understandability (Hilda et al. 2016; Liu 2014), reducing information overload (Bacic and Henry 2012), and helping decision-makers interpret and find patterns in the data (Ali et al. 2016). Data visualization works as a common language in conversations (Mucha et al. 2021) and assists in communicating complex concepts and hypotheses (Hilda et al. 2016).

1.2 Problem Statement

Data visualizations are a powerful means to provide information, which is a critical success factor influencing decision-making (Elgendy and Elragal 2016). The perception and interpretation of the information can either impair or enhance the decision (Sprehn et al. 2013). With the increased reliance on data visualizations in decision-making (Jarupathirun and Zahedi 2007), there is a need to gain an understanding of how such visualizations affect the decision-making process. For data-driven visualizations to be helpful, they must be designed and presented in a way that is easily interpreted by the consumer, and all aspects of the visualization must be considered. Information quality has long been a topic within user satisfaction literature (DeLone and McLean 2003), and in later years, research has focused more on how information quality affects decision-making (Alajmi and Said Ali 2021; Kang and Namkung 2019). However, such studies tend to focus on a few selected variables, which give a narrow picture of the effects and little empirical work demonstrating the impact of information quality in dashboards has been conducted. Jong et al. (2021) emphasize the need for more research on how aspects of data visualizations align with human processing capacity and what type of content enables efficient knowledge transfer. As the use of dashboards in the B2B field is experiencing exponential growth (Jong et al. 2021), it is interesting to research how different dimensions of information quality affect decision-making in this context.

1.2.1 Research Question

The main goal of this thesis is to determine and analyze what aspects of data visualizations are important to consider when designing data visualizations for decision-making, and the effects of information quality on the decision-making process.

- RQ1: What aspects are important when designing visualization for decision making?
- RQ2: How do users interact with the visualization designed for decision making?
  - RQ2.1: Which aspects of the visualization affect the user the most?
  - RQ2.2: How do the users perceive the information based on the visualization?
- RQ3: How does the design of the visualization affect the decision-making process?
  - RQ3.1 What are the contingencies that are relevant when designing visualization for decision-making?

1.3 Overview of Research Methodology

Figure 1.1 provides an overview of the research methodology followed in this study. A systematic literature review (SLR) was performed in Fall 2021 as part of the preparation for this thesis. The objectives of the reviews were to identify the important aspects of visualizations that may affect decision-making and examine various ways to design data-driven visualizations for decision-making. Several areas for further research were identified as a result of the literature review and created the basis for the research questions. To answer the research questions, this study employed a survey as the research methodology. The quantitative data was generated through two questionnaires, and the results were analyzed using PLS-SEM. A further description of the methodology can be found in Chapter 4.

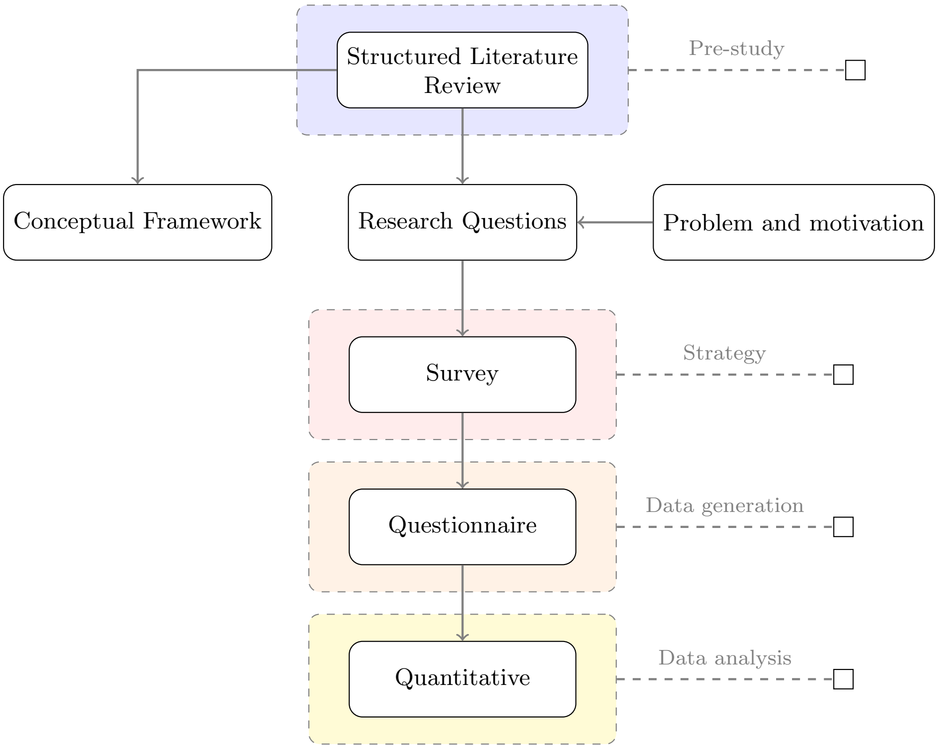


Figure 1.1: Research methodology. The suggested order is adopted from Oates (2006)

1.4 Report outline

This thesis consists of 7 chapters which are structured as follows: Chapter 2 presents the literature synthesis, which creates the basis for the theoretical framework by introducing BDA and decision-making in general and within the B2B domain, related theories, and aspects that influence decision-making from analytics. The process of developing scenarios and designing the survey used to test the research model is described in Chapter 3. Chapter 4 provides an overview of the process of developing scenarios and designing the survey used to test the research model. Chapter 5 introduces the study's results by presenting the analysis method, measurement model, and structural model. Chapter 6 discusses the findings of the study in light of the research model and its implications for research and practice, as well as the limitations of this research and suggestions for future work. Lastly, Chapter 7 presents the conclusion of this research, with final remarks on the conducted research.

CHAPTER 2

Background

This chapter is based on the literature review conducted as a part of the specialization project and the synthesis produced as a result of the literature review creates the basis for the theoretical framework of this study. First, it was necessary to establish an understanding of what big data analytics is and how it can provide value to businesses. Second, the related theories for this project are reviewed. Lastly, the aspects of analytics that affect decision-making are presented.

2.1 Data Analytics and Decision making

A rising number of businesses are striving to use big data and business analytics to analyze available data and aid decision-making (Mikalef, Pappas et al. 2018). Big data is popularly defined by its characteristics, referring to the three V's: the volume, velocity, and variety of information that constantly gets produced and processed (Ali et al. 2016). Volume refers to the size of the data, velocity refers to the creation or changing rate of the data, and variety regards the various formats and types of data, as well as the different purposes and methods for analyzing the data (Elgendy and Elragal 2016). With the increasing amount of available data follows challenges regarding the capturing, storing, analyzing, sharing, searching, and visualizing of data (Ali et al. 2016). To address these challenges, many disciplines have investigated new technologies and methods, such as visualization, statistics-based data analysis, machine learning, and data mining, to extract relevant information and develop trustworthy knowledge from previously undiscovered material (Hallikainen et al. 2020).

BDA can be defined as the process of applying advanced analytic techniques to big data (Elgendy and Elragal 2016), referring to the process of analyzing raw data to extract information from massive data sets (Kumar and Goyal 2016). Additionally, BDA encompasses the elements of tools, infrastructure, and means of visualizing and presenting insights associated with the analysis (Mikalef, Pappas et al. 2018). BDA can help users reveal meaningful patterns (Ali et al. 2016), to generate information, and gain an understanding of business processes, supporting the main motive of creating business knowledge to support decision-making (Hallikainen et al. 2020). Further, sophisticated analytics has been found to significantly improve decision-making, reduce risks, and uncover insights from data that would otherwise go unnoticed (Elgendy and Elragal 2016).

2.1.1 Data Analytics in B2B Marketing

Hallikainen et al. (2020) emphasizes the importance of customer relations in B2B marketing and how the use of BDA can enhance these relations. Maintaining a good relationship with the customers is vital, especially for B2B companies where the average number of customers is lower than for B2C companies. Therefore, it is essential to exploit BDA's capability of personalizing the customer experience in order to approach the customers with tailored offers and incentives (Hallikainen et al. 2020). To survive the competitive environment in B2B marketing, companies must leverage big data in knowledge management (Bag et al. 2021), and it is critical to fully utilize the potential of big data and BDA to achieve a competitive edge (Mikalef, Pappas et al. 2018). Further, BDA has been found helpful for optimizing business processes and enhancing the understanding of customers (Wamba et al. 2017), assisting in revealing and capitalizing on company change (Elgendy and Elragal 2016), and enhancing sales growth (Hallikainen et al. 2020).

2.1.2 Data Visualization

Any data generated from an analytical process is only beneficial if the user is able to extract useful information from that data (Kumar and Goyal 2016). Data visualizations aid the problem of extracting information by providing a comprehensive overview of huge datasets (Qin et al. 2020). Humans are visually oriented (Qin et al. 2020), and visual results have more impact on the user (Kumar and Goyal 2016), thus data visualizations can make it easier for data scientists to grasp the outcomes of data analytics. Data visualization can be defined as the process of visually presenting data to uncover patterns and generate knowledge (Bacic and Henry 2012; Kyle Phillips et al. 2014; Liu 2014). It engages human interpretation of information in order to gain insights in a specific context (Liu 2014), and assists end-users in finding patterns and trends in complex datasets (Ali et al. 2016; Bera 2016; Few and Edge 2016; Hilda et al. 2016) or compare individual values (Few and Edge 2016). Data visualizations play a key role in the data discovery process and in improving decision-making (Chawla et al. 2018). They can be used as a common language (Hilda et al. 2016) to communicate concepts and hypotheses (Mucha et al. 2021).

The dashboard is a type of visualization that has grown in popularity over the years, especially among newcomers to the B2B field (Jong et al. 2021), because of their convenience and how they provide information (Mihova 2016). Dashboards incorporate various charts and graphs in one view and are described as the most effective way to convey information to a business to enable performance management and promote effective analytics (Mihova 2016). It provides a visual overview and aims to provide users with the information needed to make decisions (Conijn et al. 2020). Dashboards differ from other decision support models as they aim to provide an overview of key metrics and try to summarize the current situation rather than forecasting the future (Clark 2020).

2.2 Related Theories

Data is unprocessed raw facts and numbers with no context or deliberate meaning, whereas information is processed data with meaning and given in context (Al-Mamary et al. 2014). Wang and Strong (1996) identified the attributes of data quality that are important to data consumers by developing a comprehensive, hierarchical framework of important data quality attributes. They argued that data could be viewed as a product of data manufacturing acting on raw data to produce output data. Thus, they chose to follow methods developed in marketing research to determine the quality characteristics of products. Through two surveys, they identified the consumers' needs, the hierarchical structure of the needs, and the importance of each need. Their study resulted in four categories of data quality: intrinsic, contextual, representational, and accessibility. Intrinsic data quality denotes that the data has quality in and of itself and consist of the dimensions believability, accuracy, objectivity, and reputation (Wang and Strong 1996). Contextual data quality may vary according to the particular task and includes the dimensions: relevance, timeliness, amount of data, completeness, and value-added (Wang and Strong 1996). Representational data quality includes aspects related to both the meaning of data (interpretability and ease of understanding) and the format of the data (concise and consistent representation) (Wang and Strong 1996) and reflects the degree to which the data is provided clear and understandable matter. Lastly, accessibility data quality refers to how easily data can be obtained, including dimensions such as accessibility and access security (Wang and Strong 1996). These data-quality categories have later been adopted by other studies as information quality categories (see Alajmi and Said Ali 2021)

The notion of *information quality* can be traced back to DeLone and McLean (1992), in their comprehensive taxonomy presenting an overview of the dimensions affecting Information System (IS) success. The taxonomy, commonly referred to as the IS success model, consists of six dimensions: system quality, information quality, service quality, usage intentions, user satisfaction and net system benefits, all interrelated and interdependent (DeLone and McLean 1992). Information quality represents the user's perception of the quality of the output of the IS, and the measures for information quality employed in the IS success model overlap with the attributes of data qualities later found by Wang and Strong (1996). Wixom and Todd (2005) developed a model connecting system and information satisfaction dimensions from user satisfaction literature (DeLone and McLean 1992) with behavioral predictors discovered in technology acceptance literature (Davis, Fred D 1985) to capitalize on the strengths of both theories. Their goal was to build a conceptual bridge between design and implementation decisions, system characteristics, and prediction of usage to improve the prediction of user satisfaction while also increasing the practical utility of technology acceptance (Wixom and Todd 2005). Their results demonstrate that the user's object-based beliefs (information quality and system quality) influence the user's object-based attitudes of perceived usefulness and ease of use, adopted from Davis (1989), which in turn affected their intention to use. Further, Wixom and Todd (2005) found that *completeness*, *accuracy*, *format*, and *currency* served as antecedents to information quality, with accuracy and completeness serving particularly important roles.

Which information quality dimension is the most influential depends on the context and domain. Alajmi and Said Ali (2021) found that the categories contextual and intrinsic information quality are used in domains such as e-service domains where the information itself is the main requirement, while contextual, intrinsic, and representational information quality are used in retail as both the product and the product information is important for the user. In their update of the IS success model, DeLone and McLean (2003) stated that the quality of the information in web content is measured by the level of personalization, completeness, relevance, understandability, and security. The results of Zhang et al. (2017) demonstrate that information completeness and relevance were the most important dimensions of information quality in virtual learning community service. Ji-fan Ren et al. (2017) found that information quality, with the attributes completeness, accuracy, format, and currency, was essential to enhance both business value and firm performance in a big data environment.

Completeness

Wixom and Todd (2005) defines completeness as the system's ability to provide all necessary information. It reflects the degree to which the information is available and has sufficient depth and width for the current task (Ahn and Sura 2020). Al-Mamary et al. (2014) found the information to be complete if it includes all necessary values and important facts, meets the users' needs, covers the needs of the task, and no information is missing. In this study, the information is considered complete if it adequately assists the users' decision-making, which implies that all necessary information is provided, that the information is relevant for the task at hand, and that the information adds value to the users' decision-making process. This definition of completeness extends the definition of Wixom and Todd (2005) by including the attributes of contextual information quality, originally found by Wang and Strong (1996). Lastly, completeness is an important dimension as it has been demonstrated to have a significant impact on user information processing in various online content (Alajmi and Said Ali 2021), satisfaction (Ahn and Sura 2020; Dastgir and Mortezaie 2012), perceived usefulness (Ahn and Sura 2020), context awareness (Wook Seo et al. 2013), and perceived complexity (Alajmi and Said Ali 2021).

Format

Format refers to how well the information is presented (Wixom and Todd 2005), the degree to which the provided information is presented in a clear manner (Alajmi and Said Ali 2021) and is easy to understand (Al-Mamary et al. 2014). As dashboards incorporate multiple types of charts and graphs in one view, the information format has great potential to affect the users' perception of information quality. The information must be presented in a way that enables users to assimilate, process, and extract insights that are relevant to their domain knowledge (Garrett 2010). Information format comprises all factors related to how the information is presented to the user, including all attributes found by Wang and Strong (1996) in the category *representational information quality*. Format is an important dimension as the users find the system more useful when the information is presented in a clear and comprehensive format (Zhang, Kem Z. K. and Benyoucef 2016).

The amount of information needed to be included depends on the desired level of completeness. However, the format can ensure that the information is concise. A concise format ensures that even though a lot of information is included, it is still compactly presented in a format that allows examination and use (Al-Mamary et al. 2014), without extraneous information. Conciseness also relates to one of the goals of dashboards: to reduce information overload (Bacic and Henry 2012).

Visualizations are stimuli able to affect the users' internal cognition and emotions (Zhang, Kem Z. K. and Benyoucef 2016), and must therefore be considered in their entirety, including design, content, and aesthetics. Although the information presented is the most significant part of the visualization, several features can affect how users perceive it. One example of such a feature is color, as looking at colors can induce feelings or emotions in the human brain (Kliger and Gilad 2012). Another example is the shape of visual objects. Rounder edges are associated with positive emotions, while angular or sharper edges are associated with negative emotions (Kliger and Gilad 2012).

Accuracy

Wixom and Todd (2005) defines accuracy as the users' perception of the correctness of the information, reflecting how accurate the information is and how many errors it contains (Al-Mamary et al. 2014). Further, the accuracy of the information can be interpreted as the degree to which information is correct, unambiguous, meaningful, believable, and consistent (Ahn and Sura 2020). This study considers the information as accurate if the user perceives the information as correct and precise and reflects objectivity and validity. Thus, this definition incorporates both Wixom and Todd (2005) definition and several attributes from Wang and Strong (1996) category *intrinsic information quality*. Ji-fan Ren et al. (2017) argues that accuracy is crucial in BDA used in financial organizations as it combines data across multiple platforms, which need to be organized and processed. Rodríguez et al. (2020) argues that complex sales processes require a higher level of information accuracy. Lastly, Al-Mamary et al. (2014) argues that management IS should be accurate to avoid potential inclusions of estimates or probable costs.

Currency

Currency represents the users' perception of how updated the information is (Wixom and Todd 2005). Al-Mamary et al. (2014) found information to be current if the information is given in time for the purpose where it is required and sufficiently up-to-date to solve the task at hand. Currency can be achieved by continuous flow and sharing of information, which helps managers make real-time decisions (Ji-fan Ren et al. 2017) and improved business agility (Mikalef, Pappas et al. 2018). When a system's information lacks currency, it provides no value to the users, resulting in a decrease in usage (Ahn and Sura 2020). Additionally, the accuracy of the information can be reduced if the information is not updated. As the success of BDA depends on its ability to provide accurate information which can be used for faster and more effective decision making (Kumar and Goyal 2016), it is essential to consider the information currency.

Other Dimensions of Information Quality

The proposed list of information quality dimensions is not exhaustive, and several other dimensions have been identified through the literature review. Accessibility information quality was proposed by Wang and Strong (1996) as a measure of how easily obtainable the information is. Accessibility has later been described by Al-Mamary et al. (2014) as the extent to which information is available and how easily it can be obtained. These criteria can be covered by completeness and format, as completeness ensures that all information is provided and the effort required to obtain the information can be reduced by both using formats that require less working memory to interpret (Padilla et al. 2018).

Another often used dimension of information quality is *relevancy*. Relevance is subjective; what is considered relevant for one user may not be relevant to others (Al-Mamary et al. 2014). However, a general level of relevance can be kept through the other mentioned dimensions. Both accuracy and currency ensure the relevancy by keeping the information up-to-date (Wixom and Todd 2005) and free of error (Al-Mamary et al. 2014). Completeness ensures relevancy by including all task-relevant information (Wixom and Todd 2005). Format can not be used directly to ensure relevancy, but the visualization can be designed to guide the user's attention toward task-relevant information (Padilla et al. 2018).

2.3 Aspects That Influence Decision-making From Analytics

One goal of BDA is to create business knowledge to support decision making (Bacic and Fadlalla 2013; Hallikainen et al. 2020). Decision-making can be defined as the choice between two or more competing courses of action (Padilla et al. 2018) and can be divided into two parts: the process required to make the decision and the result of the process. BDA aids the decision-making process by engaging human interpretation of information in order to gain insights (Liu 2014) and helps users find patterns and trends in big data sets (Ali et al. 2016; Few and Edge 2016; Hilda et al. 2016). The quality of big data has a significant effect on the quality of the decision-making, and the decision-making process is reliant on the quality and accuracy of the data, information, and knowledge (Alkatheeri et al. 2020). While BDA has been proven to improve decision-making (Alkatheeri et al. 2020; Mikalef, Framnes et al. 2017), its impact is not always predictable. According to Chan (2017), data visualization may contribute to further distancing and deadening of conscience by removing the visibility of real people and events and aestheticizing representations of catastrophes.

Information is a critical success factor influencing the performance of decision-makers, particularly the decision quality (Elgendy and Elragal 2016). The quality of the decision gives valuable insights into how BDA has affected the decision-making process. To improve decision quality, the complexity and uncertainty in the information must be reduced, and the technological capabilities must be designed to enable human abilities (Bacic and Fadlalla 2013). In most cases, big data aids in improving decision accuracy and operational efficiency (Mikalef, Framnes et al. 2017). BDA can be used to inform strategic and operational decisions (Qin et al. 2020), thus improving the decision quality, minimizing risks, and helping to uncover valuable insights (Elgendy and Elragal 2016).

Data visualization aid the decision making process by increasing understandability (Hilda et al. 2016; Liu 2014), presenting data in an effective and efficient manner (Davcheva and Benlian 2018) and reducing information overload (Bacic and Henry 2012). For visualizations to be helpful, they must align with human cognitive perception and memory abilities (Bacic and Henry 2012) and use design principles that facilitate cognitive access (Chan 2017). In other words, the visualization must be both effective and expressive to be perceived as valuable in the decision-making process (Burnay et al. 2020). The format in which the results of BDA are presented has great potential to affect the decision quality, as how it is perceived and understood can either enhance or impair the decision-making (Sprehn et al. 2013). Misuse and overuse of colors have been found to distract the user from task-relevant information (Bera 2016), affecting the time used to make a decision. Further, the decision time has been found to increase when the user must utilize working memory to interpret the information (Padilla et al. 2018), for example, when using complex visual cues (Davcheva and Benlian 2018).

CHAPTER 3

Research Model

The research model, shown in Figure 3.1, is created based on the theoretical framework presented in the theoretical section of this thesis (Chapter 2). The research model includes the constructs this study aims to explore, and the links between the constructs represent the hypotheses. This chapter will present these hypotheses by explaining how the researchers believe these constructs will affect each other and providing the theory upon which the hypotheses are built.

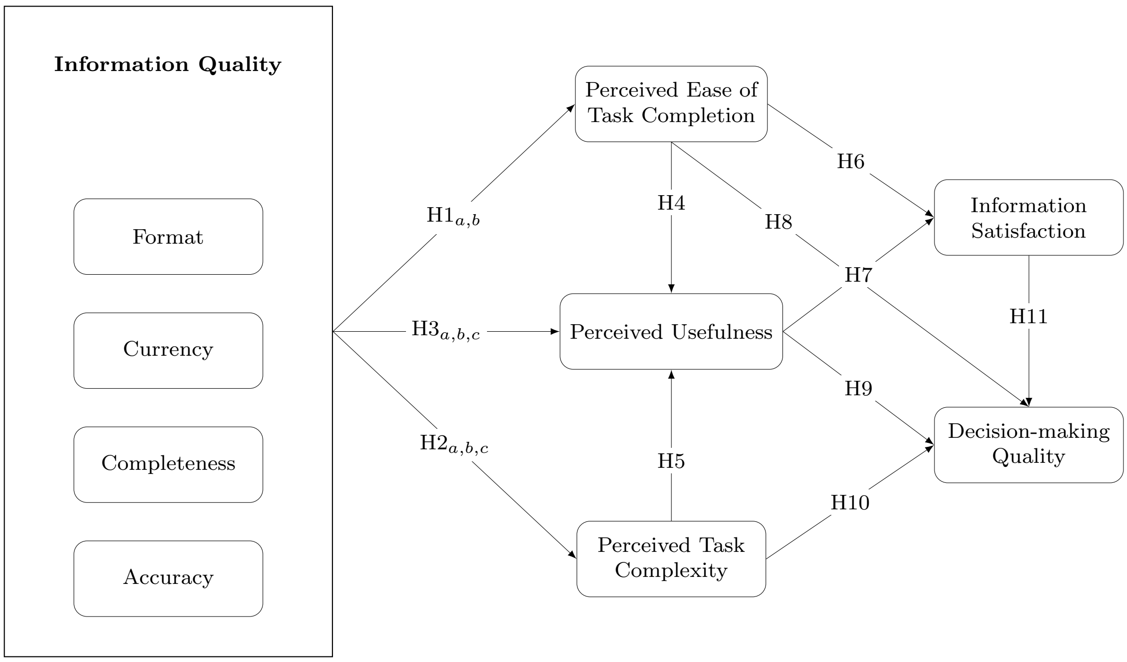


Figure 3.1: Research Model

3.1 Information Quality and Perceived Ease of Task Completion

Davis (1989) defines perceived ease of use as the degree to which a user believes using a system will be free of effort, which for this study is adopted as *perceived ease of task completion* and refers to the ease of using the dashboard to answer the task. Perceived ease of task completion includes the usability of the dashboard and how well the dashboard assists the users when identifying and extracting task-relevant information. Both Nirwanto and Andarwati (2019) and Lin et al. (2014) found a significant relationship between information quality and perceived ease of use. However, Kang and Namkung (2019) found that information quality only had a significant impact on perceived ease of use for the high-frequency buyers and that the purchase frequency influenced the choice between information quality and information credibility as the most influential factor. The choice between information quality and credibility has been removed in this study by ensuring that the user only has one source of information. Therefore, the researcher hypothesizes that information quality will impact perceived ease of task completion:

H1: Information quality will have a positive effect on perceived ease of task completion

Kuo and Lee (2009) introduces information quality as a potential variable to understand the success of Knowledge Management System (KMS) adoption. Their results demonstrate that information quality affects perceived ease of use if the information retrieved is "easy to read, meaningful and sufficiently timely". For the information to be easy to read, it must be presented in a format that minimizes the effort needed to interpret the meaning of the information. Additionally, dashboards can reduce the effort to use by choosing formats that guide users' attention to task-relevant features and minimizes distractions (Padilla et al. 2018). Therefore, the researcher hypothesizes that the chosen format will impact the perceived ease of task completion:

H1a: Information format will have a positive effect on perceived ease of task completion

This study considers information to be complete if it adequately assists the users' decision-making, and Alajmi and Said Ali (2021) demonstrated that information completeness has a significant impact on user information processing in various online content. Thus, information completeness may decrease the effort needed to use the system. As mentioned in the previous paragraph, Kuo and Lee (2009) found that meaningfulness was one information quality affecting the perceived ease of use, which further strengthened the belief that completeness will have a positive effect on perceived ease of task completion. Therefore, the researcher hypothesized that completeness will have an impact on perceived ease of task completion:

H1b: Information completeness will have a positive effect on perceived ease of task completion

3.2 Information Quality and Perceived Task Complexity

Perceived task complexity is a reaction to task characteristics that may be evoked for reasons other than the task characteristics themselves (Kyndt et al. 2011). Perceived task complexity is related to individual differences such as task-domain knowledge and cognitive capacity, as well as objective task features such as difficulty and clarity (Zou and Webster 2014). For this study, the perceived task complexity measures the reaction to the task characteristics, the information provided, and the perceived fit between the information and the task. While perceived ease of use focuses on the effort needed to find the relevant information to complete the task, perceived task complexity focuses on the effort required to understand the provided information and solve the task with the given information. The researcher hypothesizes that the quality of the information will influence the perceived complexity:

H2: Information quality will have a negative effect on perceived complexity

Kyndt et al. (2011) identifies the amount of information as an influential factor of perceived task complexity, which is consistent with the close association between task complexity and information amount suggested in information processing theory (Zou and Webster 2014). A lack of information may increase the perceived complexity of the task, as the user will not have the necessary information to understand the task. Additionally, completeness has been demonstrated to have a substantial influence on user information processing in various online content (Alajmi and Said Ali 2021). Thus, there is reason to believe that the information completeness will increase the users' ability to understand the provided information, thereby reducing the perceived complexity:

H2a: Information completeness will have a negative effect on perceived complexity

The perceived complexity includes the ease of understanding the information, meaning the clarity and comprehensibility of the information (Ahn and Sura 2020). By choosing a format which correspond with the conceptual question (Padilla et al. 2018), dashboards can contribute to ease of understanding (Kyle Phillips et al. 2014). Fehrenbacher and Palit (2013) suggest that the presentation of information may be of more importance when the complexity increases, as the need for simplifying the information increases accordingly. Therefore, the researcher hypothesizes that by choosing formats that simplify the process of understanding the information, the information format can influence the perceived complexity:

H2b: Information format will have a negative effect on perceived complexity

Increased task complexity requires extended use of short-term memory for acquiring and analyzing massive amounts of information (Zou and Webster 2014). To facilitate information processing, users may have higher expectations for consistently represented information in complex tasks (Fehrenbacher and Palit 2013). Therefore, it is reasonable to expect that accurate information will reduce the perceived complexity by reducing the cognitive effort required to evaluate the information or calculating the results:

H2c: Information accuracy will have a negative effect on perceived complexity

3.3 Perceived usefulness

Davis (1989) defines perceived usefulness as the degree to which a person believes that using a particular system will enhance their job performance. This definition is widely adopted (see Ahn and Sura 2020; Alajmi and Said Ali 2021; Nirwanto and Andarwati 2019; Wu et al. 2010), and refers to the users believe in a positive use-performance relationship (Davis, Fred D. 1989).

3.3.1 Information Quality and Perceived Usefulness

The results of Zhang et al. (2017) analysis demonstrate the positive relationship between information quality and usefulness when using a food commerce platform. Kang and Namkung (2019) researched the influence of information quality and credibility and found that both were influential factors on perceived usefulness. However, the impact of information quality increased when the users had access to information outside the platform. This study involves imaginative scenarios, and the only way to obtain task-relevant information is through the provided dashboard. By excluding the potential influence of additional information, there is reason to expect information quality to have an increased impact on perceived usefulness. The higher quality information the user can obtain from the provided dashboard, the better understanding the user will have of the task at hand. Thus, higher contentment with the information may enhance the perceived usefulness, and the researcher hypothesized that:

H3: Information quality will have a positive effect on perceived usefulness

In this study, the users' primary goal is to obtain the information necessary to answer the task. For the user to perceive the dashboard as useful, the dashboard must include all relevant information, as the user will have increased perceived usefulness if they can find all the relevant information successfully (Zhang, Min et al. 2017). The results of Zhang et al. (2017) study show that completeness and relevance was the dimension of the information qualities which influenced the perceived usefulness the most within virtual learning communities. The users found the system most useful when the information was clear and comprehensive. Therefore, the researcher hypothesizes that the perceived usefulness relates to the completeness of the information:

H3a: Information completeness will have a positive effect on perceived usefulness

As stated in the previous section, when the user can obtain all the necessary information, it will affect the perceived usefulness. However, for the user to obtain the relevant information, they must be able to both locate and understand the provided information (Nirwanto and Andarwati 2019). The effort required to locate the information can be reduced by representing the information in formats guiding the users towards task-relevant information (Padilla et al. 2018). Reducing the effort to locate may increase the likelihood of the user finding all the relevant information. Additionally, the usefulness of visualization depends on the use of design principles that facilitate cognitive access (Chan 2017). As dashboards represent information in various types of graphs and charts, it is reasonable to expect that the chosen format of the information can influence the perceived usefulness:

H3b: Information format will have a positive effect on perceived usefulness

Currency refers to the user's perception of the degree to which the information is up to date (Wixom and Todd 2005). The currency can be kept by continuously updating the information according to the users' needs, which will reduce the users' time spent looking at non-relevant information. As previously mentioned, Zhang et al. (2017) found that relevance had a significant impact on perceived usefulness. Therefore, the researcher hypothesizes that currency will have an impact on perceived usefulness:

H3c: Information currency will have a positive effect on perceived usefulness

3.3.2 Perceive Ease of Task Completion and Perceived Usefulness

As both perceived ease of use and perceived usefulness are evaluations of the consequence of utilizing a system to complete a task (Wixom and Todd 2005), it is reasonable to expect them to influence each other. The results of Lin et al. (2014) and Susanto and Aljoza (2015) demonstrate that perceived ease of use has a direct effect on perceived usefulness. The belief that using a system will enhance the users' performance is likely to reduce if the user is unable to use the system or if it requires a great deal of effort. The overall job performance is affected by how easy it is to use the system, the effort needed to operate it, and how much effort one can allocate to other activities (Wixom and Todd 2005). Therefore, the researcher hypothesizes that the perceived ease will influence perceived usefulness:

H4: Perceived ease of task completion will have a positive effect on perceived usefulness

3.3.3 Perceive Complexity and Perceived Usefulness

The user will perceive the dashboard as useful if the level of confidence about the potential benefits is high (Nirwanto and Andarwati 2019), and a lower perceived complexity may affect this level of confidence by providing understandable information. The results of Ahn and Sura (2020) support the relationship between ease of understanding and perceived usefulness, which supports the belief that reducing the perceived complexity may increase the perceived usefulness. Thus, the researcher hypothesizes that perceived task complexity will have an impact on perceived usefulness:

H5: Perceived complexity will have a negative effect on perceived usefulness.

3.4 Information Satisfaction

The definition of satisfaction is adopted from Wixom and Todd (2005), and refers to the users feelings or attitude towards a variety of factors affecting the situation. Several studies has demonstrated that perceived ease of use has an impact on the users satisfaction (see Dastgir and Mortezaie 2012; Dwidienawati 2020). Additionally, the results of Tri Yanti Rahmadani et al. (2020) indicate that ease of use, as a dimension of system quality, has a significant positive effect on end-user satisfaction. The users will be happier to work and feel satisfied if the user feels that using the system is easy and requires little effort and time to use it. Thus, the researcher hypothesizes a positive relationship between the constructs:

H6: Perceived ease of task completion will have a positive effect on information satisfaction.

Perceived usefulness can be defined as the benefits that a user will gain after using a specific system (Ahn and Sura 2020). In this study, the perceive usefulness is concerned with the benefits gained by using the provided dashboard to answer the task. If the user find the information beneficial for their performance it may increase their satisfaction with the information. This implies a positive relationship between perceived usefulness and information satisfaction, which is supported by the results of Ahn and Sura (2020) and Nirwanto and Andarwati (2019). Thus, the researcher hypothesizes that perceived usefulness will have an impact on information satisfaction:

H7: Perceived usefulness will have a positive effect on information satisfaction.

3.5 Decision-making Quality

The quality of the decision gives valuable insight into how the dashboard and belonging information has affected the decision-making process. This study measures decision quality by three dimensions: accuracy, time, and certainty. Decision accuracy refers to the correspondence between the respondent's answer and the desired answer to the task. The respondents are given two to four choices on each task, with only one correct option, making the accuracy binary as the answer is either correct or incorrect. Decision time is the second dimension of decision quality and refers to the time spent making the decision. This dimension does not include the time spent reading and understanding the task description. In other words, the decision time is only affected by the time spent processing the dashboard and choosing an answer option. The last dimension of decision quality is the subjective measure *decision certainty* which refers to the respondent's confidence in their choice.

One way of achieving improved decision quality is by designing the technological capabilities to enable human abilities (Bacic and Fadlalla 2013). If the user is able to use the dashboard to identify and extract task-relevant information, they have the necessary resources to make an informed decision. Thus, the researcher believe that the perceived ease of task completion will positively affect the decision accuracy. As an system perceived as easy to use relates to the effort needed to use the system (Davis, Fred D. 1989), there is reason to assume that the perceived ease will affect the decision time. Therefore, the researcher hypothesizes that the decision quality will be affected by the perceived ease of task completion:

H8: Perceived ease of task will have a positive effect on the decision quality.

When a user perceives a system as useful they believe it has the ability to enhance their performance (Davis, Fred D. 1989) and they are prone to be more confident (Kyle Phillips et al. 2014). Alajmi and Said Ali (2021) found that perceived usefulness was the only predictor of decision quality. The results of Kyle Phillips et al. (2014) demonstrate an increase in task performance when using visuals perceived as usable and that the post-decision confidence was significantly affected by usability. Thus, the researcher hypothesizes that perceived usefulness will impact decision quality:

H9: Perceived usefulness will have a positive effect on the decision quality.

Improved decision quality can be achieved by decreasing the complexity and uncertainty of the information (Bacic and Fadlalla 2013). Higher complexity requires more use of working memory in the information processing (Padilla et al. 2018), which may affect the decision time. The results of Davcheva and Benlian (2018) demonstrate an increase in time with complex visual cues compared with simple visual cues. Further, Davcheva and Benlian (2018) concludes that complex visualization reduces certainty and accuracy and increases the decision time due to the increased cognitive load. As increased complexity will require more time to process the information, the researcher expects the decision time to be affected. Additionally, accuracy and certainty will be affected if the complexity reduces the respondents' ability to understand. Thus, the researcher hypothesizes that the decision quality will be affected by the perceived complexity:

H10: Perceived complexity will have a negative effect on the decision quality.

Dwidienawati (2020) found a positive and significant relationship between satisfaction and perceived performance. Further, they concluded that satisfied people have more commitment, engagement, and emotional attachment, which leads to better performance. The researcher expects the respondents to be satisfied with the information if the information is applicable and complete. In other words, if the respondent is satisfied with the information provided, they may feel like they received all the information they needed and are able to make an informed decision, which can impact their decision quality. Thus, the researcher hypothesizes a positive relationship between information satisfaction and decision quality:

H11: Information satisfaction will have a positive effect on the decision quality.

CHAPTER 4

Method

This study explores how dashboards' different information quality dimensions affect the user's decision-making quality in a B2B context. This is accomplished by creating four scenarios based on fictional B2B companies with associated decision-making tasks and dashboards focusing on different information qualities. The research model described in Chapter 3 is tested empirically by conducting a survey, allowing participants to complete several decision-making tasks and evaluate the dashboards based on the constructs in the research model. First, this chapter will present the process of developing scenarios and designing dashboards. Further, it will present the method of generating data, the construct measures used in the survey, the data collection, and the ethics of the survey.

4.1 Development of Scenarios

The scenarios are based on four fictive B2B companies in various industries offering different products or services. Each scenario consists of a textual description of what the company does and the participant's role in the company. In addition, each scenario has an associated decision-making task, which the participants must answer using the information provided in a dashboard. To ensure that the information quality of the dashboard itself was tested and not just the information quality of one element, the tasks were designed to require the knowledge of several metrics to be solved correctly. The necessary metrics for each decision-making task created the basis for the information to include in the dashboard.

After creating the scenarios, the process of designing and developing dashboards began. The goal was to develop two dashboards for each scenario, where the associated dashboards emphasized the various information quality dimensions differently. For example, if one dashboard had a high level of completeness, the associated dashboard had a lower level of completeness. The following description will only address the process of creating dashboards for one scenario to simplify the explanation. However, the process was equal for all scenarios, and the described process was performed for every scenario. The process began by creating several different graphical and textual representations of the data, where each representation emphasized different dimensions of information quality. The next step was to create a dashboard by combining one representation of each metric in one view. Lastly, a second version of the dashboard was created by adjusting details or changing the representation of metrics. The following sub-sections describe each scenario and the information qualities represented in the various dashboards. The full description of each scenario and decision-making task is provided in Appendix A. An example of a dashboard is shown in Figure 4.1, and the full-size version of all the dashboards can be found in Appendix B.

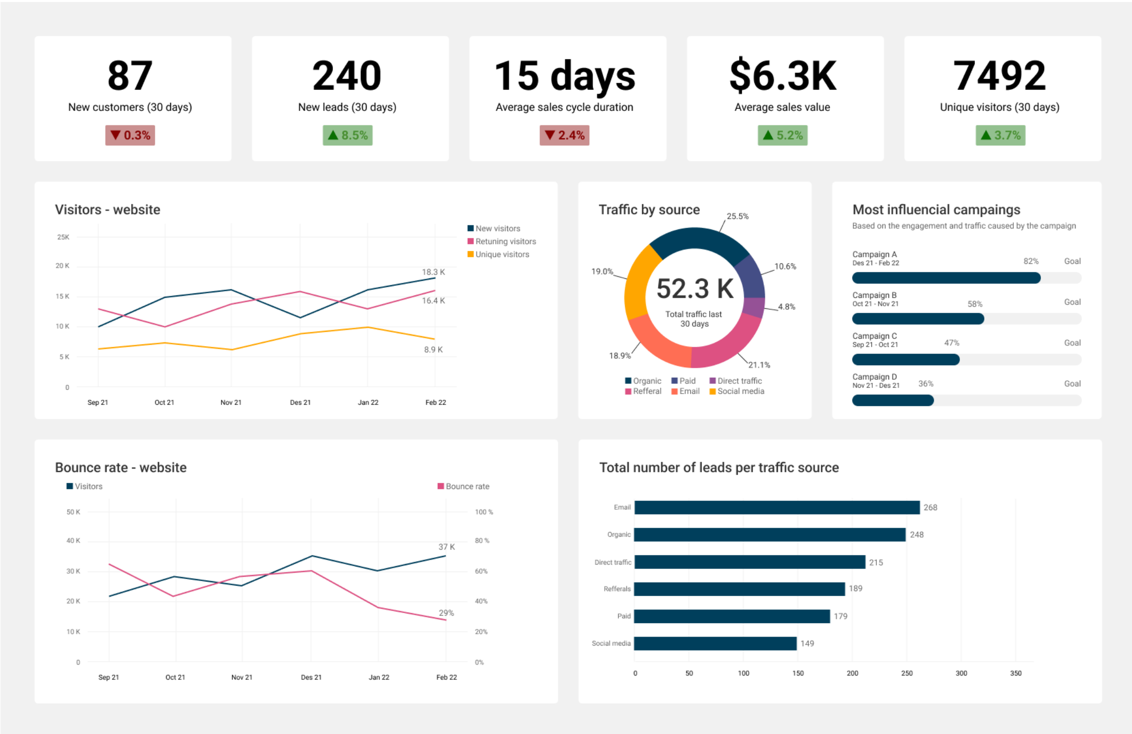


Figure 4.1: Version A of the dashboard belonging to scenario 4

4.1.1 Scenario 1

The first scenario is based on a company selling trucks to other companies in various domains. The participant's task is to use the results of a marked study to recommend the best location to open a new service location. Four location options displayed on a map in the dashboard, and the participant is informed that an optimal location has a significant amount of potential customers and as little direct competition as possible. This information must be obtained from other charts included in the dashboard and used to evaluate each of the four locations. The two dashboard versions belonging to the scenario differ only by the color palettes used, related to the information quality dimension *format*. The colors used are adopted from the study of Bartram et al. (2017) on how different color properties and the combination of colors in palettes contribute to various affective interpretations of visualizations. The color palettes used in the dashboards are created by combining the six colors chosen as "best" (according to the results of Bartram et al. 2017) in the categories *calm* and *playful*. The six colors chosen for the playful palette were also included in the palettes perceived as both exciting and positive (Bartram et al. 2017).

4.1.2 Scenario 2

The second scenario is based on an office rental service aiming to allocate resources across different marketing channels to create the greatest possible return on investment (ROI). The participant is asked to decide which marketing channel, of the four provided choices, should have the highest priority in the allocation. To make an informed decision, the participant must compare the provided information of each marketing channel. The dashboards have different formats: version A employs several textual elements, such as tables, while version B presents the same information using charts. The tables include the specific values for each marketing channel per metric, while the charts only display the accumulated metric of all marketing channels and an overview of the distribution between the channels. In addition to varying in format, the described differences could affect the perceived accuracy and completeness of the information in version B.

4.1.3 Scenario 3

The third scenario is based on an office furniture store selling products in larger quantum to other companies. The participant is asked to decide which customer group the company should focus their marketing toward, based on which group has the potential to increase the revenue the most per user. The participant is given a choice between three different customer groups. To make a decision, the participant must either evaluate each group's average customer lifetime value or compare the total revenue per group with the customer distribution. The two versions of the dashboards differ in all information quality dimensions. Dashboard version A includes charts with a historical perspective, while version B, with the exception of one graph, incorporates only charts displaying the accumulated metrics of a specific period. As the versions incorporate different types of charts, the dashboards vary in the information quality dimension *format*. Further, the dashboard versions differ in information currency. Both versions include dates in several charts; in version A, the dates are set to the current quarter (Q1 2022), while version B is set to Q1 2021. This makes the dated charts in version B outdated, and the participant must assume the currency of the remaining charts. Lastly, removing the historical perspective may affect the participant's perception of completeness and accuracy. As the participant must assume that the displayed information is representative, they are unable to make a fully informed decision.

4.1.4 Scenario 4

The last scenario is based on an IT-consulting company wanting to ensure its campaigns capture potential customers' attention. The participant's task is to determine if the company should prioritize using paid traffic sources for future campaigns. In both versions of the scenario, the participants are told which campaigns have used paid traffic sources. However, in version A this information is received from the supervisor, which is considered as a reliable source. In version B, the information is received through a rumor. The latter could affect how the participants perceive the accuracy of the information in the dashboard. Additionally, the dashboard differs in the level of detail. Version A, which can be seen in Figure 4.1, includes additional descriptions of some graphs and marks specific data values in the graphs. The additional description can affect the participant's perception of completeness, as it provides more information about each chart. Without the description, the participant may not have enough information to interpret the charts correctly. Without the inclusion of specific data values, the participant must interpret the charts to retrieve the information, which may affect how they experience the accuracy. The dashboard versions also differ in format, but the differences are less prominent than in the other scenarios.

4.1.5 Design Tools

The dashboards were created using Figma, a web-based graphics editing and user interface design application (Figma 2022). Figma provides the user with a blank canvas, and each element is created by combining basic elements, such as lines, shapes, and text, into more complex constructions. This process is time-consuming in the start-up phase. However, once a couple of composite elements have been created, they can be reused, combined, and customized to the metrics of each scenario. Thus, this process can be compared to the time needed to learn a new tool. Figma was chosen due to its ability to create realistic-looking dashboards without needing an actual dataset. Additionally, it allows the user to freely change any parts of the design, an essential feature to emphasize different information quality dimensions.

Tableau is a visual analytics platform used to explore and discover insight in large data sets (Tableau 2022). Tableau was used to create more complex graphical representations, such as map-based charts. As Tableau requires datasets to create charts, mock data was created using Mockaroo, a free data mocking library (Mockaroo 2022). The mock data set was customized to fit the formats required by the desired charts in Tableau and the measures needed in the relevant scenarios.

4.1.6 Quality Assurance

A small usability test was conducted to ensure the quality and usability of the dashboards. The usability test design follows the principles developed by the Nielsen Norman Group (Moran 2019). In order to obtain relevant results, the testing context had to be as similar as possible to the actual context. As the participants in the planned survey would not have the possibility to ask questions, the participants in the usability test were not allowed additional information or guidance during the whole test session. Each scenario was presented in a textual format to replicate the actual context and avoid influencing the participants by subconsciously emphasizing important information. The participants were presented with the goal of the user testing and how it would be conducted and asked to narrate their activities and thoughts while completing the task. After each scenario, the participants provided feedback on their experience and stated any questions they might have. The researcher did not answer the questions, to avoid influencing the results of the following scenarios. During the test, the researcher was silent and only wrote down the feedback given and observations made. If further clarification was needed, it was discussed with the participant after completing all scenarios. Six computer science students participated in the user testing. Each participant was presented with four scenarios and one dashboard per scenario. Each scenario was tested six times, and each dashboard was tested three times. The dashboard versions given to the participants were alternated to avoid biases in the results. Minor adjustments were made to the scenarios and dashboards based on the feedback from the usability testing

4.2 Survey Design

To empirically test the research model presented in Chapter 3, a quantitative study was conducted, with a survey as the chosen research strategy. Surveys are used to collect the same type of data from a large sample in a standardized and systematic manner, with the goal of finding patterns that can be generalized to a greater population than the targeted group (Oates 2006). This section will present the data generation method, the construct measures, the data collection, and the survey ethics.

4.2.1 Data Generation

This study employed a questionnaire-based survey, using two questionnaires to generate the quantitative data. The questionnaires were designed using the survey tool Alchemere[1], formerly SurveyGizmo. Alchemere was chosen based on its options to include high-quality images, a necessity for this study, which the other alternatives could not offer. From a participant's point of view, the questionnaire begins with an introduction to the study's purpose, how the participant's information would be used, and how the structure of the questionnaire. The questionnaire has no time limit; however, some tasks are timed. The participant is informed about the time limit in total and the exceptions in the introduction. Firstly, the participant is asked to fill in demographics regarding their age, education, employment status, and industry. Next is a section on the participant's previous experience with marketing, business, and dashboards. These questions are a combination of numerical input and pre-selected items with the opportunity to fill in if none of the options matches.

The rest of the study is based on the scenarios described in section 4.1, with the associated tasks and dashboards. This questionnaire section begins by explaining the structure of the following parts and gives a reminder that the decision-making tasks will be timed. Each scenario contains a textual description, an explanation of chosen terms, and a decision-making task. The participant can navigate forward after confirming that they have read and understood the task. The next page consists of the same information and a dashboard containing all the necessary information to answer the given task. The participant answers the task by deciding between 2 to 4 provided options. Additionally, the participant is informed that the timer has started when they enter the page. After answering the

[1] https://www.alchemer.com/

task, the participant was informed that the timer had stopped and asked to evaluate the provided information and their own performance. The questionnaires consist of four scenarios with decision-making tasks, and each section is structured as explained above. Both questionnaires are structured equal and only differ in which version on the dashboard is included for each scenario.

4.2.2 Data Measures

A concrete way of assessing the constructs had to be devised before statistically testing the relationship between them. All of the constructs in the final research model are derived from literature where they have been empirically confirmed, enhancing the likelihood of the constructs themself being valid. Each construct included in the questionnaire, except for the demographics questions, decision-time, and decision-accuracy, were formulated as statements measured using a 5-point Likert scale: Strongly Disagree, Disagree, Neutral, Agree, Strongly Agree. This section will present the items used to measure the construct, and a list of all items can be found in Appendix C

Information Quality

Information quality refers to the user's perception of the quality of the system's output, which in this study regards the information given in the task description and through the dashboard. Information quality consists of the dimensions *completeness*, *accuracy*, *format*, and *currency*. These dimensions are adopted from Wixom and Todd (2005) due to their extensive use, representativeness, and relevance to the context of this study. Completeness refers to the system's ability to provide all necessary information (Wixom and Todd 2005) and how well it assists the user in making a decision. Information format comprises all factors related to how the information is presented. Information accuracy refers to how correct (Wixom and Todd 2005), unambiguous and error-free (Ahn and Sura 2020) the user perceive the information (Wixom and Todd 2005). Lastly, information is current if given in time for the necessary purpose and sufficiently updated to solve the current task (Al-Mamary et al. 2014). The dimensions are measured separately using items from the study of Wixom and Todd (2005).

4.2.3 Perceived Ease of Task Completion

Perceived ease of task completion refers to the degree to which the user believes using a system will be free of effort (Davis, Fred D. 1989), and it is an evaluation of the consequence of using a system. Perceived ease of task completion is measured using items from the study of Wixom and Todd (2005) and measures how satisfied the participants were with the ease of completing the task and how easy it was to use the dashboard and acquire information.

Perceived Usefulness

Perceived usefulness refers to the degree to which the user believes using a system will enhance their performance (Davis, Fred D. 1989). As perceived ease of task completion, perceived usefulness is an evaluation of the consequence of using a system. The constructs used to measure perceived usefulness are adopted from Hardgrave et al. (2003) and measure how useful the participant found the information and if it enhanced their performance and effectiveness.

Perceived Task Complexity

Perceived task complexity refers to the user's perceived fit between the provided information and the task and the reaction to both the task characteristics and the provided information. Perceived task complexity is dependent on individual differences (Zou and Webster 2014) and includes the reaction to the task characteristics that may be evoked by factors other than the task itself. The items used to measure perceived task complexity were adopted from the study of Kyndt et al. (2011) and measured how difficult the participant found it to understand and solve the task.

Information Satisfaction

Satisfaction refers to the user's attitude or feelings towards a variety of factors affecting the situation (Wixom and Todd 2005). The constructs used to measure information satisfaction are adopted from Wixom and Todd (2005) and measure the degree to which the participant is satisfied with the information received to solve the task.

Decision-making Quality

In this study, decision quality is measured by three dimensions: decision time, accuracy, and certainty. The time is measured in seconds from the dashboard is displayed until an answer is confirmed. Decision accuracy is the correctness of the option chosen by the participant and is calculated as a binary value. Decision-certainty refers to the participant's perceived quality of their decision and is measured using items adopted from the study of Jarupathirun and Zahedi (2007).

4.2.4 Data Collection

Two questionnaires were distributed through Amazon Mechanical Turk (MTurk) in April 2022, and the data collection period lasted until it was used for the current research in May 2022. MTurk is a crowdsourcing platform that helps people and organizations outsource procedures and jobs to a distributed workforce that can accomplish them virtually (MTurk 2022). MTurk is a good alternative when the goal is to obtain insights from a global perspective (MTurk 2022). In total, the survey got 121 respondents, 60 from version A and 61 from version B. Of all the records, 39 were partially completed, giving a response rate of 62.8%: 66.7% for version A and 59.9% for version B. In total, the records of 76 participants were included and analyzed.

As displayed in Table 4.1, the most significant proportion of respondents are between 25 and 34 years old (48.7%), followed by 35-44 (27.6%) and 45-54 (11.1%). Only 6.6% of the respondents were between the age of 18 and 24, and none of the respondents were above the age of 54. The majority of the respondents have either a master's degree (31.6%) or a bachelor's degree (57.9%). The largest nationality represented in the records was India, with 63.2%, followed by the United States (22.4%) and Norway (13.2%).

Table 4.1: Descriptive statistics about the sample

Factor	**Samle Version A (N=x)**	**Sample Version B (N=x)**	**Sample Total (N=x)**	**Proportion Total (%)**
Age				
18-24	1	4	5	6.58%
25-34	20	17	37	48.68%
35-44	12	9	21	27.63%
45-54	7	6	13	17.11%
55 or older	0	0	0	0%
Education level				
10 years of school	0	1	1	1.32%
12-13 years of school	4	3	7	9.21%
Bachelor	25	19	44	57.89%
Master	11	13	24	31.58%
PhD	0	0	0	0.00%
Nationality				
India	27	21	48	63.16%
United States	12	5	17	22.37%
Sri Lanka	0	1	1	1.32%
Norway	1	9	10	13.16%

As shown in Table 4.2, the dominating employment status was full-time employed, making up 78.6% of the total sample. The remaining respondents were either self-employed (10.5%) or students (9.21%). Concerning the participant's industry, more than half of the respondents belong to technology (57.9%), followed by the industries of service (14.5%), health (9.21%), and economy/business (7.9%). The remaining 10.5% reported belonging to a variety of different industries, including education, retail, entertainment, finance, and manufacturing. The majority have either work experience (52.8%) or some general knowledge (31.6%) of marketing and business, with only 6.6% without any experience with marketing and business. The greatest proportion of the respondents has experience with dashboards from either school (17.6%), work (53.8%), or personal use (22.2%). Only 6.5% have never made or used a dashboard before.

Table 4.2: Descriptive statistics of work and experience in the sample

Factor	**Samle Version A (N=x)**	**Sample Version B (N=x)**	**Sample Total (N=x)**	**Proportion Total (%)**
Employment status				
Employed full-time	34	26	60	78.95 %
Employed part-time	0	1	1	1.32 %
Freelance/contract employee	0	0	0	0.00 %
Self-Employed	5	3	8	10.53 %
Student	1	6	7	9.21 %
Experience with marketing and business				
None	5	2	7	9.21%
Some general knowledge	11	13	24	31.58%
Work experience	23	17	40	52.83%
Personal experience	1	4	5	6.58%
Experience with dashboards				
School	10	9	19	17.59%
Work	32	26	58	53.79%
Personal	14	10	24	22.22%
Have not made or used a dashboard	3	4	7	6.48%

4.2.5 Survey Ethics

Questionnaires are used to allow participants to complete them independently without observation. As the questionnaire was distributed through mTurk, the participants had no opportunity to ask the questionnaire developer for clarification on any parts. A pre-test was conducted before gathering quantitative data to minimize the risk of poorly formulated questions or illogical ordering affecting the study results. The goal of the pre-test was to ensure that the questionnaire was comprehensible regardless of experience level, increase the likelihood that the actual participants would understand the survey as intended, and locate any errors that might have been overlooked during development. The pre-test was conducted by three Ph.D. candidates with experience in the field and three computer science students with limited experience with business and marketing, in addition to reviews by the supervisor and researcher. All participants of the pre-test provided written feedback after the completion. Minor changes to the phrasing and ordering of questions were made based on the feedback, and grammatical errors were corrected. Additionally, the quality and usability of the scenarios and dashboards were established through the usability test described in Section 4.1.6.

In the introduction of the questionnaires, the participants were informed that the information would remain confidential and anonymous and be used solely for academic purposes. The questionnaire gathered no sensitive information from the participants, and thus the researcher did not need to submit an application to the Norwegian Center for Research

Data (NSD). Each submitted response is anonymous, and the researcher has no possibility to trace the response to a specific participant. The only way to differentiate the responses is through the automatically generated IDs, which are solely based on the order in which the questionnaire was conducted. Lastly, the participants had to withdraw from the survey at any point without having to give an explanation.

CHAPTER 5

Results

This chapter presents the analysis of the research model and the results from the conducted survey. Firstly, it presents the analysis used to analyze the data and find patterns. Followed by the measurement model, which describes the relationship between the constructs and their indicators and the methods used to assess the validity and reliability of the model. Lastly, this chapter presents the structural model, which describes the relationships between the constructs of the research model (Figure 3.1).

5.1 Analysis Method

A PLS-SEM analysis was applied to assess the validity and reliability of the research model, using the software SmartPLS3 [1] to conduct all necessary analyses. PLS-SEM is considered as an appropriate methodology for this study as the path model includes multiple formatively measured constructs, and the method is often used in B2B research as the small population limits the sample size (Hair, Joseph F. et al. 2019). In many research areas, including (Ahammad et al. 2017; West et al. 2016), PLS-SEM is frequently used in data analysis to estimate the complex relationships between constructs.

Hair et al. (2011) presents two requirements for achieving an appropriate sample size for PLS-SEM analysis: (1) the sample size should be ten times larger than the highest number of formative indicators used to measure one construct, and (2) the sample size should be ten times larger than the highest number of structural paths in the structural model aimed at a particular latent construct. This study meets these requirements if the sample size exceeds (1) 80 and (2) 50. The study had 76 respondents, and as each participant conducted four scenario-based decision tasks, the sample size consisted of 304 records, which significantly exceeded both requirements. Lastly, as this research aims to develop a theory, PLS-SEM is considered an appropriate to use as a predictive tool (Hair, Joe F. et al. 2011).

[1] https://www.smartpls.com/

5.2 Measurement Model

The measurement models represent the relationships between the observed data and the latent variables. The model must be examined to evaluate the results of PLS-SEM before the structural model can be assessed (Hair, Joseph F. et al. 2019). The measurement model is solely constructed by reflective constructs, and the same assessment criteria were used to evaluate each construct. Tests of reliability, convergent validity, and discriminant validity were conducted on each latent construct. Table 5.1 gives an overview of the results from the conducted tests. The examination of the measurement model shows minor deviation, but as the deviations do not affect the validity of the results, the constructs are not changed.

Reliability was evaluated both on item and construct level. The construct-to-item loading was examined to assess the indicator reliability. Acceptable item reliability is achieved with loadings above 0.70, as this value indicates that the construct explains more than 50% of the variance of the indicator (Hair, Joseph F. et al. 2019). The cross-loadings can be found in Appendix D. At the construct level, the internal consistency reliability is assessed by examining the Composite Reliability (CR) and Cronbach Alpha (CA) values, which both should be above the threshold of 0.70 (Nunnally 1978). CR differs from CA as the items are weighted based on the construct indicators' individual loadings (Hair, Joseph F. et al. 2019), while CA assumes all factors have the same loading. Thus, CA can be seen as the lower bound and CR as the upper bound for internal consistency. The CR and CA values are presented in Table 5.1. The convergent validity of each construct is assessed by checking if the Average Variance Extracted (AVE) is above the lower limit of 0.50 (Mikalef, Krogstie et al. 2020). The lowest observed values are 0.487 for Currency and 0.426 for Decision-making Quality, which indicates that these constructs explain a bit under 50% of the variance in the items (Hair, Joseph F. et al. 2019). The remaining values are above the threshold and are represented in Table 5.1.

Further, three means were used to establish discriminant validity. The first method was using the Fornell-Larcker criterion (Fornell and Larcker 1981). According to this method, discriminant validity is established if the square root of AVE is higher than the correlation with any other latent construct. This criterion assures that the constructs better explain the variance of their own indicators than the variance of other latent constructs. The second mean tested whether the outer loadings of each indicator were greater than the correlation with any other construct. Lastly, the discriminant validity was assessed using the Heterotrait–Monotrait ratio (HTMT) ratio of the correlations. The criteria were proposed by Henseler et al. (2015) as a better assessment indicator of discriminant validity. The HTMT is defined as the average of the indicator correlations across constructs relative to the average of the indicator correlations within the same construct. High HTMT values indicate the presence of discriminant validity problems. Thus the values should be below a threshold of 0.90 (Hair, Joseph F. et al. 2019). As shown in Table 5.1, only one value (perceived usefulness) exceeds this threshold. The validity of this construct was assessed further by ensuring that the outer loading of each indicator was greater than all the cross-loadings.

Table 5.1: Assessment of reliability, convergent, and discriminant validity of reflective constructs

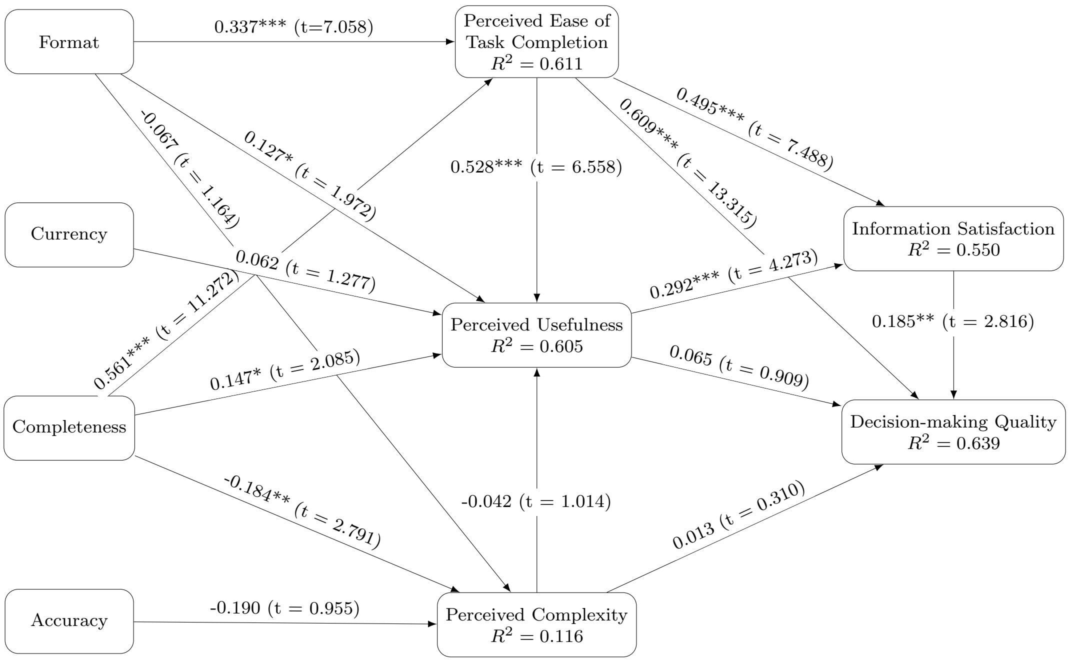
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1)									
(2)	0.644								
(3)	0.612	0.660							
(4)	1.069	0.940	0.783						
(5)	0.775	0.668	0.911	0.861					
(6)	0.690	0.615	0.789	0.742	0.945				
(7)	0.241	0.183	0.325	0.473	0.456	0.368			
(8)	0.691	0.594	0.735	0.759	0.914	0.835	0.268		
(9)	0.616	0.662	0.770	0.882	0.934	0.746	0.339	0.792	
Mean	3.921	3.944	3.872	3.818	3.874	3.967	2.882	3.803	14.613
Standard Deviation	0.835	0.811	0.848	0.955	0.871	0.886	1.264	0.870	179.923
AVE	0.519	0.487	0.549	n/a	0.551	0.594	0.680	0.639	0.426
Cronbach's Alpha	0.759	0.655	0.781	0.226	0.787	0.814	0.863	0.780	0.863
Composite Reliability	0.760	0.655	0.783	n/a	0.786	0.814	0.861	0.780	0.821

(1) Format, (2) Currency, (3) Completeness, (4) Accuracy, (5) Perceived Ease of Task Completion, (6) Perceived Usefulness, (7) Perceived Complexity, (8) Information Satisfaction, (9) Decision-making Quality

5.3 Structural Model

Figure 5.1 summarizes the structural model from the PSL analysis and includes the coefficient of determination (R^2) and the standardized path coefficients (β). The coefficient of determination measures the variance explained in each of the endogenous variables (Hair, Joseph F. et al. 2019) and is used to verify the structural model. Its value ranges from 0 to 1, and greater values indicate a higher explanatory power (Hair, Joseph F. et al. 2019). The values of the path coefficient range between -1 and 1 and describes the strength of the (positive or negative) relationship among constructs (Wibowo et al. 2021). The significance of the PLS analysis results (t-statistics) is obtained by performing a bootstrap analysis in SmartPLS3 with 5000 subsamples. A two-tailored test was used with a confidence level of 95%, meaning significance is ensured if $p < 0.05$. The significance level of the path coefficients is shown in asterisk in the structural model.

As presented in Table 5.2, 10 of the 16 hypotheses were empirically supported. Format is found to have a positive and significant effect on perceived ease of task completion ($\beta = 0.612$, $t = 14.564$, $p < 0.001$) and perceived usefulness ($\beta = 0.127$, $t = 1972$, $p < 0.05$). However, no significant effect was found on perceived complexity ($\beta = -0.067$, $t = 1.164$, $p > 0.05$). Further, the results does not support the relationship between information currency and perceived usefulness ($\beta = 0.062$, $t = 1.277$, $p > 0.05$) or information accuracy and perceived complexity ($\beta = 0.190$, $t = 0.955$, $p > 0.05$). Information completeness was found to have a positive and significant effect on both perceived ease of task completion



Note: *** p < 0.001, ** p < 0.01, * p < 0.05

Figure 5.1: Structural model

($\beta = 0.561$, $t = 11.272$, $p < 0.001$) and perceived usefulness ($\beta = 0.147$, $t = 2.085$, $p < 0.05$). Additionally, completeness was the only information quality found to have a significant effect on perceived complexity ($\beta = -0.184$, $t = 2.791$, $p < 0.01$). Perceived ease of task exert a positive and significant effect on perceived usefulness ($\beta = 0.528$, $t = 6.558$, $p < 0.001$), information satisfaction ($\beta = 0.495$, $t = 7.488$, $p < 0.001$) and decision-making quality ($\beta = 0.609$, $t = 13.315$, $p < 0.001$). Perceived complexity was not found to have a significant effect on either perceived usefulness ($\beta = -0.042$, $t = 1.014$, $p > 0.05$) or decision-making quality ($\beta = 0.065$, $t = 0.909$, $p > 0.05$). Perceived usefulness was found to have impact on information satisfaction ($\beta = 0.292$, $t = 4.273$, $p < 0.001$). Contrary, no such significant effect was found on the impact of perceived usefulness on decision-making quality ($\beta = 0.065$, $t = 0.909$, $p > 0.05$). Lastly, information satisfaction was found to have a positive and significant effect on decision-making quality ($\beta = 0.185$, $t = 2.816$, $p < 0.01$). The structural model explains 61.1% of the variance for perceived ease of task completion ($R^2 = 0.611$), 60.5% of perceived usefulness ($R^2 = 0.605$), 11.6% of perceived complexity ($R^2 = 0.116$), 55.0% of information satisfaction ($R^2 = 0.550$) and 63.9% of decision-making quality ($R^2 = 0.639$).

Table 5.2: Summary of the hypothesis testing

Hypothesis	**Hypothesis effect**	**Effect**	**t−value**	**Findings**
H1a: Information format → perceived ease of task completion	+	0.337	7.058***	Supported
H1b: Information completeness → perceived ease of task completion	+	0.561	11.272***	Supported
H2a: Information format → perceived task complexity	−	−0.067	1.164	Not supported
H2b: Information completeness → perceived task complexity	−	−0.184	2.791**	Supported
H2c: Information accuracy → perceived task complexity	−	−0.190	0.955	Not supported
H3a: Information format → perceived usefulness	+	0.127	1.972*	Supported
H3b: Information currency → perceived usefulness	+	0.062	1.277	Not supported
H3c: Information completeness → perceived usefulness	+	0.147	2.085*	Supported
H4: Perceived ease of task completion → perceived usefulness	+	0.528	6.558***	Supported
H5: Perceived task complexity will have a negative effect on perceived usefulness	−	−0.042	1.014	Not supported
H6: Perceived ease of task completion → information satisfaction	+	0.495	7.488***	Supported
H7: Perceived usefulness → information satisfaction	+	0.292	4.273***	Supported
H8: Perceived ease of task → decision quality	+	0.609	13.315***	Supported
H9: Perceived usefulness → decision quality	+	0.065	0.909	Not supported
H10: Perceived complexity → decision quality	−	0.013	0.310	Not supported
H11: Information satisfaction → decision quality	+	0.185	2.816**	Supported

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.1$

CHAPTER 6

Discussion

This chapter aims to discuss the findings by assessing the hypotheses and the implications of the research. Section 6.1 provides an overview of the results of each hypothesis by explaining what the results mean and how they connect to previous research. A further analysis of the results implications for research and practice is provided in Section 6.2 and Section 6.3. Lastly, Section 6.4 provides an overview of limitations that may have had an impact on the results and suggestions for future work.

6.1 Analysis of Hypotheses

H1: Information quality will have a positive effect on perceived ease of task completion

The model explains 61.1% of the variance in perceived ease of task completion, implying that the chosen dimensions of information quality explain more than half of the variance in how free of effort the user experiences the process of using the dashboard for making a decision. The results of the study show a significant positive effect of information format on perceived ease of task completion, with a significance level of 0.01% and a path coefficient of $\beta = 0.337$. This result is coherent with the results of Kuo and Lee (2009). They suggested that the perceived ease was affected if the information was easy to read, which can be adjusted by the format chosen to present the information. Further, the results support a positive effect of information completeness on perceived ease of task completion, with a significance level of 0.01% and a path coefficient of $\beta = 0.561$. This relation is not previously established by any of the studies found during the SLR. However, the result makes sense as completeness has been found to significantly affect users' information-processing abilities (Alajmi and Said Ali 2021), which may have affected the effort needed to solve the task. Additionally, the results are in line with Kuo and Lee (2009), who found that meaningfulness positively affects perceived ease of use.

H2: Information quality will have a negative effect on perceived task complexity

The results of the study do not support the model's predictive validity of perceived complexity, with only, with only 11.6% of the variance explained by the model. The only significant effect on perceived complexity was found from completeness, with a significance level of 0.1% and a path coefficient of $\beta = -0.184$. This result can be explained by the association between the amount of information and perceived complexity suggested in information processing theory (Zou and Webster 2014). This result is in line with the findings of Kyndt et al. (2011), who confirmed the influence the amount of information has on perceived task complexity. It was hypothesized that format would have a negative effect on perceived complexity. However, the results do not support such a relationship with a significance level of 30% and a path coefficient of $\beta = -0.067$. This is inconsistent with the results of Fehrenbacher and Palit (2013), who suggested that the way the information is presented is of more importance when the complexity increases. Further, it was hypothesized that accuracy would negatively affect perceived complexity. Neither this hypothesis was supported by the results, with a significance level of 40% and a path coefficient of $\beta = -0.190$. This result is surprising as it was expected that inaccurate information would increase the working memory needed to analyze the information. However, this result is coherent with Fehrenbacher and Palit (2013), who found that accuracy was less important in a complex setting when satisfaction decreased.

H3: Information quality will have a positive effect on perceived usefulness The model explains 60.5% of the variance in perceived usefulness, implying that the chosen dimensions of information quality explain more than half of the variance in how the participants perceive that the information will affect their performance (Davis, Fred D. 1989). The results of the study support that completeness positively affects perceived usefulness with a significance level of 5% and a path coefficient of $\beta = 0.147$ This finding is coherent with the results of Zhang and Benyoucef (2016), who argue that information quality affects perceived usefulness, and Ahn and Sura (2020), who found that completeness positively affects the perceived usefulness of Social Networking Site-based commerce. Further, the empirical findings of this study support the positive effect information format has on the user's perceived usefulness with a significance level of 5% and a path coefficient of $\beta = 0.127$. This relationship is in accordance with the results of Alajmi and Said Ali (2021), who found that representational information quality positively affects perceived usefulness. The significant positive relationship between information format and perceived usefulness can be explained by the effect the use of design principles that facilitate cognitive access has been proven to have on perceived usefulness (Chan 2017). Unlike the results of Kuo and Lee (2009), this study does not support a significant effect of information currency on perceived usefulness, with a significance level of 30% and a path coefficient of $\beta = 0.062$.

H4: Perceived ease of task completion will have a positive effect on perceived usefulness

In addition to being affected by information quality, the findings also support that perceived ease of task completion positively affects perceived usefulness. This hypothesis was accepted with a significance level of 0.01% and a path coefficient of $\beta = 0.528$. This relationship seems reasonable as both constructs are evaluations of the consequence of using the dashboards for solving the tasks (Wixom and Todd 2005). The relationship between perceived ease of using a system and perceived usefulness was originally suggested in Technology Acceptance Model (TAM) (Davis, Fred D. 1989), and has later been confirmed in several studies (see Ahn and Sura 2020; Kuo and Lee 2009; Lin, Ting-Wei et al. 2014; Wu et al. 2010).

H5: Perceived task complexity will have a positive effect on perceived usefulness

The results of the study do not support a negative effect of perceived task complexity on perceived usefulness, with a significance level above 50% and path coefficient of $\beta = 0.013$. No previous empirical studies on such a relationship were found during the literature search. However, the hypothesis was based on the belief that a decrease in perceived task complexity could increase confidence in the potential benefits of the dashboards, which has been found to affect the perceived usefulness (Nirwanto and Andarwati 2019). Ahn and Sura (2020) found that ease of understanding positively affected perceived usefulness. As perceived task complexity includes the effort needed to understand the provided information, it was surprising that no effect was found on perceived usefulness. However, the results are coherent with Alajmi and Said Ali (2021), whose results did not support the relationship between the perceived information-task fit and perceived complexity.

H6: Perceived ease of task completion will have a positive effect on information satisfaction

The model explains 61.1% of the variance in information satisfaction, implying that perceived ease of task completion and perceived usefulness explain more than half of the variance in how satisfied the users are with the provided information. In line with the findings of previous studies (Dastgir and Mortezaie 2012; Dwidienawati 2020; Tri Yanti Rahmadani et al. 2020), the results of this study support the hypothesized positive effect of perceived ease of task completion on information satisfaction. With a significance level of 0.01% and a path coefficient of $\beta = 0.495$, perceived ease of task completion is the most influential factor of information satisfaction. This result suggests that the effort needed to use the dashboard to find relevant information significantly impacts the user's satisfaction with the information.

H7: Perceived usefulness will have a positive effect on information satisfaction

The results of the study support a positive effect of perceived usefulness on information satisfaction, with a significance level of 0.01% and a path coefficient of $\beta = 0.292$. This result is coherent with the results of both Ahn and Sura (2020) and Nirwanto and Andarwati (2019) and suggests that when the user finds both the dashboard and information useful, they will be more satisfied with the information they are provided.

H8: Perceived ease of task completion will have a positive effect on decision-making quality

Regarding the decision-making quality, the study's results support a positive effect from perceived ease of task completion, with a significance level of 0.01% and a path coefficient of $\beta = 0.609$. No previous empirical studies on such a relationship were found during the SLR. However, as the perceived ease reflects the user's perception of their ability to use the system, the relationship between the constructs can be seen as a result of the user's increased ability to identify and apply relevant information to solve the decision-making task.

H9: Perceived usefulness will have a positive effect on decision-making quality

Unlike Alajmi and Said Ali (2021), who found that perceived usefulness was the only predictor of decision quality, the results of this study do not support a significant effect of perceived usefulness on the decision-making quality, with a significance level above 50% and path coefficient of $\beta = 0.065$. This result is surprising, as the user is prone to be more confident when they find a system useful and believe it will enhance their performance (Kyle Phillips et al. 2014), which was hypothesized to affect their certainty in the decision.

H10: Perceived task complexity will have a negative effect on decision-making quality

The result of the study does not support that perceived task complexity has a negative effect on decision-making quality, with a significance level way above 50% and a path coefficient of $\beta = 0.013$. Decreasing the complexity has been demonstrated to improve decision quality (Bacic and Fadlalla 2013). Thus, it was hypothesized a negative relationship between the two constructs. The path coefficient was positive, which is surprising, but as the significance level is above 0.5, it can not be proven that the positive effect on decision-making quality is caused by perceived task complexity.

H11: Information satisfaction will have a positive effect on decision-making quality

The results of the study support a positive relationship between information satisfaction and decision-making quality, with a significance level of 0.1% and a path coefficient of $\beta = 0.185$. This result is coherent with the findings of Dwidienawati (2020), who found that satisfaction positively influences perceived performance in e-learning and suggests that when the user is content with the provided information, they are more confident with their decision.

6.2 Implications for Research

This study contributes to further investigation of the influence of BDA with visualizations on decision quality in a B2B context. Few studies have empirically examined how information quality affects the decision-making quality of B2B marketers using dashboards. To assess this shortcoming in the literature, this study proposed and tested a scenario-based decision-model by applying four dimensions of information quality to determine their influence on decision quality through the mediation of perceived ease of task completion, perceived complexity, and perceived usefulness. By varying the information quality dimensions of the dashboards, this study investigates how users respond to the dimensions and how it affects their perceived task performance and decision-making quality.

This research contributes an empirical foundation to the theoretical framework on decision-making with visualization. Through a survey with 76 respondents, answering four scenario-based tasks each, the study empirically explored the relationship between dimensions of information quality and three subjective evaluations of task performance: perceived ease of task completion, perceived task complexity, and perceived usefulness. The result of the study indicates that completeness is perceived as the most important dimension of information quality as it had a significant effect on perceived ease of task completion, perceived task complexity, and perceived usefulness. These empirical findings support the notion of completeness as an important antecedent of information quality (Wixom and Todd 2005) and underline the importance of providing comprehensive, relevant, and meaningful information in visualizations. This research makes an important contribution to the literature on information quality by providing empirical evidence on the relation between information completeness and perceived ease of task completion, which was not found during the literature review. Information format was found as the second most influential dimension of information quality, affecting both perceived ease of task completion and perceived usefulness. These findings support the notion that visual presentation of information affects the user (Kumar and Goyal 2016) and has the ability to facilitate cognitive access (Chan 2017). It emphasizes the importance of presenting the information in an understandable and concise matter.

Surprisingly, the result of the study did not support a significant effect of information currency on perceived usefulness. This result contradicts the findings of Kuo and Lee (2009), but it is coherent with Ahn and Sura (2020), who also could not provide evidence of such a relation. The study was based on fictive scenarios, and as the choice made by the participant had no real-life repercussions, it may have affected how the participant evaluated the consequence of not having updated information.

Of the five hypotheses based on perceived complexity, only one was empirically confirmed by the study's results: information completeness was found to have a negative impact on perceived complexity. Perceived complexity was included as a dependent variable, affected by changes in the information quality dimensions. Some of the studies the hypotheses are based on, such as Fehrenbacher and Palit (2013), includes perceived complexity as an independent variable, varied to test the effect on dependent constructs, which may explain the inconsistency between the results of this study and previous studies.

During the literature review, it was found that a system's ability to provide accurate information is a crucial success factor of BDA and that information accuracy was especially important in complex processes with many factors (Rodríguez et al. 2020). However, the study's results do not support a significant relationship between information accuracy and perceived complexity. Cheung et al. (2008) suggested that accuracy is related to the confirmation or disconfirmation of information. If a user encounters parts of information they know are factual, they are more inclined to assume that the information as a whole is accurate (Cheung et al. 2008). As the information the participants were to evaluate was based on fictive scenarios, the results might have been affected by the participant's lack of ability to confirm information with previous knowledge or additional sources. Additionally, accuracy may have been evaluated based on how the information displays information. For example, if data values have to be assumed by the participant based on graphs, they are unable to confirm their assumption, which may have affected the perception of accuracy. Ahn and Sura (2020) suggested that when accuracy is hard to achieve, users search for information completeness, which may explain why information completeness was the only information quality that significantly impacted perceived task complexity.

Several TAM-based studies have argued that perceived ease positively affects end-user satisfaction (Tri Yanti Rahmadani et al. 2020) and perceived usefulness (Lin, Ching-Yi et al. 2018). The results of this study contribute to the literature by empirically confirming the relationship between perceived ease of task completion and both perceived usefulness and information satisfaction. Further, the study makes an important contribution to decision-making literature by providing empirical evidence of the positive effect perceived ease of task completion has on decision-making quality, a relation not described in previous studies during the SLR. The path coefficients show that perceived ease of task completion was the construct most impacted by the information quality dimensions and the construct with the most impact on other constructs. These results suggest that perceived ease of task completion is a necessary construct to consider in future studies in the field of BDA and decision-making with visualizations.

This research contributes to the decision-making literature by explaining the influence of information quality on marketing decisions through the mediation of perceived ease of use and information satisfaction and provides a model suitable for assessing and explaining the effect of information quality in data visualizations. Finally, the results support BDA's ability to aid the decision-making process and improve decision-making quality.

6.3 Implications for Practice

The findings of this study present several interesting implications for practice, which provide valuable insights to analysts in general and within the B2B domain. By establishing how information quality affects decision-making quality through the mediation of perceived task performance, this study can help data analysts develop and design beneficial dashboards. This study adds value to B2B companies by providing evidence that dashboards can serve as an aid in improving decision-making quality. The results provide evidence that improving the information quality of dashboards can reduce the effort required by the user during the decision-making process. Further, this study provides evidence that perceived ease of task completion significantly impacts several constructs in the model, suggesting that the user's evaluation of using a system is an essential factor to assess. Analysts should therefore strive to produce dashboards that require little effort to use by ensuring that the information is complete and provided in an appropriate format. Companies can benefit from reducing the effort needed in decision-making as the saved time can be allocated toward other activities (Wixom and Todd 2005).

This study provides a model for assessing how information quality affects perceived task performance and decision-making quality. This model can be used by practitioners (such as data analysts or marketing specialists) to assess their current dashboards and in usability testing to discover possible improvements which could enhance decision quality. The results on information completeness suggest that users find it important that the information in the dashboard adds value to the decision-making process. For B2B marketers to make an informed decision, their aids must provide comprehensive, relevant, and unambiguous information. Further, the information must be provided in a well-organized and understandable format, enabling human abilities (Bacic and Fadlalla 2013). To enhance the benefits of using BDA and visualizations, companies should strive to establish an understanding of how the aspects of each information quality dimension affect their decision-making process. Such understanding can be fostered by including decision-makers in usability testing. To ensure consistency in their dashboards, companies could establish design principles based on the insights gathered in internal studies using the model provided in this research.

6.4 Limitations and Future Work

Regardless of this study's contributions, it has its limitations that may have influenced or impacted the interpretation of the research, which should be addressed by future research. First, Google Scholar was used as the main search engine for finding relevant literature, which may have excluded relevant literature only available through other sources. During the literature review, the researcher assessed each record's title and abstract, which may make the choices subjective and create biases in the selection process. These factors may have excluded studies that could have affected the theoretical background for this research.

Secondly, the study sample only represents participants from India, the United States, and Norway, with participants from India making up over half (63.3%) of the sample. As the work culture is different across the world, the results could have been different if it had included participants from more cultures. Further, the study did not require the participant to have relevant experience with B2B marketing, or marketing i general. Although 91.8% of the participant reported having experience with marketing and business, the inclusion of participants outside the B2B domain might have affected the validity of the results. Hair et al. (2019) state that the small population in B2B research may limit the sample size if the study is restricted to only include participants with experience. However, a suggestion for further research would be to recreate the study using a sample of exclusively participants from the B2B domain, if possible, or aiming for a higher percentage of participants with relevant work experience.

Thirdly, the researcher did not have any contact with the participants, which implies that the participant had no opportunity to ask any questions regarding the questions in the questionnaire or about the included dashboards and scenarios. Therefore, the results may have been affected by possible misunderstandings or confusion. The dashboards and scenarios were designed by the researcher with guidance from the supervisor. Although the design process was inspired by previous literature, the researcher's minimal previous professional experience with B2B marketing might have affected the results of the design process. However, the quality and usability of the dashboards were ensured through the conducted usability testing. The quality and understandability of the questionnaire were ensured through a pre-test with three Ph.D. candidates and three computer science students.

Forth, as mentioned in Section 5.2, the examination of the measurement model showed minor deviation, which may have impacted the structural model. The CA value of the information quality dimensions accuracy and currency was below the recommended threshold, which may suggest an issue with the internal consistency reliability of the two constructs. The constructs were not altered as the CR value of accuracy was above the recommended threshold, and both the CR and CA value of currency was above 0.60, which is considered acceptable in exploratory research (Hair, Joseph F. et al. 2019). The convergent validity of currency was found to be a bit lower than wanted. The construct explained

48.7% of the variance in the items,and further research should consider using other items to measure information currency. Further, the convergent validity of the decision-making quality construct was lower than the suggested threshold due to the low indicator loading of decision accuracy and decision time. Decision certainty is measured using a 5-point Likert scale, decision accuracy is measured as either 0 or 1, and decision time consisted mostly of three-digit numbers as it was measured in seconds spent answering the task. These differences are likely the reason for the problems with the convergent validity of the construct. The model was re-run without the indicators for decision time and accuracy to examine how the indicators affected the structural model. Excluding the indicators did not affect the significance of the results, implying that the effects on decision time and accuracy are not considered in the results. Therefore, future research should explore different methods for investigating how information quality and visualizations affect the time used to make a decision and the accuracy of the final decision.

In addition to the suggestion mentioned above, there are still unexplored areas that could be interesting for future research. A particularly interesting topic would be to compare the results of this study to a similar study using interactive dashboards. By allowing users to interact with the dashboard freely, one could investigate how it affects the user's perception of the information quality and if it changes which dimensions they find important. To further investigate the effects of information quality on perceived complexion, future studies could include aspects that would create more variance in the perceived complexity, for example, by varying the difficulty level of the tasks or of the visual elements. Additionally, including the time needed to read and understand the task information in the calculation might give a different image of how complexity is affected or affects other constructs in the model. Lastly, future research could create a more realistic environment during the study by introducing a reward system for making the correct decision. This would create outside factors affecting the participant's decision-making process and make the process more similar to the context in which the results could be used in B2B marketing.

CHAPTER 7

Conclusion

The purpose of this study was to investigate the influence of BDA and data visualizations on the decision-making process in a B2B context, with emphasis on the effects of information quality on the decision quality when using dashboards. The study began by conducting a comprehensive SLR and literature synthesis to gain an overview of existing findings and reveal areas for further investigation. This process created the basis for the research model used to explore the impact of the information quality dimensions *completeness*, *format*, *accuracy*, and *currency* on decision quality and information satisfaction through the mediation of perceived ease of task completion, perceived usefulness and perceived task complexity. A questionnaire-based survey was developed to empirically analyze the hypotheses presented in the research model. Four fictive B2B scenarios were developed, and two versions of a dashboard, with varying emphasis on the different information qualities, were designed for each scenario. Quantitative data from 76 respondents were analyzed using PLS-SEM, and the validity of the measurement model was assessed through tests of reliability, convergent validity and discriminant validity. The empirical findings of this research revealed that perceived usefulness, perceived ease of use, information satisfaction, and decision-making quality was significantly affected by the information quality, even though not all individual information quality dimensions contributed to the results.

The findings of this research have several implications for both research and practice. This study contributes to the BDA literature by investigating how users respond to the different dimensions of information quality and how the dimensions affect the user's perceived task performance and decision-making quality. The results of this study suggest that information completeness is the most important information quality dimension as it affects all three constructs of perceived performance, followed by information format, which was found to positively affect both perceived ease of task performance and perceived usefulness. Further, this research makes an important contribution to the BDA literature by providing empirical evidence of the effect perceived ease of task completion has on decision quality and the construct's importance in the proposed model. These results suggest that companies can benefit from considering the completeness and format of the information, as both have been proven in this study to positively affect perceived ease of task completion. Lastly, the proposed model can be used by practitioners to evaluate their dashboards, and the findings of this study can serve as a guide for implementing design principles for data visualizations.

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APPENDIX A

Scenarios

Scenario 1

Imagine you are working as a marketing specialist in a company providing trucks to companies in different sectors. You have conducted a marked study of current competitors to figure out where to open a new service facility. An optimal spot for a new service facility would be a location with a significant amount of potential customers and as little direct competition as possible.

Your task is to find out which of the given locations (1, 2, 3 or 4) is most optimal for a new service facility based on the information gathered in the dashboard.

Additional information:

- Leads are a person or company who has the potential to become a client

Decision task:
Which of the given locations is most optimal for a new service facility based on the information gathered in the dashboard?

- Location 1
- Location 2
- Location 3 (Correct)
- Location 4

Scenario 2

Imagine you are working as a marketing specialist at an office rental service, with the goal of providing affordable office spaces to start-ups and other small businesses.

The company wants to allocate financial resources across different marketing channels to create the greatest possible return on investment (ROI). Your task is to choose which marketing channel should have the highest priority in the allocation, based on the information provided in the dashboard.

Additional information:

- Leads are a person or company who has the potential to become a client
- Converted leads are leads that have given indication that they are interested in further action (for example
- by signing up for newsletters).
- First touch: The channel where a customer interacted with your company for the first time.
- Last touch: The channel where the last interaction before a purchase took place or deal was made.
- Reach: total number of people who have seen your content.
- Engagement: total number of interactions with your content.
- Engagement rate = reach / engagement * 100.

Decision task:
Which marketing channel should have the highest priority in the allocation, based on the provided dashboard?

- Facebook (Correct)
- Twitter
- LinkedIn
- Email

Scenario 3

Imagine you are working as a marketing specialist at an office furniture store. The company sells office furniture such as chairs and desks to companies of different sizes in several sectors. One company is considered as one customer. You have divided your customers into 3 groups (Group A, Group B, and Group C) based on the company demographics, and how much and often they buy new office furniture.

Your task is to choose which of the groups (A, B, or C) future campaigns should be focused on reaching. The goal of the campaign is to reach new customers within the group that will increase the revenue the most per customer.

Additional information:

- Customer lifetime value (CLV): measures how much a business can plan to earn from the average customer over the course of the relationship. It considers the products bought, purchase frequencies and volume, and the cost associated with acquiring the customer and producing the product.

Decision task:
Which group should future campaigns be focused on reaching?

- Group A
- Group B (Correct)
- Group C

Scenario 4

Version A: Imagine you are working in an IT-consulting company. Your job is to make sure that the marketing campaigns of the company capture the attention of potential customers (leads). Your supervisor has told you that campaign B and campaign C made more use of paid traffic sources to minimize the work effort necessary for success. The remaining campaigns used more traditional ways of creating engagement and traffic.

Version B: Imagine you are working in an IT-consulting company. Your job is to make sure that the marketing campaigns of the company capture the attention of potential customers (leads). You have heard rumors that campaign B and campaign C made more use of paid traffic sources to minimize the work effort necessary for success. The remaining campaigns used more traditional ways of creating engagement and traffic.

Following information was the same for both versions

Based on the dashboard provided, should your business prioritize paid traffic sources in future campaigns?

Additional info:

- Leads are a person or company who has the potential to become a client
- Bounce rate is the percentage of all sessions on the website where the user only visited one page

Decision task:
Should your business prioritize paid traffic sources in future campaigns?

- Yes
- No (Correct)

APPENDIX B

Dashboards

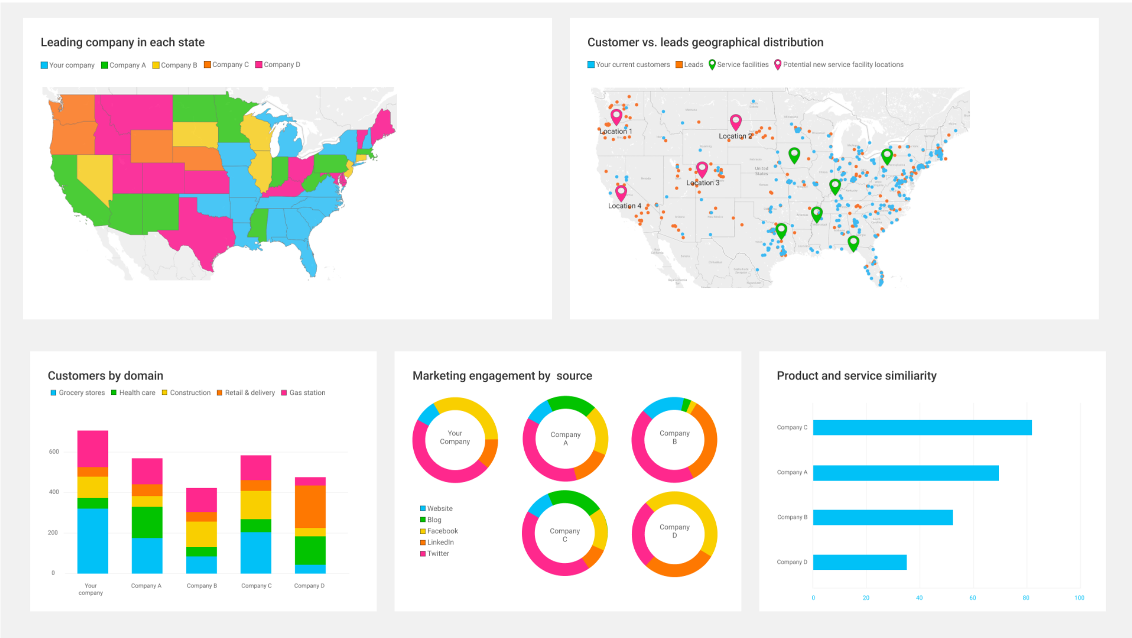

Figure B.1: Dashboard scenario 1 version A

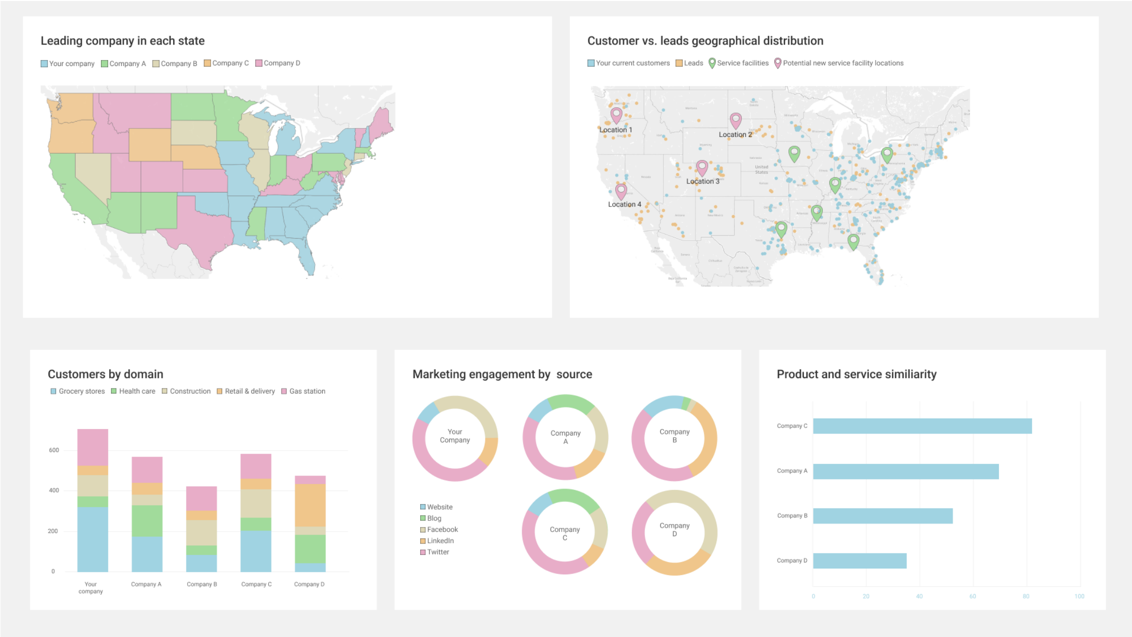

Figure B.2: Dashboard scenario 1 version A

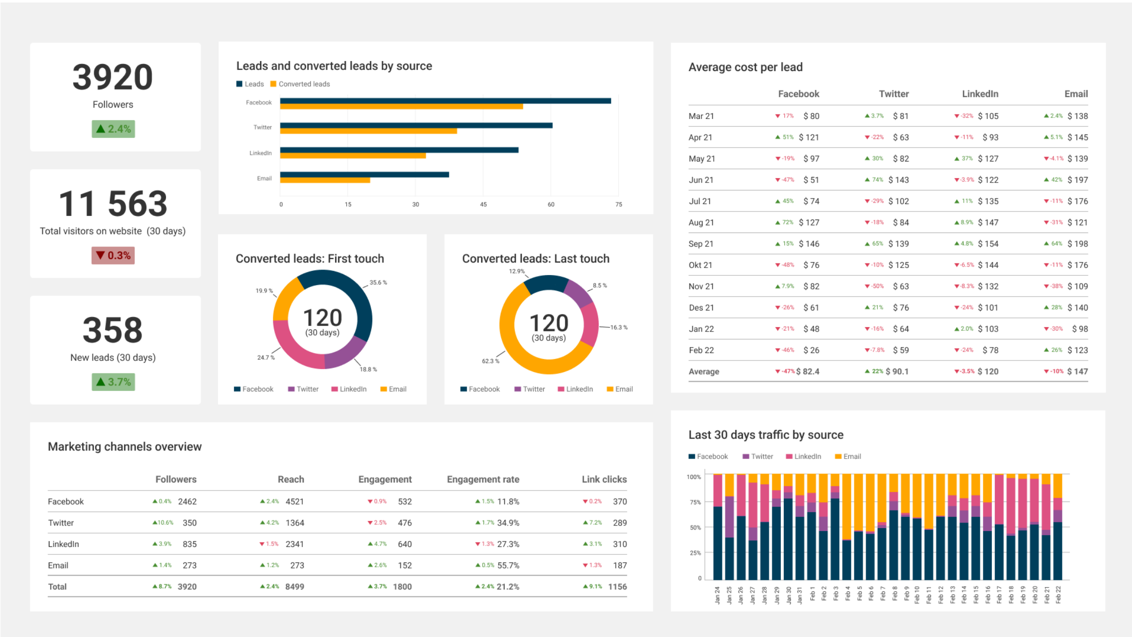

Figure B.3: Dashboard scenario 2 version A

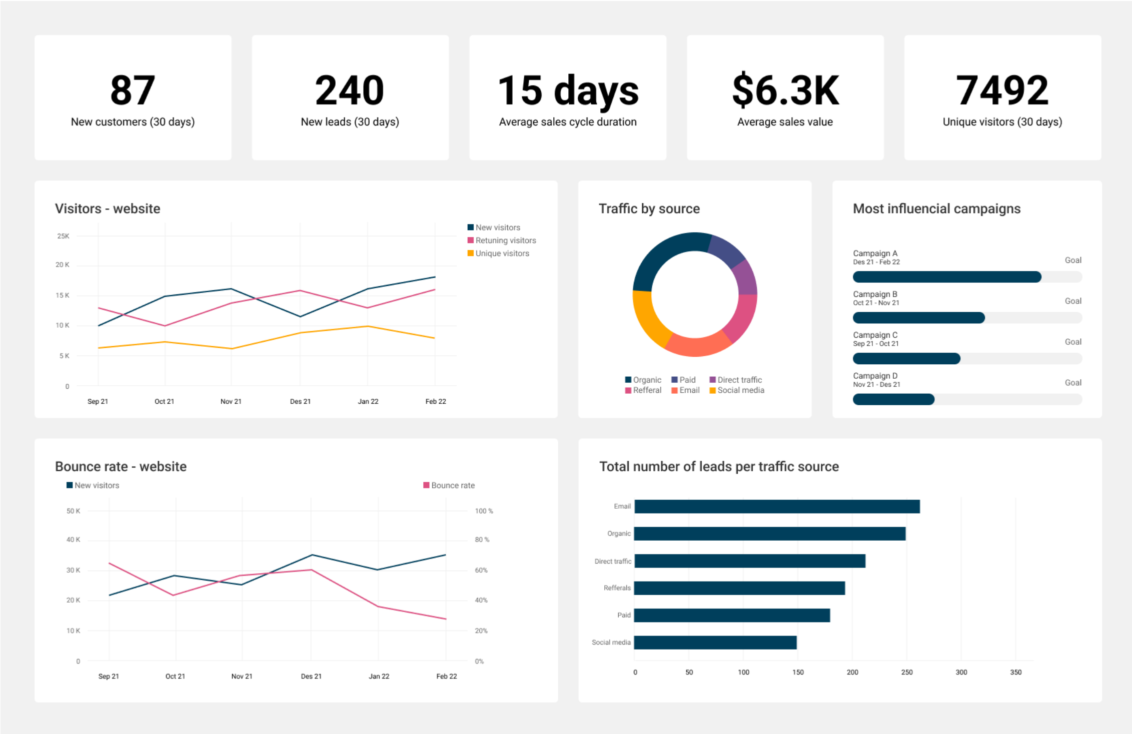

Figure B.4: Dashboard scenario 2 version B

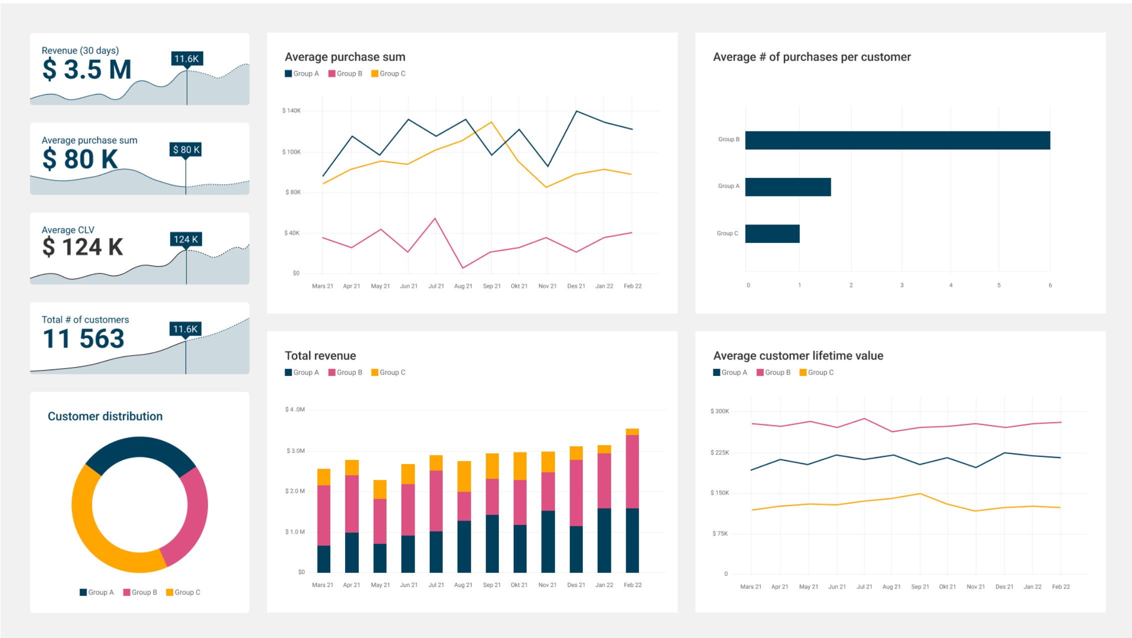

Figure B.5: Dashboard scenario 3 version A

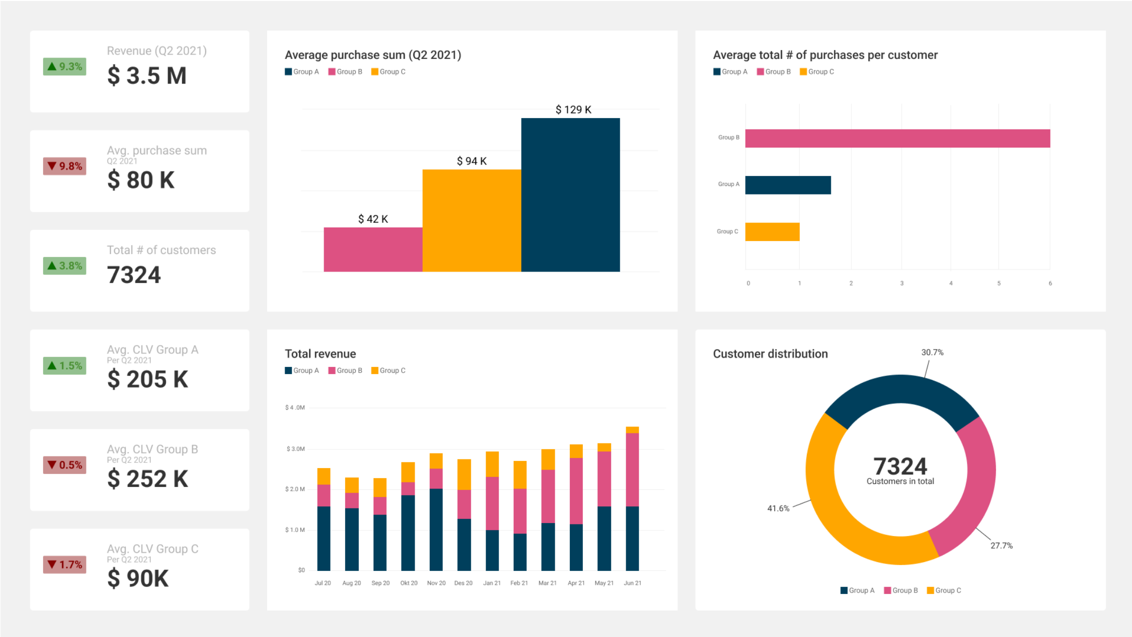

Figure B.6: Dashboard scenario 3 version B

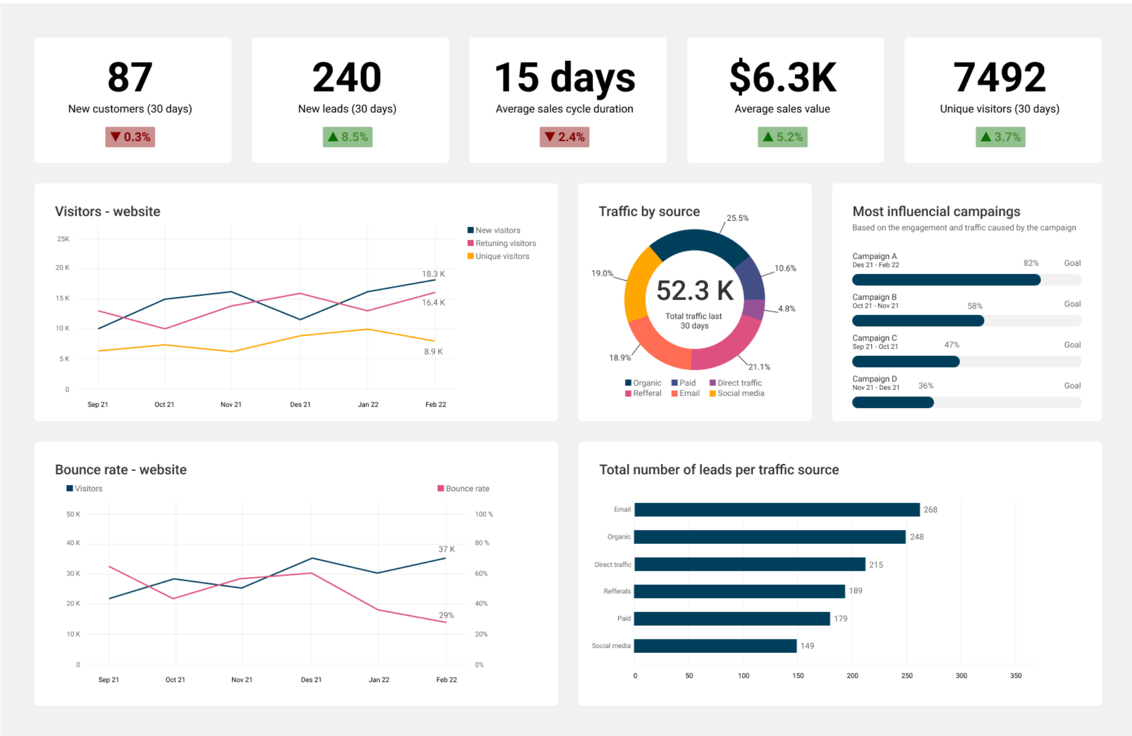

Figure B.7: Dashboard scenario 4 version A

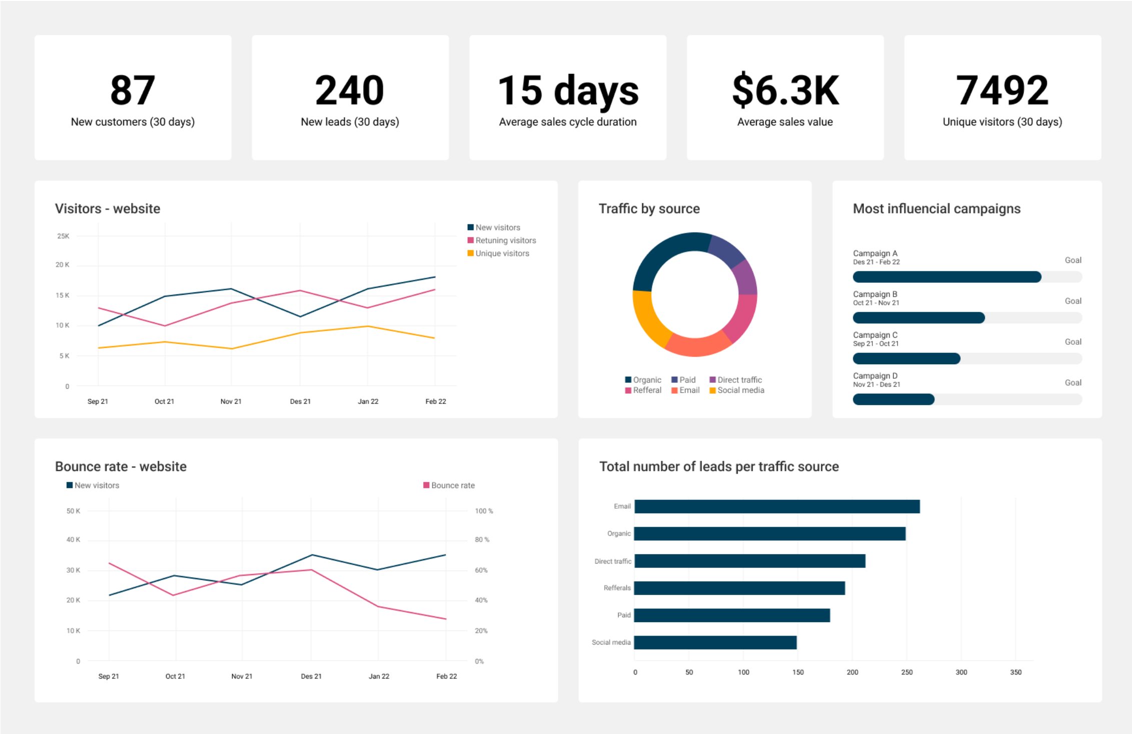

Figure B.8: Dashboard scenario 4 version B

APPENDIX C

Questionnaire Measures

Information Quality (Wixom and Todd 2005)

Information completeness

Please evaluate the level to which the given dashboard fulfilled the following statements on a scale from Strongly disagree (1) to Strongly Agree (5).

The dashboard...

- comp1: provides me with a complete set of information
- comp2: provides comprehensive information
- comp3: provides me with all the information I need

Information format

Please evaluate the level to which the given dashboard fulfilled the following statements on a scale from Strongly disagree (1) to Strongly Agree (5).

The dashboard...

- form1: form1 provides me with well formatted information
- form2: provides me with well laid out information form3: presents the information clearly on the screen

Information accuracy

Please evaluate the level to which the given dashboard fulfilled the following statements on a scale from Strongly disagree (1) to Strongly Agree (5).

The dashboard...

- iacc1: appears to provide correct information
- iacc2: provides information with few errors

Information accuracy

Please evaluate the level to which the given dashboard fulfilled the following statements on a scale from Strongly disagree (1) to Strongly Agree (5).

The dashboard...

- : curr1: provides me with timely information
- : curr2: provides up-to-date information

Perceived Ease of Task Completion (Wixom and Todd 2005)

For each statement below, select the option you agree with on a scale from Strongly disagree to Strongly agree.

- ease1: Overall, I am satisfied with the ease of completing the task in the scenario
- ease2: The dashboard was easy to use
- ease3: It was easy to get the information I need for the task at hand

Perceived Usefulness (Hardgrave et al. 2003)

For each statement below, select the option you agree with on a scale from Strongly disagree to Strongly agree.

- usef1: The dashboard was useful for completing the task
- usef2: The dashboard improved my performance in completing the task
- usef3: The dashboard enhanced my effectiveness in completing the task

Perceived Complexity (Kyndt et al. 2011)

For each statement below, select the option you agree with on a scale from Strongly disagree to Strongly agree.

- comx1: I found the task complicated
- comx2: The information was difficult to understand
- comx3: I found the task difficult

Information Satisfaction (Wixom and Todd 2005)

For each statement below, select the option you agree with on a scale from Strongly disagree to Strongly agree.

- sat1: Overall, the information I got from the dashboard in relation to this task is very satisfying
- sat2: I am very satisfied with the information I received from dashboard to perform this task

Decision-making Quality (certainty) (Jarupathirun and Zahedi 2007)

For each statement below, select the option you agree with on a scale from Strongly disagree to Strongly agree.

When using this dashboard, I am confident that the decision I made is...

- dmq1: Accurate
- dmq2: Correct
- dmq3: Precise
- dmq4: Flawless
- dmq5: Error-free
- dmq6: Dependable

APPENDIX D

Cross Loadings

Table D.1: Cross Loadings

	Accuracy	Completeness	Complexity	Currency	DM Quality	Ease	Format	Satisfaction	Usefulness
comp1	n/a	**0.8231**	-0.3908	0.4629	0.5735	0.7309	0.4187	0.5053	0.5923
comp2	n/a	**0.6418**	-0.1905	0.4117	0.4644	0.5287	0.4398	0.4751	0.5154
comp3	n/a	**0.7470**	-0.1495	0.5792	0.6890	0.7482	0.5135	0.6445	0.6336
comx1	n/a	-0.2969	**0.9044**	-0.1689	-0.3100	-0.4048	-0.2114	-0.2468	-0.3502
comx2	n/a	-0.2032	**0.6268**	-0.1258	-0.1723	-0.2868	-0.1967	-0.1446	-0.2102
comx3	n/a	-0.3209	**0.9108**	-0.1578	-0.3056	-0.4354	-0.1815	-0.2713	-0.3490
curr1	n/a	0.5105	-0.1190	**0.6786**	0.4689	0.4516	0.4670	0.4133	0.4179
curr2	n/a	0.4061	-0.1374	**0.7169**	0.4545	0.4802	0.4494	0.4154	0.4415
dacc	n/a	0.1199	-0.1440	0.0209	**0.1796**	0.1076	0.0296	0.0952	0.0961
dmq1	n/a	0.6759	-0.3378	0.4487	**0.8744**	0.8106	0.4794	0.6653	0.6381
dmq2	n/a	0.6720	-0.3564	0.5546	**0.9114**	0.8333	0.5567	0.6348	0.6631
dmq3	n/a	0.6103	-0.2383	0.5557	**0.7253**	0.7248	0.4497	0.6283	0.5489
dmq4	n/a	0.3468	-0.0169	0.4107	**0.4410**	0.4780	0.3389	0.4932	0.3938
dmq5	n/a	0.4438	-0.1781	0.3922	**0.5956**	0.5647	0.3409	0.5164	0.4591
dmq6	n/a	0.6820	-0.2140	0.6338	**0.8388**	0.7486	0.6208	0.6325	0.6637
dtime	n/a	-0.0033	-0.0599	0.0355	**0.0218**	0.0479	0.0094	-0.0116	-0.0082
ease1	n/a	0.7783	-0.4311	0.4495	0.6374	**0.7236**	0.5132	0.6297	0.7549
ease2	n/a	0.5961	-0.3483	0.5129	0.6728	**0.7774**	0.6896	0.6804	0.6983
ease3	n/a	0.6602	-0.2495	0.5243	0.7773	**0.7247**	0.5300	0.7265	0.6548
form1	n/a	0.4434	-0.2314	0.5342	0.4703	0.5976	**0.7698**	0.5419	0.5231
form2	n/a	0.3052	-0.1528	0.2967	0.3515	0.4444	**0.5628**	0.3885	0.3802
form3	n/a	0.5490	-0.1267	0.5504	0.5148	0.6291	**0.8047**	0.5540	0.5840
iacc1	**n/a**	0.5064	-0.1891	0.5768	0.5209	0.5581	0.5536	0.4672	0.5041
iacc2	**n/a**	0.0170	0.1798	0.1612	0.1336	0.0991	0.2682	0.1271	0.0787
sat1	n/a	0.5760	-0.2210	0.4708	0.6010	0.7163	0.5743	**0.7962**	0.6782
sat2	n/a	0.5904	-0.2184	0.4777	0.6601	0.7448	0.5363	**0.8022**	0.6591
usef1	n/a	0.5922	-0.3181	0.5531	0.6168	0.7153	0.5211	0.6718	**0.7888**
usef2	n/a	0.6302	-0.2757	0.4193	0.5323	0.6760	0.4745	0.5900	**0.7189**
usef3	n/a	0.5940	-0.2741	0.4479	0.5992	0.7916	0.6124	0.6686	**0.8009**

Cross Loadings: comp = Completeness, comx = Perceived Complexity, curr = Currency, dacc = Decision Accuracy (Decision Quality), dmq = Decision Quality, dtime = Decision Time (Decision Quality), ease = Perceived Ease of Task Completion, form = Format, iacc = Accuracy, sat = Information Satisfaction, usef = Perceived Usefulness

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