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ICT in Business and the Public Sector

Self-Service Business Intelligence: Causal Factors for Success and Failure.

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MASTER'S THESIS

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Abstract

Overall project investments in self-service business intelligence (SSBI) constituted $13 billion in 2017, and about 70% of these projects eventually fail. This research examines the potential user- and software-related success and failure factors affecting these projects. There is scientific consensus that associated problems arise when users are required to adopt SSBI software, their technical competence regarding information management, and their shared perceptions of its related concepts. This study concentrated on identifying the factors determining SSBI success. Included factors are users' abilities, environmental factors, supporting activities, the software manufacturer's applications, the software's shared functions, users' personal background, and their educational level. Participants within the research sample conducted exercises in SSBI software, and a survey with which the associated factors were detectable. With these detected factors, a statistical analysis concluding classifiable differences, correlations, and parabolic quadratic relations was conducted. Findings confirmed the following: 1) inexperienced users are capable of creating simple visualizations within a limited time in SSBI software; 2) information- and data-management-trained users perform better; 3) users technical and visual abilities increase their created visualization quality; 4) users with business education or computer science work experience accomplish enhanced visualization quality; 5) users' with a higher educational level had improved metric identification and utilization skills; 6) middle-aged users create information with greater visual understandability; and 7) a Dunning-Kruger effect is demonstrated in users' confidence in their own capabilities and performance. Hence, this research recommends training users accordingly before and during their involvement in (SS)BI processes, selecting higher-educated, middle-aged users with business and computer science backgrounds, and raising awareness of false perceptions originating from a potential Dunning-Kruger effect in which lesser-performing users are unaware of their lacking expertise.

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Disclaimer

Research methods changed based on the RIVMs advice that working in groups was not recommended due to the COVID-19 outbreak at the time of the research. Since the original methods described included using focus groups, research was conducted digitally by participants in their own environment or onsite in accordance with the RIVMs recommendations. Thanks to time-tracking software, we were able to record the participant's performed processes to minimize any time-based bias. Thereby, the possibility of COVID-19 spread due to this research was eliminated or minimized where possible, as participants and researchers were not in direct contact with each other.

Thesis overview

The following bulleted list describes chapters' contents:

- *The introduction introduces this paper's topic, included definitions, problem, and research question;*
- *the literature review presents the current scientific understanding regarding this research topic;*
- *the methods describe the constructed hypotheses, the sample selection and approach, the software selection, the assignment and data set-up, and validity and reliability determination;*
- *the results characterize the general research figures;*
- *the analysis construes results specifying the sufficient comparisons;*
- *the discussion compares the analysis' results authentication in validity measurements, experts opinions, and literature's confirmation;*
- *the conclusion summarizes the valid and reliable claims, presents the study's validity and reliability, the research's biases and limitations, implications and recommendations, and future research suggestions;*
- *the references list all associated literature within this paper;*
- *the appendixes cover all images, lists, and tables that were too substantial to be included in the main text.*

1. Introduction

Organizations worldwide have increasingly realized the importance of their generated data originating from various implemented applications due to technological advancement and globalization (Imhoff & White, 2011; Lennerholt et al., 2018; Jansson & Persson, 2016; Amara et al., 2012). According to Bhageshpur of Forbes (2019), “data is the new oil.” Technology has rapidly advanced in the past 50 years, as computers have become twice as fast every two years (Simonite, 2016). Due to faster computers, businesses are able to progressively digitalize their administrative tasks and generate related data (Hani et al., 2017). This led to the development of analytical software tools and job positions within businesses throughout sectors (Hani et al., 2017). Therefore, numerous business intelligence (BI) software packages are available to support organizational analytics, such as the self-service business intelligence (SSBI) package. These software packages are understandable user-friendly applications to perform simple business analytical tasks (Harms, 2018).

According to Alpar and Schulz (2016), 22% of businesses have implemented BI in some specific form. Many companies perform BI through integrated modules in other software or spreadsheets. Furthermore, according to Lennerholt et al. (2018) and Mudzana and Majaraj (2017), more than 50% of SSBI implementation attempts fail due to a variety of reasons which are explored in this thesis. Moreover, organizations keep venturing into business intelligence, which constituted $13 billion of investments in 2017 (Mudzana & Maharaj, 2017; Watson & Wixom, 2007). Consequently, SSBI implementations have not been directly successful (Peters, 2013).

1.1 Definitions and models

A few concepts and frameworks have to be presented to comprehend the failed attempts’ problem for SSBI software and understand the research thesis. Therefore, the following paragraphs illustrate the concepts of user IT intelligence, BI, information demand and supply, self-service, and governance. Furthermore, the frameworks cross industry standardized process for data mining (CRISP), the Amsterdam information model, strategy maps, the data warehouse model, the BI maturity model, and semantic layers are explained.

- **User IT intelligence** is the average intelligence end-users possess when adopting, exploring, and exploiting their accessible software (Aggarwal et al., 2015). Hence, it is the previously existing or learned capabilities of using a specific software application. In this research, user intelligence is relevant to SSBI software.
- **Business intelligence (BI)** is a collective term for strategies and technologies providing historical, current, and predictive information on business operations (Verhagen, 2011; Gangadharan & Swami, 2004; Harms, 2018; Watson & Wixom, 2007; Jansson & Persson, 2016; Olszak & Ziemba, 2007; Peters, 2013; Jooste et al., 2016; Wieder et al., 2012; Elena et al., 2013; Kulkarni et al., 2017). Specifically, BI includes several processes and software genres associated with transforming data into useful information for organizations that commonly use it to back and support decision-making processes (Rajterič, 2010; Berthold et al., 2010; Mudzana & Maharaj, 2017; Gangadharan et al., 2004; Harms, 2018; Jansson & Persson, 2016; Lönnqvist & Pirttiäki, 2006; Olszak & Ziemba, 2007; Peters, 2013; Amara et al., 2012; Wieder et al., 2012; Elbashir et al., 2008).
- **Information demand and supply** is the organizational mechanism concerning information between end-users and IT staff (Heunks, 2014). Namely, the information users need to support business decisions based on generated data reports performed by the IT staff. Hence, end-users are the demand-side, and the IT staff is the supply-side.
- **Self-service (SS)** refers to users being required to perform actions to build models and processes to serve their own needs. Specifically, users become self-reliant by removing certain dependencies from their desired process (Kosambia, 2008; Harms, 2018). For example, with SSBI, users do not directly need the IT staff to satisfy their information needs.
- **Governance** is the criterion used to decide whether certain products, processes, technologies, or strategies comply with laws, organizational rules, and best-practices (Calder, 2009; Jansson

& Persson, 2016). Specifically, the term encompasses the processes of developing these laws, rules, and best-practices, the monitoring of staff, and the consequences of governance failure.

- **The CRISP model** shows how the BI process is generally performed (see Appendix A) through the following steps: 1) identifying business information needs, 2) preparing related data, 3) building the information model, and 4) evaluating resulting information. After evaluation, if changes to the model are desired, the model reiterates; if not, the information model gets deployed (El Sheikh & Abdel, 2011; Landes et al., 2013).
- **The Amsterdam information model** characterizes various IT-related functional roles within organizations. The model is viewable in Appendix B (in Dutch). The roles defined in the model detail the functions needed within the relationship between an IT department and the organization's business operation (Heunks, 2014).
- **Strategy maps** define a scorecard in which an organization is able to monitor its business processes (Hu, Leopold-Wildburger, & Strohhecker, 2016). An example is provided in Appendix F. Strategy maps are representations able to measure an organization's directional success factors. Success factors are depicted as critical success factors (CSF), and measurements are key performance indicators (KPI).
- **Data warehousing** is a set of techniques to design and manage organizational data. Its target is to produce an accessible data structure for decision-support information (Adamson, 2010; Gangadharan et al., 2004: Harms, 2018; Watson & Wixom, 2007; Jansson & Persson, 2016; Olszak & Ziemba, 2007; Wieder et al., 2012). This data can originate from various internal and external sources. Two well-known techniques that are a part of data warehousing are the ETL procedure and the star-scheme. ETL stands for "Extract" (retrieving data from a multitude of business applications), "Transform" (changing and cleaning data to make it usable within one model), and "Load" (delivering the produced model to analytical software). The star-scheme is a method to assemble one model out of various sources centered on a business fact. For example, sold items are a fact, which is in turn intertwined with dimensions like, customer information and product information. This model is viewable in Appendix C.
- **Maturity models** are models to evaluate certain functions of or concepts within organizations (Brooks, 2013; Rajterič, 2010). For this research, BI and SSBI maturity models are used and viewable in Appendix D and Appendix E, respectively. The models identify situations concerning BI and SSBI in which viewers can recognize which stage their organization is positioned.
- **Semantic layers** are layers introduced within data warehouses to facilitate SSBI for users (Hani et al., 2018). A data warehouse consists of an extraction and transform layer. However, instead of a load layer, a semantic layer is introduced. In a semantic layer, cleaned data is kept within separate "islands" individually usable for users to construct their own reports.

1.2 BI developments

Traditional BI software managed in businesses has evolved into complicated structures (Burke et al., 2016; Imhoff & White, 2011). Data warehouses are not easily changeable once deployed without any negative side effects. However, adding new layers to a data warehouse is relatively harmless. Consequently, to satisfy new information requests of business users, these new layers are added over the years. This slowly creates a complex structure in which these added layers become dependent on each other via data relations. Furthermore, BI has experienced a diverse set of innovations over the years. Among traditional BI and the more current SSBI software packages, the market offers numerous semi-fit packages designed for different purposes while incorporating BI software modules (Passlick et al., 2017; Schlesinger & Rahman, 2015; Olszak & Ziemba, 2007). Examples of semi-fit BI software packages are Microsoft Excel, Exact Online, and Zoho CRM. Due to faster computer and network speeds, performing BI with real-time added data is currently possible as well. Traditional BI systems depended on batch processes performed at night by refreshing the data warehouse with new data (Lennerholt et al., 2018). Modern BI software packages are also equipped with game theory mechanics. These mechanics make it possible for BI software packages to generate decision workflows, give recommendations, and alert users when certain thresholds are reached (Imhoff & White, 2011; Watson & Wixom, 2007). These game theory mechanics are based on artificial intelligence with which the BI application can maximize a possible outcome with a to-be-made decision. With recommendations, users can collaborate with other users on a particular course of action. Furthermore, current BI software packages contain online or internal knowledge bases that users can view to increase their effectiveness with the BI software or create more effective reports (Imhoff & White, 2011; Rajterič, 2010; Berthold et al., 2010; Issa & Haddad, 2007).

Currently, measurement sensors are implemented all around us. These sensors generate data about what they measure, and this data is usable in BI software, making more different information available to organizations (Acito & Khatri, 2014; Hani et al., 2017).

Likewise, the amount of data-integration methods available for BI software is increasing. This boosts the data volume available to organizations while frequently overwhelming the organization's data managers and users (Obeidat et al., 2015; Jansson & Persson, 2016; Olszak & Ziemba, 2007). Traditionally, this data originates from the IT department, which supplies data to the business, which in return demands and receives data. However, with more data sources available to them, users supply and implement data themselves as well, shifting the demand and supply relation (van der Meulen & Rivera, 2015; Amara et al., 2012). As there is a shortage of analytical data staff at IT departments, SSBI solutions are more attractive since they partly shift the data cleaning responsibility to users.

Moreover, data mining makes it possible to analyze log files and generate processes among this data (van der Meulen & Rivera, 2015; Olszak & Ziemba, 2007). Therefore, with data mining, identifying new data opportunities, such as integrating these processes within SSBI software or adding them to data warehouses, becomes possible.

Scientific research available on BI, end-user psychology, data analytics, and business operations is plentiful, as these terms have been around for some decades. However, since new SSBI software packages are recently becoming more popular, scientific research on this topic has only been available for the past ten years, and the amount of papers is limited (Imhoff & White, 2011). Additionally, numerous papers reviewed for this research either propose or demand a framework for SSBI implementations (Schlesinger & Rahman, 2015; Passlick et al., 2017; Poonnawat & Lehmann, 2014).

In the past 50 years, computer speeds have rapidly increased to the point that, in theory, users have access to every form of business information quickly (Acito & Khatri, 2014). In the past ten years, users have apprehended the possibilities of large quantities of data for their business operations. Hence, organizations are turning to alternative solutions such as SSBI, knowledge bases, and software training. These solutions all contain a factor of collaboration between users and IT experts, as these solutions require a transfer of analytical knowledge to the end-user (Schlesinger & Rahman, 2015; Passlick et al., 2017; Poonnawat & Lehmann, 2014; Bani-Hani et al., 2018; Olszak & Ziemba, 2007). Additionally, knowledge bases and software training do not offer a complete solution. Therefore, this problem persists. SSBI implementations fail due to lack of data-related user intelligence, lack of organization support, lack or excessive governance controls, and lack of accessibility (Passlick et al., 2017; Burke et al., 2016; Schlesinger & Rahman, 2015).

1.3 Research question

A research question was constructed to support research on this topic. This question forms the basis for the proposed hypotheses:

What user analytical capabilities are determinants for successful organizational SSBI implementations?

This question arose from a combination of reviewed scientific literature, own experiences, and BI field experts. Consensus from the mentioned sources indicate that users generally lack data literacy, as revealed by data managers and applies to business managers and everyday users. To improve an organizational analytics, analytical intelligence needs to be present on both the business and IT-side. Furthermore, by increasing relating responsibility, users are inclined to reserve more time to acquire analytical knowledge to manage the process. By improving knowledge, that user can manage their analytical obligations effectively and efficiently, thereby possibly relieving the necessary time and responsibility for the IT department.

However, data managers are primarily concerned with incidents and problem management; hence, no staff and time are available for development or knowledge sharing. Furthermore, users generally do not possess the knowledge and responsibility concerning analytical tasks within an organization. Consequently, they do not have a direct incentive to improve an organization's analytical capabilities. According to the literature review, this problem concerns the data warehouse to the most considerable extent. This occurs as users generally maintain the least amount of analytical knowledge regarding data warehouse processes. A possible situational improvement would be to make them partly responsible for some analytical tasks within the company. This will relieve time for the data manager with which they can invest in development and knowledge sharing. The situation may improve by increasing users' responsibility, thereby improving an organization's analytical features, such as the data warehouse. However, the analogy described in this and the previous paragraph is based on research models, assumptions, and problem research and is thereby profoundly generalized. Model visualizations on the presumed problem and proposed solution are available in Appendix I.

The research question includes the following terms: "user analytical capabilities," "are determinants," "successful," "organizational," and "SSBI implementations." In the following subparagraphs, these terms are described in the research question's context.

- **User analytical capabilities**: end-users' capabilities to understand what they are doing, producing, exploring, exploiting, or benefiting when handling software or data. User capabilities are applicable to SSBI software. Furthermore, users should have sufficient mathematical knowledge to perform necessary calculations BI processes, be aware of where to acquire support for their questions or information needs, and aware of the necessary governance for SSBI and BI processes (Kulkarni et al., 2017).
- **Are determinants**: in what way is a user's analytical capabilities are an influence, impact, or a deciding factor for successful organizational SSBI implementations. Therefore, "a determinant" will assess if a causal relationship is present between users' analytical capabilities and successful organizational SSBI implementations.
- **Successful**: the user's perceptual view when clarifying any data-related questions with the proposed SSBI software package. To achieve a favorable SSBI implementation, users need to perceive their results successive. Similarly for company entities, they need to treat their software package as their first-choice analytical software. Furthermore, the proposed SSBI software package should be more cost- and time-saving and generating more probable returns than traditional BI counterparts.
- **Organizational**: the software is suitable for businesses, governments, and non-profit organizations.
- **SSBI implementations**: the SSBI software contained in this research is formally introduced and decentralized, operating stand-alone on the user's desktop system. Therefore, research participants got a predefined crash course into the research-chosen SSBI software before participating.

The research question's term "successful" in implementations does also include perceived success in addition to technical success. Users' convictions likewise determine the success rate. According to Issa and Haddad (2007), since organizations commonly do not consider perceptional factors in implementation projects, implementation failures increase (Elbashir et al., 2008). Therefore, various perceptional measures were utilized in the research to evaluate user convictions on SSBI.

As specified previously, more than 50% of SSBI implementations fail, and only 22% of businesses have implemented BI applications (Alpar & Schulz, 2016; Lennerholt et al., 2018). According to Mordor Intelligence (2020), BI is expected to grow by 12% annually. In 2021, about 39% of businesses would have implemented BI systems if the growth percentage is multiplied five times, as data originates from 2016. We did not expect the failure rate to be this high in 2020 and expected more companies to have implemented specific BI software. Furthermore, we spotted similar problems in previous researches. The problems described within these studies were either: the organizations suffered from BI-specialized staff shortages; or not taking BI seriously enough to allocate the necessary time or budget to SSBI implementation failure. Due to data warehousing processes, lack of budget or time, strategic support, and other variables determining BI's success, many organizations struggle with BI, whose management quickly becomes chaotic.

2. Literature review

The literature review presents the current scientific understanding of SSBI. Thus, SSBI's business impact, current market position, end-user intelligence psychology, data literacy, data science, the computer science of SSBI software, and success and failure factors of SSBI implementations are described.

2.1 Business factors

Generally, BI lets users identify business opportunities for their organizations and make effective business decisions supported by data-based spotted opportunities rather than intuition (Imhoff & White, 2011; Rajterič, 2010: Harms, 2018; Watson & Wixom, 2007; Jaklic et al., 2009; Lönnqvist & Pirttimäki, 2006; Olszak & Ziemba, 2007; Peters, 2013; Amara et al., 2012; Jooste et al., 2013; Wieder et al., 2012). These business opportunities are achieved by spotting inefficiencies in business processes through the data process-supporting applications. They can thereby determine the best decision options through data categorization and trend analysis. In sequence, visualized data by BI allows managers to view simple information forms based on large amounts of data for which these decisions are executable (Platts & Tan, 2004). When performed accurately, BI can strengthen an organization's learning capability, knowledge management, innovation ability, and overall performance especially strategic performance. Strategic performance is enhanced since knowledge sharing between management layers is promoted and enhanced by BI (Peters et al., 2016; Lee & Widener, 2016; Elbashir et al., 2008). As IT departments struggle with keeping up with user information demand leading to the rise of SSBI software packages, generating these business opportunities is progressively becoming the responsibility of the end-users themselves. End-users are more able to perform these processes since modern software can make data analytics user-friendly (Lennerholt et al., 2018; Poonnawat & Lehmann, 2014; Jansson & Persson, 2017). However, most cases still require help from the IT department, but the latter fulfills a supporting and expertise-providing role (Santhanam et al., 2014). SSBI increases the business agility of organizations since it gives end-users more freedom to address their information needs (Imhoff & White, 2011; BARC, 2019; Schlesinger & Rahman, 2015; Hani et al., 2017; Rajterič, 2010). Conversely, end-users are not directly aware of the data structure from which their usable data originates nor have the direct mathematical knowledge to design effective measurements. Therefore, SSBI increases the likelihood of inaccurate data while keeping errors in only a few user systems; hence the importance of governance (Harms, 2018). Additionally, the IT department is less dependent on either internal or external expertise. However, instead of a centralized information responsibility, SSBI requires end-users to be individually responsible. This hinders information-sharing potential throughout the organization since SSBI software packages operate on stand-alone desktops (Schlesinger & Rahman, 2015). Conversely, when SSBI is implemented within an organization, two varieties of end-users emerge: power users and casual users (end-users who are willing to learn analytical processes to create information reports and dashboards yet need support to do that) (Lennerholt et al., 2018; Moran, 1981; Olszak & Ziemba, 2007). Consequently, in most observed cases, power users can support casual users to the point that the latter progressively evolve into power users.

Due to SSBI's system decentralization, IT departments prefer to have a standardized framework solution to obtain reliable processes and software to implement SSBI (Schlesinger & Rahman, 2015). However, no default standard has materialized yet (Passlick et al., 2017; Poonnawat & Lehmann, 2014; Schlesinger & Rahman, 2015; Zaghloul et al., 2013).

Considering that BI has primarily advanced to support strategic decision-making, it has increasingly been used within operational decision-making recently (Alpar & Schulz, 2016; Rajterič, 2010; Mudzana & Maharaj, 2017; Jansson & Persson, 2016; Elbashir et al., 2008). Since operational decision-making requires limited time, supporting applications are obligated to be fast and easily understandable for operational usage. End-users become empowered to generate their own information. Therefore, instead of constantly requesting information, users are helped in producing their own. Instead of producing information, the IT department's staff can focus on improving users' analytical capabilities or other tasks.

As more external data is available for organizations, SSBI software makes it simpler to integrate it with internal organizational data. SSBI functions on an individual level. Therefore, external data does not directly spread throughout the organization, and stricter governance regulations are not directly necessary (Imhoff & White, 2011; Olszak & Ziemba, 2007).

2.2 Perceptional factors

Generally, end-users want to use BI software to test if their hypotheses are correct (Hani et al., 2017). Data-based hypothesis testing is required to prove any hypothesis' claim or assumption (Singh, 2020). Data warehouses commonly contain a relatively large amount of data. In a substantial number of cases, the same data is described different terms and used in different departments within the organization due to multiple data warehouse layers. As this occurs within the data warehouse, users do not directly know if this data has the same origin and is usable in the same way (Schlesinger & Rahman, 2015; Stone & Woodcock, 2014; Van der Meulen, 2015). Repeatedly, power users can identify these issues and perform their analytics accordingly. Thus, if power users are sufficiently spread throughout the organization, they can spread the knowledge about these issues. If users trust their respective peer and possess managerial guidance, knowledge spreading about these issues is further enhanced (Aggarwal et al., 2015; Lennerholt et al., 2018; Van der Meulen, 2015; Bani-Hani et al., 2018; Olszak & Ziemba, 2007; Issa & Haddad, 2007; Kulkarni et al., 2006). Hence, collaboration between IT staff, power users, and casual users is crucial to accomplish an analytical organization. According to Santhanam et al. (2014), Olszak and Ziemba (2007), and Peters (2013), to improve the analytical organization, regular meetings between IT staff, power users, and casual users should be encouraged. These meetings can advance collective analytical capabilities, promote sharing of analytical knowledge, and solve each others' analytical problems; a helpdesk role is not enough to support this (Imhoff & White, 2011). Conversely, a lack of training diminishes support and leads to a less developed organization (Poonnawat & Lehmann, 2014; Santhanam et al., 2014). With a lack of user training, misconceptions, false perceptions appear and are shared throughout the organization. This establishes ineffectiveness and inefficiencies (Schlesinger & Rahman, 2015; Van der Meulen, 2015; Mudzana & Maharaj, 2017; Jansson & Persson, 2016; Jooste et al., 2013). However, knowledge perception increases the adoption speed of new software within an organization due to a user's false convincement of their capabilities. Analytically critical users are more hesitant to directly support new software implementations (Aggarwal et al., 2015). Possibly due to the limitations of Wieder et al. (2012) study, a paradox in user satisfaction was found in BI usage. If an organization contained a larger than average scope in their BI processes, users tended to possess a higher amount of dissatisfaction in BI usage. Conversely, organizations investing a higher than average amount of effort in BI usage presented higher user satisfaction. However, Wieder et al.'s study had a small sample size, and It would be impossible to find substantial associations if the sample size is too limited. Peters et al. (2016) study determined that SSBI software users supposedly felt higher user satisfaction due to freedom to participate in BI processes within the application compared to traditional BI applications. In addition, most of them are not completely aware of *all* their available data (Passlick et al., 2017; Rajterič, 2010). Therefore, users are not aware of the full potential of their analytical software and data. The emergence of user-to-user knowledge reduces this problem (Hani et al., 2017). However, with user-to-user knowledge, misconceptions are more easily sharable as well. According to Aggarwal et al. (2015), a U-type knowledge relation is present among users in organizations. Therefore, there is a difference in a user's own perceived IT knowledge and their actual IT knowledge. In their research, the authors found the presence of the Dunning-Kruger effect in which individuals are unaware of their ignorance in a relating topic. This occurs as they lack experience to understand their knowledge-deficiencies, this effect is shown in Figure 1. However, when users have a higher amount of relating knowledge, they are more critical of their abilities.

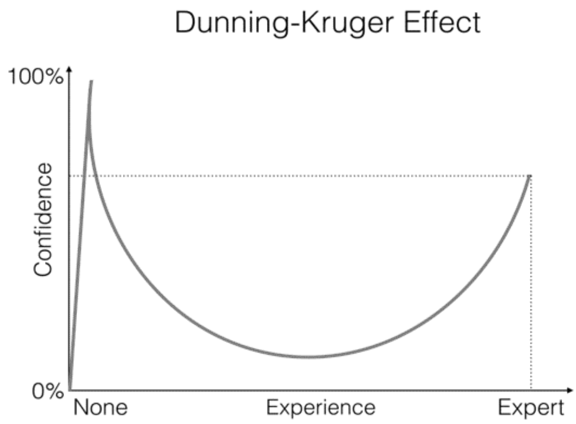


Figure 1 - (Kruger & Dunning, 2000; Experiments, n.d.)

2.3 Design factors

Software design can differ depending on their targeted customer segment. Some software designs are to be more user-friendly since everyday users use it, leads to more user satisfaction, and will let them produce more effective and faster results (Moran, 1981; Passlick et al., 2017; Rajterič, 2010). Moran (1981) distinguishes users in "novice", users new to the software and with no IT experience and "expert", familiar with the software and possessing experience. Moran defined a personal conceptual framework as a set of guidelines, envisioned templates, rules, best-practices, models, and workarounds devised by a user while they learn from their experiences. According to Moran's research, novice users do not own a personal conceptual framework for the to-be handled software and need to explore it in order to construct their framework. Contrarily, expert users already possess a conceptual framework and exploit the software to increase their effectiveness and the efficiency of its result generation (Moran, 1981). In the past decades, design principles to improve user-friendliness to increase a novice user's exploitation have largely been associated with user experience (UX) design (Unger & Changler, 2012; Jooste et al., 2016).

2.4 Literacy factors

The ability to read, comprehend, develop, and communicate data as knowledge is referred to as data literacy (Baykoucheva, 2015). Data literacy, like literacy as a general term, focuses on the skills needed to work with data. While data literacy is generally not embedded in organizational culture yet, knowledge about data benefits society and organizations in general. Society is becoming more data-centered, as advanced related technology is available (Bhargava et al., 2015; Prado & Marzal, 2013; Riksdale et al., 2015; Olszak & Ziemba, 2007; Peters, 2013; Jooste et al., 2013; Peters et al., 2016). Although data literacy does not always include difficult-to-measure concepts, organizations are investing in data-driven decision-making (DDDM). DDDM leads to more successive decisions and investments therefore rise. Regardless of the Dunning-Kruger effect, data literacy is becoming a skill. It reduces misunderstanding and knowledge gaps, and improves meeting organizational needs due to a better focus on organizational data. Commonly, data literacy comes across four problems:

1. Data literacy involves multiple disputable definitions because it is a relatively new concept and encompasses a broad range of processes, skills, and subjects (Riksdale et al., 2015; Bhargava et al., 2015).
2. Since BI processes, time investments, information architecture, and organizational importance is largely unknown to users, data sources and translation processes lack transparency (Al-Barashdi & Al-Karousi, 2018).
3. While investments increase, organizations cannot fully control their data-generating capabilities. BI procedures can contain a vast number of integrated systems and the required human capital is not present (Al-Barashdi & Al-Karousi, 2018).

4. The literature research suggests that information demand is not sufficiently met due to data collection being performed by technical programmable scripts. Furthermore, data translation requires advanced analytical knowledge for algorithm production and relating human capical is difficult to obtain (Al-Barashdi & Al-Karousi, 2018).

The data literacy concept entails increasing knowledge with teachers, librarians, and students. Moreover, data literacy originated in various scientific fields, and it is increasingly used in organizations (Sternkopf & Mueller, 2018; Schield, 2004). Data literacy advances an organization's ability to learn due to the capability of generating fast and accurate insights in its business field and time reduction for analytical tasks. However, organizations experience difficulties with data literacy improvements (Sternkopf & Mueller, 2018). Therefore, they opt for practical approaches such as data carpentry, a term used for processes in user-friendly analytical applications such as SSBI software (Riksdale et al., 2015; Morris & Dillon, 1997).

Four fundamental pillars enhance data literacy. These pillars define investing opportunities with which users' data literacy is strengthened (Bhargava et al., 2015): 1) data management; teaching users what data is and where to find it; 2) data modeling, whereby users need to be able to judge what data is combinable and understand how it is processed; 3) data visualization; designing information and understanding information interpretation to cause comprehension to the information demanders; 4) data evaluation and communication, evaluate information production methods and where to share information so that data is purposively used in the organization.

Organizations tend to adopt two types of approaches to data management: apply quantitative research on data originating from qualitative sources and vice versa (Bhargava et al., 2015). Depending on a data manager's strengths and weaknesses, organizations tend to assign different expertise responsibilities to different data managers. For instance, one data manager might specialize in developing algorithms and another data visualization (Prado & Marzal, 2013). As data managers with a broader data-literacy-relating experise experience greater individual success, these data managers may not always be available. However, collaboration between multiple available data managers is needed to assist users in data-literacy-promoting applications (Prado & Marzal, 2013; Riksdale et al., 2015; Olszak & Ziemba, 2007; Peters, 2013).

Although success may differ, maturity models help organizations improve their current data literacy status. These models define general occurrences among different levels and provide organizations with a roadmap. Although multiple maturity models are proposed, they share the following elements (Sternkopf & Mueller, 2018; Prado & Marzal, 2013; Riksdale et al., 2015):

1. At the start, an idea or uncertainty is present whereupon a research is proposed to find out the feasibility of the presented idea or clearing up its uncertainty.
2. Commitment in the organization is needed due to arrangement requirements, such as resources and approval to conduct any process.
3. Due to privacy concerns, a discussion on ethics and security will occur.
4. To improve efficiency and effectiveness, organizations will question and doubt their used methods.
5. To build the foundation of the desired insight, identifying, retrieving, and verifying the necessary data is performed.
6. Data is cleaned, combined, and visualized to construct information functional for interpretation.
7. For decision backing or support, information is communicated, interpreted, and assessed.

2.5 Software factors

As specified in the introduction, data warehousing and BI have experienced various innovations over the years (Lennerholt et al., 2018; Obeidat et al., 2015). An increasing number of data channel options have become available in data warehouses and SSBI software. These channels range from data files, databases, online cloud storage, SAAS and PAAS platforms, and deep-learning platforms (Stone & Woodcock, 2014). These options allow organizations to better customize their data, reports, and dashboards, as multiple dimensions and measurements are available. Thereupon, SSBI software engineers are provided with feedback to increase their products' quality. This can provide users with more data integration methods and available communities, and can amplify the number of external data possibilities for users (Alpar & Schulz, 2016; Imhoff & White, 2011; Olszak & Ziemba, 2007). Users requesting more data is relatively effortless, although performing the ETL tasks to make more data available for users by the IT staff is counter-intuitively time-consuming (Amara et al., 2012). Thus, the more users have access to BI software, the higher the likelihood the IT staff is obligated to process their data requests (Van der Meulen & Rivera, 2015; Peters, 2013). BI systems are often complex. Due to Moore's law, with which computer system become twice as fast every two years, the systems BI systems operate on have become rapidly faster in previous decades (Simonite, 2016).

2.6 Security factors

IT departments' security concerns also increase with SSBI, as they have less control over external data that users introduce in a self-service situation. This could lead to additional misconception sharing within the organization and the infiltration of malicious software within the IT network. Conversely, IT staff and users have more access to data than ever. Users are progressively becoming aware of the data available within their organization and their external environment, which indicates that BI is maturing (Zaghloul et al., 2013; Wieder et al., 2012). Additionally, most scientific works proposing a framework for SSBI data warehouses contain a semantic layer. The semantic layer then fulfills a governance function and encourages SSBI for their users (Alpar & Schulz, 2016; Berthold et al., 2010; Hani et al., 2017; Passlick et al., 2017; Schlesinger & Rahman, 2015; Harms, 2018). The IT department keeps control over the data available for users, and, in a data warehouse containing a semantic layer, adding new layers to support specific reports is not necessary. To improve an analytical organization, providing accessibility to BI software for the whole organization is encouraged. With full accessability, all users will have the opportunity to engage in BI processes (Alpar & Schulz, 2016). However, this is not advised due to security reasons and limited human capital in data managers. Involved data could be confidential, and if the entire organization has access, the IT department is compelled to deliver support for all users.

2.7 User factors

SSBI software is becoming easier to use, evolving more casual users to power users (Alpar & Schulz, 2016; Lennerholt et al., 2020). The software's ease of use is one of the factors persuading users to use it (Imhoff & White, 2011; Stone & Woodcock, 2014). Furthermore, the ease of use makes user training and expertise sharing less complicated. However, users perceiving SSBI to be easy to use achieve more disadvantageous results. Users are commonly convinced to be capable of performing analytical tasks despite needing more time to complete them at the same quality level (Aggarwal et al., 2015).

2.8 Organizational factors

As SSBI software is becoming more popular, BI systems are also more distributed within the organization (Stone & Woodcock, 2014). IT departments have to decide where to draw the governance boundary. Therefore, they are required to define which parts of the data warehouse and analytical software they want to monitor, control, supervise, and support in addition to which parts they want to relinquish the control over to end-users (Imhoff & White, 2011; Van der Meulen, 2015).

2.9 Success factors

Successful implementation of SSBI software throughout the organization depends on a multitude of variables (Acito & Khatri, 2014). According to Alpar and Schulz (2016), introducing users to SSBI software through a social approach allow users to adapt more harmoniously and induces more attachment to the software and SSBI. Accomplishing this demands executive support. Executive support is one of the factors with which an analytical organization is realizable (Van der Meulen & Rivera, 2015; Watson & Wixom, 2007). According to Kulkarni et al. (2006), corporate or executive management needs to keep up with technological changes to create SSBI or BI systems successes; hence, a leading role is required. Nevertheless, the authors recommend that BI systems be at least partly introduced within every organizational and hierarchical layer to increase the organization's change management support.

BI effectivity and efficiency are decided by usage and information sharing. A standard software solution does not directly function with customized organization data and different users from different departments. Therefore, acquired software has to be tweaked to suit the organization. A flexible data model is needed to fit unique and changing user needs and the architectural IT landscape of the organization (Acito & Khatri, 2014). Flexibility gives the IT department and users the freedom to import, combine, and send data more effectively. However, this approach magnifies governance concerns, as more freedom is available for IT staff and users. SSBI implementations encounter more success if the SSBI application and contained data structure are learnable for users (Hani et al., 2017; Harms, 2018; Watson & Wixom, 2007; Jansson & Persson, 2016). According to Morris and Dillon (1997), though measured among students, software with high perceived ease of use results in more usage and more effective usage, as measured with the technology acceptance model (TAM). Furthermore, SSBI software encouraging visual methods to perform report operation developments and visualizations within reports themselves experience more success (Imhoff & White, 2011; Jooste et al., 2014). Having an operable SSBI system also increases the chances of success (Hani et al., 2017). An operable system keeps the system to predefined requirements, functioning, reliable, and safe during its operation. A centralized data warehouse and a distributed SSBI application aligned with the organizational IT architecture is also crucial to successful SSBI implementation. The data warehouse and SSBI applications need to communicate with other systems within the IT landscape (Zaghloul et al., 2013; Berthold et al., 2010; Elena, 2011; Peters et al., 2016).

The following list summarizes the SSBI success factors of the literature review:

- Implementing the SSBI system with a social approach ensures organization-wide support.
- Executive support ensures that technological changes, such as SSBI systems, are kept up to date.
- Near-complete user and data accessibility ensures the SSBI system's usability, such as preventing data shortages and maintaining access to the SSBI system. This also reduces the need for shadow-applications.
- Introducing and maintaining a learnable, operable, and flexible data and applications to ensure that the SSBI system is understood and can be relied upon.
- Governance controls ensure that the security of the application and data is maintained.
- The data structure and SSBI application must be compatible with the IT environment of the organization.
- To ensure proper usage and user confidence, users must be trained and introduced to the SSBI application and its data structure.
- In order to reap the benefits of SSBI, users must collaborate on data collection, information development, and communication.

2.10 Failure factors

Implementing SSBI is considered a low opportunity-cost investment (Burke et al., 2016; Schlesinger & Rahman, 2015; Van der Meulen, 2015; van der Meulen & Rivera, 2015; Jaklic et al., 2009; Olszak & Ziemba, 2007). Hence, there are often more tasks on the agenda with a larger expected short-term profitability. Therefore, due to a short-term orientation, executives regularly lack the strategic insights and willingness to support organizational BI (Kulkarni et al., 2017; Hung et al., 2016). Moreover, while possible in other systems, successive SSBI is difficult to measure. Return on investment on effective decision-making does not always generate accurately measurable data, a form of BI is needed to measure its success (Rajterič, 2010; Jaklič et al., 2009; Lönnqvist & Pirttimäki, 2006; Peters, 2013). The total cost of ownership (TCO) model divides an organization’s costs into several groups such as staff, workplace environment, software, network and data availability, server and storage, data and phone lines, and contracts. Despite differing result validity, measuring performance with the TCO model after implementing data-driven decision may indicate BI’s performance (Lönnqvist & Pirttimäki, 2006). However, defining associated business results and related costs implies certain forms of biases and subjectivity. Despite criticism, BI system success has traditionally been graded along information systems (IS) measurements in terms of their quality. BI systems are a form of IS since they partly fulfill

ETL roles in an organization’s information management (Mudzana & Maharaj, 2017; Peters, 2013; Amara et al., 2012; Jooste et al., 2013; Elena, 2011; Kulkarni et al., 2017). Support throughout the organization for the software is also necessary for providing a successful SSBI implementation. Users require to use the specific selected software, and the proposed software may be perceived as too technical for users (Berthold et al., 2010). Thus, users tend to have a critical approach when presented with the proposed selected software. Furthermore, if they remain with negative perceptions towards it, they may share their distrust throughout the organization. Negative perceptions will lessen the chances of successful implementation (Issa & Haddad, 2007). Perceptions may relate to truthful critical reviews but also false persuasion concerning the software’s user-friendliness, possibilities, and feasibility. This augments a possible Dunning-Kruger effect presence (Aggarwal et al., 2015). Furthermore, users may endorse a tunnel vision towards the software, whereby one and only one factor convinces them to discourage the software application (Lennerholt et al., 2018). Repeatedly, users are impatient for data due to a general time underestimation for data preparation processes (Hani et al., 2017; Jooste et al., 2014; Imhoff & White, 2011; Jansson & Persson, 2016; Elena et al., 2013). Therefore, they request data or acquire them too late to support their decision, thus lacking the necessary time to process data (Lennerholt et al., 2018). Without data expertise, time, and resources, the likelihood of inaccurate data rises, and information is misconceived and spread throughout the organization (Wieder et al., 2012). When users or data managers work with the same data structure long enough, inaccuracies are spotted and improved as organizational BI processes and systems mature (Jaklic et al., 2009; Jansson & Persson, 2016). Moreover, organizations are not consistently accurate in determining which users should or should not have access to analytical software. Procedures required to obtain access may be too bureaucratic for users (Lennerholt et al., 2018; Jaklic et al., 2009). SSBI decreases the governance control the IT department upholds for its data (Van der Meulen & Rivera, 2015; Harms, 2018; Watson & Wixom, 2007; Jansson & Persson, 2016). Therefore, SSBI solutions may only work for part of an IT department’s available data due to confidentiality or necessary yet complicated measurements. Additionally, if a data warehouse and SSBI software are not aligned with the IT landscape, essential data may not be accessible to users or they may not be usable within other applications (Burke et al., 2016; Schlesinger Rahman, 2015; Van der Meulen, 2015; Van der Meulen & Rivera, 2015). This regularly occurs within organizations when acquiring data warehouses, BI applications, or other software.

The SSBI failure factors of the literature review are summarized in the following list:

- Because BI is difficult to measure, SSBI system success is frequently overlooked. The potential benefits of SSBI should be understood and communicated to decision-makers.
- SSBI, or data analytics in general, is a necessary investment in today's markets and economies. However, because benefits take time to develop and are considered a long-term investment, it is frequently overlooked.
- If data in a BI application is inaccurate, it will produce low-quality results. An organization's data and data structure must be accurate before implementing an SSBI application ("*garbage in, garbage out*") (Fuechsel, n.d.).
- Users must be able to use certain SSBI applications. Expecting business users to program their own insights in R, for example, would result in user confusion and an inability to produce information. As a result, individuals who are less technologically oriented are advised to work with user-friendly applications. If the SSBI application is not suited for their targeted user group, the implementation will fail.
- Bureaucracy creates a sense of impatience when it comes to data and application accessibility. As a result, associated procedures should be kept to a bare minimum and completed quickly, as said system is overly governed.
- Negative convictions, perceptions, and views about SSBI systems, related investments, data collection methods, and collaboration efforts can spread throughout the organization. This reduces the likelihood of successful implementations. This can be reduced by properly introducing and training users.

2.11 Implementation factors

The model in Figure 2 (further summarized) offers an overview of the failure factors concerning SSBI implementation. However, the list is incomplete, as implementation and exploitation methods vary widely, and the factors are based on trends found in the literature. The research's hypothesis, participants' assignments, surveys, grading processes, and measurement definitions are all based on these model elements, which serve as the foundation for research methods, viewable in chapter 3.1, 3.3, 3.4, 3.5, and 3.6 respectively.

Change support

- Troughout the organization
- From strategic management

Return on investment

- Too transparent
- Low opportunity cost
- Long-term investment

Subjected data

- Shortage
- Inaccessable
- Inaccurate

User behavior

- Viewed too technical by user
- Incorrect user perceptions
- Overconfident in their own capabilities
- Impatient for results
- Used to support confirmation biases
- Lack of introduction
- Lack of context
- Lack of system accessability
- Lack of collaboration

Software & architecture

- Shadow-system introduction
- Implemented system does not align
- System too governed
- Lack of governance

Figure 2 - Overview of failure factors

The model elements in Figure 2 are strongly related to each other. For example, 1) BI application support diminishes as contained data in the BI application is inaccurate and users lose their trust in the system; 2) if the BI system is too governed, users may need to apply for further access at the IT department, which leads to impatience, leading users to implement a shadow-system; 3) the BI system does not contain all required data, and acquiring them entails a long-term investment, leading to user impatience.

While changing technological systems is perceived as difficult, organizations tend to find it easier to change them rather than the processes and human behavior related to them. Required process or behavior changes lean towards long-term solutions that require several years and are often overlooked (Bennis, 1966; Fogg, 2009). As information system manufacturers demand more sales incentives to improve their sales, manufacturers are generally inclined to design their software as technological-centered. More or improved features support straightforwardly competing mechanisms (Eason, 2010; Davenport, 1994). According to Legris et al. (2003) and Castle (2001), the low success rate of IS implementations is due to nonadherence to the technological acceptance model. Human behavior is not recognized as a critical component; hence, users cannot perceive their software as useful. According to Fogg (2009), users need three incentives to use the software successfully: 1) sufficient motivation (convincement of the software's usefulness), 2) ability to perform the software's process (training), and 3) incentives to perform software's processes (process integration). To fully change an organization's user behavior, organizations need to adhere to the manufacturing's marketing and invest in their training and consultancy. This regularly requires timely decisions and budget investments (Castle, 2001). SSBI applications are a type of IS system. However, SSBI applications are designed to be user-oriented. Nonetheless, whether SSBI applications can be correctly user-oriented is debatable, as the scientific community has not conducted any research on this topic yet.

3. Methods

Researching all failure factors (see Figure 2) in the time available would be impractical because it would require far too much substantial research for a master thesis. This research did not entirely focus on the "lack of introduction" and the BI "usage to support a user's confirmation bias" because it would have required long-term measurements within researched organizations, specific resources, and rights to access organizational BI systems. Therefore, this thesis includes the following factors: "lack of collaboration," "viewed too technical by user," "incorrect user perceptions," "overconfident in user's capability," "impatient for results," and "lack of context." The research's measurements were designed to include them.

3.1 Hypotheses

To devise the research methods based on the research question, three hypotheses were set up. Accordingly, this research's hypotheses were based on the research question, not the failure factors. The first hypothesis can be contextualized as follows:

H1: Users can conduct general BI processes in SSBI software to produce decision-support information in an environment with their peers, with limited help functions and training.

Users need to be able to generate decision-support information to prove if the concept of SSBI is feasible. Therefore, they need to be able to create insights suited to sway choice-making positions. Furthermore, help functions need to be defined as well. Help functions shorten a participant's necessary exploration time since some participants may be confronted with a relatively new knowledge field. BI applications are including collaboration features in their software and collaboration is among users is encouraged by the scientific community. Therefore, participants were allowed to support each other given their research conducting environment. Further help functions were fulfilled by a predefined crash course before the research started and a web page manual. Users were able to consult the manual during the research in which information from the crash course is presented.

While BI procedures are measurable in different ways, the mentioned help functions and users' presence in an environment with their peers are aspects that are included in the first hypothesis. The first hypothesis can therefore measure the differences between these variables. Due to COVID-19 restrictions, multiple environments were available for participants, such as their home and the office, with or without us. Furthermore, participants got multiple forms of training. Every participant acquired the short crash course before the research started, and participants with BI training beforehand could take part in the research provided they declared their previous training.

H2: Among SSBI software, users experience differences in its usability to produce decision-support information.

Users' analytical skills were measured across different SSBI software packages. The SSBI software in question was the current market-leading software, whose selection is further illustrated and described in following paragraphs.

H3: Differences in users' in SSBI applications skills depend on educational background, work experience, and hobbies.

Participants' different backgrounds were included in the research and assessed based on scoring classes and perceptional measures. Moreover, the different backgrounds were categorized in education, work experience, and hobbies. This categorization is defined in following paragraphs.

Multiple dependent variables are included in this study as a consequence of a separate research question and multi-variable hypotheses. It's important to think about the sequence in which numerous dependent variables are assessed. The selected method is to systematically change the order in which the research question and hypotheses are determined by counterbalancing their proposed measurements (Price et al. 2013). How the research question and hypotheses are ordered and sequenced based on the proposed measurements, is explained in chapter Proposition definitions and constraints at 3.8.

3.2 Participant sample

To select a sample, a list of companies within our region was chosen. These organizations were selected from Google Maps, Indeed (vacancy website), InnovatieHub (intern-supporting organization), LinkedIn, and social contacts. All selected organizations were accepted since a relatively large non-response bias was expected. Organizations with a hundred staff members or more were prioritized. As Krejcie and Morgan (1970) report, to represent a population of one million or higher, a sample size above 384 is needed. Estimating the amount of reporting users in the Netherlands to be around half a million, a suitable sample was necessary (Nielson & Wulf, 2012; CBS, 2021; Ahmed, 2019). According to Polasek and Lachlan (2013), differences between companies in terms of BI goals, deployment, adoption, and success become evident with a size over a hundred staff members. Moreover, according to Horakova and Skalska (2013), BI procedures and implementations in small companies are more distributed, not standardized, and more dependent on the organizational business process. SSBI software manufacturers therefore tend to focus on larger enterprises. However, the participant's individual results were used for the measurements. Furthermore, concerning the research's recent COVID-19 outbreak, a collaboration element was therefore still supported. Considering that participants were required to perform assignments in their own environment or in socially distanced groups, collaboration was still supportable. However, participants were allowed to get digital support by calling colleagues, speaking to colleagues, retrieving information from web pages, or requesting help from us (a maximum of three times).

Organization selection had to satisfy two requirements: the organization ought to operate in a different industry than other selected organizations, and only three organizations could operate in the same sector.

Furthermore, participant selection required the following:

1. Participants had at least some analytical experience, such as experience in spreadsheets, ERP, MRP, WMS, or related systems.
2. Participants had at least some data analytical responsibility, such as generating or creating reports or working with data tables.
3. The responsibility of deciding about selection requirements had to be left to the organization's representative for the research. The organization's representative was thus responsible for providing the list of participants from their organization.

As IT personnel and participants with specific SSBI-related expertise were not inherently excluded from participation, they represent a small proportion within this research. Nonetheless, they presumably produced fruitful results. Inclusion of more qualified individuals is always possible in random sample selections but these individuals probably only represent a small proportion; hence, these participants were not excluded.

Participants were recruited through a process to standardize the recruiting approach, increasing speed, and improve its validity (see Appendix K). We contacted organizations and asked for a research representative. Contacts through organizations were used because organizations generally had many suitable candidates that could potentially benefit from this research. However, this could also introduce a social bias, as personal contacts reduce the sample's randomness. Nonetheless, a relatively significant non-response bias was expected and prioritizing personal contacts was considered acceptable. The recruitment process aimed at gathering participants who would abide by the requirements, have the time to participate, perceive the research's benefits, and have an interest in the research results. The recruitment process served as best practice. Given that organizations' representatives and selected participants have possibly different research interpretations or relative busy agendas, suitability of the approach process will differ.

3.3 Software sample

Participants conducted assignments in one of the three selected SSBI applications. Choosing SSBI applications had to guarantee similar software genres, design principles, specific manufacturers, and market leadership measures. The following requirements were set up:

1. Selected applications had to be only oriented to end-users. Therefore, the selected software needed to conduct BI processes with enough contained user-friendliness such that the general end-user would be capable of performing BI processes. SSBI software manufacturers have enough confidence in their software being capable of supporting (casual) users in their BI demands when it is advertised toward users (anyone).
2. The software is thinly designed such that users only view their required functions and are not overwhelmed by the software's possibilities. Hence, advanced options are hidden or not even available, and the easy or most used functions are preprogrammed for aggravated usage. With this approach, software manufacturers can guarantee successful use for the casual user (anyone).
3. The application was designed to get results fast. Casual users generally cannot or do not wish to spend substantial amounts of time on BI. Traditionally, casual users tended to be impatient for BI results (Hani et al., 2017; Jooste et al., 2014; Imhoff & White, 2011; Jansson & Persson, 2017). Therefore, software capable of generating data structures and formulating insights in an accelerated fashion among its traditional counterparts leaned towards the SSBI software genre.
4. The software had to contain elements of BI result presentation or communication. Business users perform information transitions within the organization, and SSBI software supposedly supports these transitions. Elements could be presentation modes, decentralized dashboard sharing features, and decentralized report generation.
5. Software had to be specifically designed with BI in mind. Likewise, it had only this target and did not fulfill any other purposes. The selected software was only designed to aid BI processes.
6. Selected applications needed to be decentralized. Hence, the selected software was usable in stand-alone environments. Therefore, software such as Qlikview, Infor Birst, Looker, and Splunk was not included, as they were not directly self-service BI applications and included governed server-side systems.
7. To comply with research limitations, only three applications are included. The number of usable applications that can be used are limited due to licensing and resource restrictions. Each included application requires one test license per participant and specifically designed crash courses. Since this study is supported by only one researcher and the field research lasts half a year, research preparations had to be kept at a minimum.
8. To increase this study's validity, only one application per software manufacturer was included. Since three applications were selected in total, including two applications from the same manufacturer decreased the research's validity.
9. SSBI applications consistently and consecutively mentioned in Gartner's Magic SSBI quadrant over the past five years have been selected. Additionally, many studies have based their software selection on Gartner's quadrant, with Gartner's quadrant being considered the most reliable and valid (Victa, 2016; Cadran Consultancy, 2020; Allington, 2020; Sallem et al., 2017; Tripathi et al., 2020; Howson et al., 2019; Bik, 2016; Gerads, 2020; Senturus, 2020; King, 2019).
10. Selected software is the most popular in the researched area; the Netherlands. A complete list of BI software was gathered from Gartner (2020), BA times (Aspari, 2019), and M Opinion (Haije, 2019). The resulting list was further examined against its social media, SEO, and search term popularity in the Netherlands (https://trends.google.nl/, https://www.semrush.com/, https://app.neilpatel.com/en/ubersuggest/overview). Used terms were the software's name and "bi," as specific software names may mean different things in various languages. Results are available in Appendix J.

The three selected software packages resulting from the selection criteria were Microsoft Power BI, Tableau Desktop, and Qlik Sense. Each package's pros and cons were analyzed with software's version available in March 2020. However, new updates may introduce new software functions, changing their pros and cons (referenced in Table 1).

Table 1: SSBI software's pros and cons (Gartner, 2020; Harms, 2018; Amara et al., 2012)

	MS Power BI	Tableau	Qlik Sense
Analytical features	+	++	-
Visualization features	-	+	+
Data formatting features	+	--	+
Data warehousing features	+	-	++
Code necessity	-	++	--
Costs	++	--	+
Filter and sortation features	+	+	++

Pros and cons described in Table 1 were determined by analytical, visualization, data formatting, data warehousing, filter and sortation features, code necessity, and their relative costs. These features and comparison factors are common for SSBI software packages. To explain them, a description is provided in the following:

Analytical features: The possibilities that the software provides to analyze produced graphs, such as reference lines, trend lines, predictions, artificial intelligence usage, and smoothing constants.

Visualization features: The various options that the software offers for the user to visualize data.

Data formatting features: The software's capabilities to change data formats and fields and add calculated fields.

Data warehousing features: The software's ability to merge data and configure data relations.

Code necessity: The extent to which the software requires users to program insights or data integrations.

Costs: The software's cost compared with its competition.

Filter and sortation features: The possibilities that the software provides to sort visual data and filter among measures and dimensions.

3.4 Assignments

Participants provide information through an online form created by us and send it before and after the research. Furthermore, before the research, for each projected SSBI software application, data warehouse, and assignment, a crash course was provided with multiple short videos. Moreover, the provided web page manual was based on these videos. Participants could consult these documents before and during their assignments when help was necessary. As four assignments were available for participants, multiple versions of web page manuals per selected SSBI application, data warehouse, and assignments were constructed.

For each individual participant, specific curriculum vitae (CV) elements were requested to support the third hypothesis (H3). Furthermore, participants were asked to provide their perceptions before and after the research (Morris & Dillon, 1997). Therefore, the following questions were asked at the research's start:

Table 2: Survey questions

1	Did you have any previous training in data analysis, data management, database management, or reporting?	Nominal
2	What is your educational background?	Array
3	What are your current and previous work experiences?	Array
4	What are your (previous) hobbies or pastimes?	Array
5	Do you believe SSBI is a good solution for organizations to enhance their analytical culture?	Nominal

6	Do you believe you are able to work with SSBI software?	Nominal
7	Could you give your SSBI capabilities a grade?	Ordinal
8	Do you believe your organization is able to work with SSBI software?	Nominal
9	Could you give your organization's SSBI capabilities a grade?	Ordinal
10	Do you believe any of your organization's future plans concerning business analytics and reporting are any good?	Nominal
11	Could you give your organization's future plans a grade?	Ordinal

Education, work experiences, and hobbies were categorized based on users' backgrounds to support the third hypothesis. Both the educational and work experience categories are based on the list in Appendix G, an education provider's list (https://study.com/academy/course/). Since people generally study to work in the same branch, the same categories could be used for education and work experience measures, whereas hobbies do not work in the same way, they were categorized with the list situated in Appendix H (https://en.wikipedia.org/wiki/List_of_hobbies).

Participants were tested on their affiliated strategic intellect. Despite the fact that many strategic models exist with which an organization's strategy is definable, in this research, a simplified form of a strategy map was used. The used model could be characterized quickly, contained a relatively complete strategy form, and was easy to explain. First, participants needed to define a CSF (see Definitions at 1.1). Participants needed to define a leading and influencing concept that describes or even improves an organization's strategy. However, for minor faults or mistakes, 1 point was taken off and 1.5 points for critical faults or mistakes. The CSF constituted 3 out of the possible 9 points in the strategic category.

Alongside CSFs, participants needed to devise a key performance indicator, a metric that takes the lead in measuring organizational results in a data expression. This will complete the elements necessary to construct a strategy map. KPIs also have related terms in other theories, such as measurements, metrics, goals, or targets. Participant scores on KPIs followed the same definition as scores awarded for CSFs. Furthermore, they were required to show a relation between their devised CSF and KPI. Therefore, the devised KPI supported and was related to its CSF. Admittedly, some gray area in what this link constituted might exist, and we had to decide if this link was present. Likewise, scores for the link were defined the same way as the CSF and KPI. As relationships are key in strategy maps, if participants were able to show that they could connect their CSF and KPI to make their strategy map functional, 3 points were awarded for the link. In total, strategic scores were separately defined for the CSF, KPI, and the link.

The practical questions faced by participants were structured differently than the strategic questions. Practical questions asked for specific metrics, were open, and required physical analytical capabilities to answer, an SSBI application, and a data warehouse. Examples of questions are: "What are the ten least profit-generating products?;" "What are the top five customers?;" and "Which employees have been available the most?" Crash courses in the data warehouse and the selected SSBI application were needed, as participants were forced to use it to answer these questions. Furthermore, not every participant had the capacity or willingness to invest time in discovering the software and data warehouse. However, we hoped that the majority would be able to solve the practical questions in their selected version. In total, every participant got three questions: two simple questions (one predefined dimension and predefined expression) and one more difficult question (with multiple dimensional categories, multiple measurement expressions, or even programmed expression required). Participants were allowed to divide any question answering visualization into further dimensions. Each correctly answered question was awarded 3 points. For small faults, 1 point was subtracted and 1.5 for critical mistakes.

The participant's technical scores were defined by use of BI-related software functions within the SSBI application. Measuring their technical score was relevant for their capabilities regarding connecting data and designing visualizations. Participants' exploration and adoption were thereby determinable. Because SSBI applications are designed to be user-friendly, participants were expected to embrace these software functions fairly quickly. The following grading criteria were measured per produced visualization by the participants:

Table 3: Technological criteria

1	Data	Insertion into data warehouse or usage in visualizations.
2	Field	Proper definition of fields such currency, numbers, text, etc.
3	Relation	A relationship diagram with connected tables or visualizations with data originating from multiple tables.
4	Visual	Usage of a visualization or visual elements with data tables.
5	Dimension	Usage of dimensions in visualizations or data tables.
6	Expression	Usage of aggregated measurement expressions in visualizations or data tables.
7	Filter	Instances of filtered objects or usage of objects to filter.
8	Sortation	Visualizations or data tables sorted in a functional way, e.g., time or value.
9	Multi	Usage of two or more dimensions or expressions with a visualization or data table.
10	T.R.F	Usage of trend lines, reference lines, or forecasts.
11	Cluster	Visuals grouped either by color, dimension, or expression.
12	Geo	Usage of geographical analysis and location support.

Grading criteria 1 to 8 are basics that users need to perform to at least functionally use SSBI applications. Criteria 9 to 12 are more advanced and were included for more capable participants.

Participants were not required to complete all these grading criteria. If a criterion was present in participant-produced visualizations, 1 point per criterion was added to the participant's technical score. However, if a visualization was too saturated, points were subtracted from the visual score.

Although visualization methods could differ for each type of used technique, participants had to consider design principles to share information effectively, reduce misconceptions, and prevent miscommunication. Distorted information will also distort any decision-making process as decision-makers will not accurately absorb intended information (https://material.io/design/communication/data-visualization.html; Platts & Tan, 2004). According to Cawthon and Vande Moere (2007), visualization-method aesthetics affect a user's interaction effectivity and efficiency in information retrieval and visualization/dashboard popularity. Furthermore, poorly designed visualizations can frustrate viewers, and users are willing to spend less time for information retrieval. Measuring any visual distortions is subjective to its viewer and the used visualization type. Therefore, participants were required to recognize these principles during conducted assignments and graded on their followed data-visualization principles.

Table 4: Visual criteria

1	Undefined data	Data is visible in the visualization.
2	Method	Visualization methods are suited for represented dimensions and expressions.
3	Etiquette	Measurement codes are labeled in their context.
4	Label	Exact values are obtainable, e.g., through tooltips or labels on values.
5	Label orientation	Categorization labels are oriented so that they are completely visible.
6	Orientation	Visualizations are oriented to which information is instantly understandable.
7	Logarithm	Visualizations do not use the logarithmic scale without added benefit.
8	Saturation	Visualizations are not cluttered; hence, information interpretation is not hindered.
9	Overscrolling	Visualizations or dashboards are not scrollable; information is viewable in one glimpse.

Visual principles constitute participants' visual criteria and are graded like the technological score. Therefore, if any of the stated criteria in Table 4 were present in participants' visualizations, 1 point was subtracted from their visual score, except for the "label" criterion where 1 point was added. In general, each criterion makes the visualization unclear, except for the "label" criterion, which would make it clearer. Grading participants based on these criteria did not come without a gray area because the examination contained an inevitable bias. However, participant results were returned, and participants had the option and were encouraged to dispute their examination.

According to Behrisch et al. (2018), proper visualizations are produced by representing the most information in the simplest form. Therefore, introducing constructive dialog, minimalist design, and the appropriate visualization method, improves BI processes. Users will look for clustering, correlations, outliers, and trends via information combinations to communicate information and discuss their findings. For instance, implementing three axes in a bar chart requires 3D modeling and comparison between bars becomes problematic for human interpretation.

As multiple effectiveness measurements such as the previously stated strategic, practical, technical, and visual scores were available, these metrics were combinable to create one effectiveness calculation. This combinable score was also measurable with other accumulated data within the research.

Time-monitoring was needed, as the recent COVID-19 outbreak forced this research to be conducted at participants' homes, we were unable to survey the research conduction. Therefore, time spent by participants to complete the research was measured alongside other data. As participants' application time was monitored per click, their used methods became trackable. Thus, monitoring the participant's usage of contacting other parties or internet usage was possible. With participants sending in screenshots of their assignments, it was possible to view their results of what they had visualized or if they made any mistakes.

Participants produced a number of visualizations, and this amount of visualizations constitutes their visualization cardinality. However, this measurement would not reflect any quality because it only assessed participants' production. Participants' efficiency was calculable by dividing the number of visualizations produced by the time they took to complete the research. However, this measurement would not conclude any quality value because it only assessed the participant's speed.

3.5 Input data

To obtain scores for each conducted assignment, scores were based on previously stated criteria, as shown in Table 5.

Table 5: Score distribution

Data	Score	Domain
Strategic (S)	3 possible points per CSF, KPI, or link	0, 9
Practical (P)	3 possible points per question	0, 9
Technical (T)	1 per criterion	0, 12
Visual (V)	-1 per each per criterion (reversed for introduced labels)	-9, 1
Effectiveness (e)	$\frac{(\bar{S}+\bar{P}+\bar{T}+\bar{V})}{n}$	-∞, ∞
Visualization cardinality (A)	1 per visualization	0, ∞
Time (I)	1 per spent hour	0, ∞
Efficiency (f)	$\frac{\mathrm{I}}{A}$	0, ∞

Scores in Table 5 represent the main ordinal scales for participant' grading criteria. As perceptions, strategic questions, educational, and general participant information were included as well, more ordinal data were applicable (see Table 6).

Table 6: Aditional ordinal data

Data	Number	Domain
Age (G)	Requested participant's age	23, 68
Level (R_{2b})	Requested participant's educational levels.	Vocational, Bachelor, Master
Own grade (R_7)	Participant's grade of their own BI performance.	0, 10

Organization grade (R_9)	Participant's grade of their organization's BI performance.	0, 10
Organization's plan grade (R_{11})	Participant's grade of their organization's BI plans.	0, 10
CSF (S_1)	Participant's strategic score on its CSF.	0, 3
KPI (S_2)	Participant's strategic score on its KPI.	0, 3
Link (S_3)	Participant's strategic score on its link between CSF and KPI.	0, 3

Ordinal data are comparable with nominal categories as well, such as general participant properties, perceptions, education, work experience, and hobby backgrounds. Accordingly, usable categories for measurement are characterized in Table 7.

Table 7: Categories

Category	**Origin**	**Domain**
Gender (E)	Participant's specified gender	[Male, … , Female]
Onsite (K)	Environment of researched participant	Yes, No
Software (L)	Prescribed software for the participant	MS PowerBI, Tableau, Qlik Sense
Help (J)	Requested help from the research by the participant	Yes, No
Training (R_1)	Participant's previous BI-related training	Yes, No
Level (R_{2b})	Participant's educational level	Vocational, Bachelor, Master
BI opinion (R_5)	Participant's thoughts SSBI concept suitability	Yes, Maybe, No
Opinion own capabilities (R_6)	Participant's thoughts on their SSBI capabilities	Yes, Maybe, No
Opinion organization's capabilities (R_8)	Participant's thoughts on their organization's SSBI capabilities	Confident, Yes, Maybe, No
Opinion organization's plan (R_{10})	Participant's favorability on organization's BI-related plan	Yes, I don't know, No
Hobby category (R_{4a})	Assigned category for participant's stated hobby	[Collection inside, … , Sport/competitive outside]
Hobby name (R_{4b})	Participant's stated hobby	[Anime, … , Zumba]
Work experience category (R_3)	Assigned category for participant's stated work experience	[Agriculture, … , Visual Arts]
Education category (R_{2a})	Assigned category for participant's stated educational course	[Agriculture, … , Visual Arts]

These categories were essential to answer the research question and assess hypotheses, field notes, and perceptions. Categories were divided into the applicable ordinal data such as Table 3, 4, and 7.

All ordinal data scales and categories were collected in a database to support the proposed measurements within this research. This measurement data is collected in analytical software to clean data resulting from participants. The software Qlik Sense was used for all quantitative measurements since we are acquainted with Qlik Sense. The web application Voyant text analysis tools were used for further qualitative measurements, because we are acquainted with this software, too. Within this software, the database was designed with seven tables:

1. hobbies (containing hobby information);
2. experience (containing work experience information);
3. education (containing educational information);
4. surveys (containing the participant's opinions on the BI-concept, their own capabilities, their organization's capabilities, and their organization's plan favorability);
5. participants (containing the participant's properties, their strategic score, their practical score, and their assignment information);

6. visual (containing the participant’s visual understandability scores on their visualizations);
7. technical (containing the participant’s technical performance scores on their visualizations).

All tables had a relationship with the participant table and relations all enclose cardinality and multiplicity constraints. The complete model is available in Appendix L.

During the research, certain patterns emerged as repeated instances among multiple assignments, participants, or software. These patterns could be described in field notes to support or create theories resulting from this research. Field notes were listed and registered by us for analysis. However, not all field notes were provable with the described data, as analysis depended on predefined research variables.

3.6 Output data

Research results are portrayed by relatively simple calculations. Calculations are projected on the total research results. Usable calculations are characterized in Table 8.

Table 8: Result measurements

Name	Formula	Description
Count	$n = n(x)$	Number of observations.
Unique count	$\theta = \theta(x)$	The unique number of observations.
Mean	$\mu = \frac{\sum x}{n}$	The average of observations.
Median	$\tilde{x} = \frac{n(x)}{2} + \frac{1}{2}$	The middle average of observation.
Mode	$\check{x} = (\theta(x)_1)$	The largest frequency in observations.
Standard deviation	$\sigma = \frac{\sum(x - \bar{x})}{n}$	The average error rate in observations.
Range	$[x] = \lceil x \rceil - \lfloor x \rfloor$	The domain between the maximum and minimum value in observations.
IQR	$IQR = O(Y)_{n(\frac{3}{4})} - O(Y)_{n(\frac{1}{4})}$ St. $O = O: \{\lceil O \rceil, \dots, \lfloor O \rfloor\}$	The inner fractural or quartile range of observations.

Alongside the calculations present in Table 8, the previously stated efficiency and effectiveness scores were calculated (see Table 5). Research cardinality is represented by the count and the unique count. The mean, median, and efficiency score are functions that use cardinality in their calculation. Standard deviation is the measurement used to determine the error rate in the observations. The calculations present in Table 8 were used on available ordinal data available in Table 5 and Table 6. No dimensional selection was performed to summarize the results. Therefore, these calculations did not determine an analysis, as they were not performable for the stated categories, except for the mode.

3.7 Analysis

For analysis, multiple functions were used to compare ordinal data scales with other ordinal data scales and ordinal data scales with the previous tables’ categories. The research analysis focused on classifications, correlations, and quadratic relations. With classifications, differences in mean between a control and experimental group were possible (e.g., trained or untrained participant. Likewise, classification allowed for selections to become apparent if the category included more than three classes (e.g., vocational, bachelor, or master). Correlations define the relationship between two subjected ordinal data scales, and quadratic relations illustrate relation types (∪,∩) to determine predictable fluctuating patterns.

Ordinal data was filterable per class, resulting in a list with associated data per class (x), which included metrics to compute its delta, strength, amount, and significance. Classes are found for each dividable categories stated in Tables 3, 4, and 7. For every ordinal data scale, the measurements in Table 9 were calculable.

Table 9: Classification measurements

Name	Formula	Description
Delta mean	$f(\overline{\Delta}) = \left(\frac{\sum x}{n}\right) - (\frac{\sum f(x)}{n} : n(f) \neq n(x))$	The difference between the selection mean and total mean.
Selection strength	$s = f(\overline{\Delta}) \cdot f(n)$	The delta mean times the selection count used to denote a claim's strength.
Selection *N*	$f(n) = n(x) : x \in f$	The number of observations in the selection.
Total *N*	$n = n(x)$	The total number of observations for its measurement.
Selection standard deviation	$f(\sigma) = \frac{(\sum f(x) - \sum f(\bar{\bar{x}}))}{n(f)}$	The average deviation of the selection observation from the selection mean.
T-value	$t = \frac{\bar{x} - x}{\left(\frac{\sigma}{\sqrt{n(x)}}\right)}$	The figure that can be used to calculate the difference between the sample mean or its null hypothesis.
P-value (H_0)	$p = \frac{f(x) - x}{\sqrt{x \cdot \frac{(1-x)}{n(f(x))}}} : < 0.05$	The calculable figure to determine if the null hypothesis can be rejected.
P-value (H_α)	$p = \frac{x - f(x)}{\sqrt{f(x) \cdot \frac{(1-f(x))}{n(x)}}} : > 0.05$	The calculable figure to determine if the claimed hypothesis is acceptable.
f (selection)	$f = \{f : (f \neq \emptyset) \cup (f \subset \{T, V, R, E, H\})\}$	The possible selections for classification analysis.

Through analysis with these calculations in Table 9, classes that differed from the category's mean were evaluated for their abnormality, strength, and significance.

A probability function that defines how variable values are distributed is known as the normal distribution. The majority of the observations cluster around the center peak, with probability of values that are significantly different from the mean dropping in both directions equally. Extreme values in the left and right tails of the distribution are therefore rare occurrences (Frost, 2018a). Multiple test statistic variables, such as a *t*-value, a H_0 *p*-value, and a H_α *p*-value, were used in the classification analysis. These test statistic variables, when combined with the sample mean and standard deviation of the selections, which were reported in the results, produced a normal distribution and determined the position of the selection within it. The classification analysis concluded whether a selection is a significant deviation from the normal distribution. By using these variables, a t-value indicated the deviation's position, and it is part of hypothesis testing theory (Hayes, 2020). *P*-values were used to determine the significance of the selection's position. A subproposition and a related null proposition are created when a selection deviates from the mean. For example, consider the following subproposition: trained users perform better in SSBI software, and the following null proposition: trained users do not perform better in SSBI software. Both propositions examples were testable with two p-values. The null hypothesis was rejected if the H_0 *p*-value was less than 0.05, indicating a deviation from the norm. The significance of the selection's deviation was indicated by the H_α *p*-value; the higher the H_α *p*-value, the further the selection deviates. This technique is likewise part of hypothesis testing theory (McLeod, 2019).

A variation of Kendall's τ coefficient system was used to rank classification results on their significance, which is noted in Table 9 as "Selection Strength" (Magiya, 2019). However, because ties were uncommon in this analysis, only the ranking system was used, and Kendall's theory on tied paires was ignored. The delta mean ($f(\overline{\Delta})$) was defined on the x axis, and the selection number (*N*) was defined on the y axis, to define Kendall's concordants and discordants. As a result, high concordants were chosen from observations with large numbers and significant deviations, while low concordants were chosen from observations with small numbers and minor deviations. Observations with only large numbers or significant deviations are called discordants. Only high resulting concordants were chosen for this study because they were most likely definable as the most supportable and significant results.

Concerning correlations, various formulas were assembled to formulate relations between ordinal data scales and the correlation's strength and its coefficient. These formulas are presented in Table 10.

Table 10: Correlation measurements

Name	Formula	Description
Association	$r_{xy} = \frac{\sum(x-\bar{x})\cdot(y-\bar{y})}{\sqrt{\sum(x-\bar{x})^2 \cdot \sum(y-\bar{y})^2}} : r > \frac{1}{10}$	With the association calculation, the summation of the mean difference from *x* and *y* was multiplied. This was divided by its squared form and the root from both *x* and *y*.
N	$n = \lceil n_x, n_y \rceil$	*N* represents the number of observations from the largest counted ordinal data scale.
Strength	$s = r_{xy} \cdot n$ $st.$ $(\lceil s \rceil_1, \dots, \lceil s \rceil_{1,\dots,10}) \cup (\lfloor s \rfloor_n, \dots, \lfloor s \rfloor_{(1,\dots,10)})$	The correlation strength was calculated by multiplying the association value by its *N* value. Only the top and bottom ten values of all available associations were accepted to include the most abnormal correlations.
Standard deviation	$\sigma = \frac{(\sum xy - \sum \overline{xy})}{n_{xy}} :\ \sigma_x > \sigma_y\ ;\ \sigma_x\ [\sigma_y]$	The standard deviation was measured with the same method as previously stated methods. However, only the highest value was accepted.
Coefficient	$b = \frac{\sum x \cdot y}{\sum x^2}$	The slope characterizes the trend's coefficient and was calculated by multiplying the *x* and *y* values and dividing this by the cumulative square *x* value.

By calculating the coefficient, the relation between the two subjected scales was distinguishable. The correlation association technique used in this research, was the Pearson correlation coefficient (van den Berg, 2016). Correlation strengths could differ due to differences in observation numbers and association calculations. Therefore, the strength calculation was used to differentiate between the correlations. The strength calculation determined the extent of the association (r_{xy}) and foundation (*N*) of the observation, similar to Kendall's τ coefficient. The standard deviation was only calculated to show the error rate of the measured correlation, and the slope was introduced to exhibit the correlation's trend. To be considered minimally acceptable, a correlation must have at least a 10% association. This limit has been set in accordance with industry guidelines. A weak correlation was defined as one that is between 10% and 50%, while a strong correlation was defined as one that is between 50% and 100%. Negative correlations, such as between -10 and -50%, and between -50 and -100%, were defined similarly (Zira, 2021).

The Jaccard index was used to measure the correlations between nominal values and drilled-down ordinal scales. The Jaccard index employs set theories' cardinality and measures the percentile difference between the intersection and union of two sets (Jaccard, 1912). These calculations are visible In Table 11.

Table 11: Jacard index

Name	Formula	Description
Intersect cardinality	$\lvert A \cap B \rvert$	Tallying the number of associated observations within the two example sets.

Union cardinality	$\lvert A \cup B \rvert$	Tallying the total observations within the two example sets.
Correlation coefficient	$J(A,B) = \frac{\lvert A \cap B \rvert}{\lvert A \cup B \rvert}$	Indicating the percentile difference between intersect and union cardinalities.

Quadratic formulas are employed to detect any ∪- and ∩-type relations. By establishing these relationships, effects such as the Dunning-Kruger effect were calculated by including the formulas that can be viewed in Table 12.

Table 12: Quadratic measurements (Casio, 2020)

Name	**Formula**	**Description**
Mean *x*	$\bar{x} = \frac{\sum x}{n}$	Determining the average of the x variable.
Mean *y*	$\bar{y} = \frac{\sum y}{n}$	Determining the average of the y variable.
xx (*d*)	$d = \sum x_i^2 - n \cdot \bar{x}^2$	Defining the linear correlation coefficient for the double *x* value.
xy (*e*)	$e = \sum x_i y_i - n \cdot \bar{x}\bar{y}$	Defining the linear correlation coefficient for the *x* and *y* value.
*xx*2 (*g*)	$g = \sum x_i^3 - n \cdot \bar{x}\bar{x}^2$	Defining the linear correlation coefficient for the *x* value and combining the quadratic correlation coefficient for the *x* value.
*x*2*x*2 (*h*)	$h = \sum x_i^4 - n \cdot \overline{x^2 x^2}$	Defining the quadratic correlation coefficient for the double *x* value.
*x*2*y* (*k*)	$k = \sum x_i^2 y_i - n \cdot \bar{x}^2 \bar{y}$	Defining the quadratic correlation coefficient for the *x* value and combining the linear correlation efficient for the *y* value.
Q_1 intercept	$Q_1 = \bar{y} - Q_2(\bar{x}) - Q_3(\bar{x}^2)$	Exemplifying the start and end positional intercepts.
Q_2 intercept	$Q_2 = \frac{eh - kg}{dh - g^2}$	Exemplifying the first downwards intercept until min(*y*) is reached.
Q_3 intercept	$Q_3 = \frac{kd - eg}{dh - g^2}$	Exemplifying the second upwards intercept from min(*y*) to the graph's end.
Trend	$\hat{y} = Q_1 + Q_2 x + Q_3 x^2$	Showing the ∪-type relation within the graph by combining the intercepts.
Left top (*a*)	$a = \lceil \hat{y} \rceil_{x_1}$	Identifying the top left value of the measured trend line.
Down (*b*)	$b = \lfloor \hat{y} \rfloor$	Identifying the 'middle' lowest point of the measured trend line.
Right top (*c*)	$c = \lceil \hat{y} \rceil_{x_n}$	Identifying the top right value of the measured trend line.
Amount n(*x*)	$n(x)$	Indicating the number of *x* values.
Median ($\tilde{x}$)	$\tilde{x} = \frac{n(x)}{2} + \frac{1}{2}$	Indicating the median point of *x* values.
Min point (X_b)	$X_b = x(\lfloor \hat{y} \rfloor)$	Indicating the *x* value of the defined *b* point.
Strength	$q = \sqrt{\left(\frac{\left(\frac{(a-b)+(c-b)}{n(x)}\right)}{\lvert \tilde{x} - x_b \rvert}\right)} \cdot n \cdot 10$	Calculating a relation strength value by averaging the differences from the top and bottom trend values and dividing it by the distance from *x*'s median point.

Quadratic correlations are only possible between ordinal data scales. Consequently, correlations are either not definable or insignificant, as nominal data do not have to contain integers. Depending on the relation type, coefficients can differ. If a ∪-type relation is to be calculated, the *x* and *y* values are usable as stated in Table 12, whereas if a ∩-type relation is to be calculated, the *x* and *y* values have to be reversed. When the trend line is visualized within a graph, the coordinates (*a*, *b*, *c*, *n*(*x*), $\tilde{x}$, and X_b) are identifiable. Coordinates can be used to calculate a relation's strength. The R-squared model, which fits upwards and downwards trend curves, was used to define the ∪-, and ∩-type relationships (Frost, 2018b). The average slope was therefore calculated by combining the R-squared slopes from both sides. Similarly, a version of Pearsons Mode Skewness method was used to account for skewness (Glen, 2017). It was possible to perform a measurement defining the trend's significance and symmetry by combining these calculations. A Kendall's τ coefficient was created by multiplying this calculation by the number of observations. However, when compared to the results of the classification and correlation analyses, the range of Kendall's τ coefficient was smaller. Because the coefficients differed by a factor of ten, the quadratic strength calculation was multiplied by ten, resulting in quadratic strength results that were comparable to those of others.

3.8 Proposition definitions and constraints

As stated in the hypotheses chapter at 3.1, the selected method is to systematically change the order of the hypotheses due to the way they can be measured. The research question, hypotheses, and field notes (propositions) are measureable by classification, correlation, quadratic relation, and text analysis, and thereby divided into subpropositions. For example, if hypothesis one is measureable with a classification and correlation analysis, two subpropositions are created, resulting in H1a and H1b respectively. How the research's propositions were split, is explained in the following paragraphs.

To address the research question, hypotheses, perceptions, and field notes, classifications, correlations, and quadratic relation measurements had to be subjected to these propositions. Along with classifications, correlations were essential to assess the second and third hypotheses. All calculation methods were used for the perceptional measurement and registered field notes along with selections to prove, disproof, or define them as significant. Furthermore, concerning each category and calculation, the top and bottom results are presented to show the most significant research findings.

All the corresponding formulas in Table 9 were calculated and compared with the scores listed in Table 5 and the additional ordinal data scales in Table 6. The resulting strength values and *p*-values were subjected to the following constraints to determine its validity. The measured classification strength had to be a member of the top and bottom of all classifications, classifications' H_α *p*-values had to be above 0.05, and classifications' H_0 *p*-values had to be below 0.05. Correlations were likewise included. To validate a measured correlation, the effectiveness and efficiency scores were defined on *x*, and the strategic, practical, technical, and visual scores were defined on *y*. Measuring the strongest affecting capability set for user performance is thereby achieved. When correlations were calculated, a correlation coefficient, the amount, the standard deviation, the cardinality, and the slope were provided. If the correlation coefficient was above 0.10, the correlation's strength was calculated by multiplying the correlation's cardinality with the correlation coefficient. To include the correlation for the research question, only the highest and lowest among correlation strengths were selected. With this procedure, strong correlations were incorporated to answer the research question. Quadratic relations were likewise included and calculated by the formulas present in Table 12. If the *x* value of the *b* constant was not the lowest point of the trend line, the *x* and *y* values needed to be reversed, and the quadratic relation had to be recalculated. If the strength calculation was above 20, the relation was deemed sufficient enough to be included in the analysis. The following formulas were thus used to define the subjected calculation methods and constraints for the research question:

$$RQ_a(x) : (\forall f \subset \{T, V, R, H\}) \cap (\forall s \geq 100) \cap \left(\forall p_\alpha > \frac{1}{20}\right) \cap \left(\forall p_0 < \frac{1}{20}\right)$$

$$RQ_b(xy) : (\forall x \subset \{e, f\} \wedge y \subset \{S, P, T, V\}) \cap (\forall r > \frac{1}{10}) \cap (\forall s \geq 100)$$

$$RQ_c(xy) : (\forall x \subset \{e, f\} \wedge y \subset \{S, P, T, V\}) \cap (\forall b(x) = \lfloor t \rfloor) \cap (\forall q > 100)$$

For a result to be qualified, its strength value had to result above 100 to only include the most stable measurements. If the constraints returned a true statement, the observation was considered an answer to the research question. Once the field research was complete, this procedure was usable for each separate observation. There are 351 $(27 \cdot 13)$ possible classifications included in the research question analysis. Concerning any correlations, a possible 8 $(2 \cdot 4)$ correlations and quadratic relations are possible.

Hypothesis one determines the feasibility of users concerning the SSBI concept. Therefore, participants' default averages among the different scores, stated in Table 5, was measured. To determine validity along this measurement, a calculation conforming to the mean, median, and mode (MMM) and the standard deviation, range, and IQR (SRI) was included. Substantial differences between the MMM measurements conclude that ordinal data scales fluctuate and thus decreasing its measurement validity. The unpopulated range was calculated by subtracting the standard deviation and IQR from the ordinal data scale's range. If these calculations' results were low, its measurement's validity increased. The first hypothesis also contain the same classification algorithm as the research question. Hence, classification analysis was used among stated categories and formulas. However, for the first hypothesis, the necessary categories differ. As the first hypothesis assesses the participant's environment-type and available help functions, selections concern these nominal categories (training, help, and onsite). Furthermore, only the top and bottom three observations were included for the first hypothesis to keep possible results to a minimum. Hereby, only the strongest classifications were included. The first hypothesis was defined as following:

$$H_{1a}(x) : (\forall f \subset \{S, P, T, V, e, f\})$$

$$MMM = (|\mu - \tilde{x}|) + (|\mu - \check{x}|)$$

$$SRI = [x] - IQR - \sigma$$

$$H_{1b}(x) : (\forall f \subset \{K, J, R_1\}) \cap (\forall s \in \{\lceil s \rceil_1, \lceil s \rceil_2, \lceil s \rceil_3\}) \cap (\forall s \in \{\lfloor s \rfloor_n, \lfloor s \rfloor_{n-1}, \lfloor s \rfloor_{n-2}\}) \cap \left(\forall p_\alpha > \frac{1}{20}\right) \cap \left(\forall p_0 < \frac{1}{20}\right)$$

A possible 6 calculations were achievable, determining participants' average regarding each score. There are 117 $((3 \cdot 3) \cdot 13)$ possible classification observations included in the first hypothesis analysis.

The second hypothesis was measured by classification and correlation. Moreover, this hypothesis was separable in multiple category and ordinal data selections, and two calculation parts. Therefore, three definitions were constructed. They identified which SSBI software features and SSBI applications indicated greater user performance. It similarly indicated whether users' visual and technical abilities were correlated with supplementary ordinal data:

$$H_{2a}(x) : (\forall f \subset L) \cap (\forall s \in \{\lceil s \rceil_1, \lceil s \rceil_2\}) \cap (\forall s \in \{\lfloor s \rfloor_n, \lfloor s \rfloor_{n-1}\}) \cap \left(\forall p_\alpha > \frac{1}{20}\right) \cap \left(\forall p_0 < \frac{1}{20}\right)$$

$$H_{2b}(x) : (\forall f \subset \{V, T\}) \cap (\forall s \in \{\lceil s \rceil_1, \lceil s \rceil_2\}) \cup (\forall s \in \{\lfloor s \rfloor_n, \lfloor s \rfloor_{n-1}\}) \cap \left(\forall p_\alpha > \frac{1}{20}\right) \cap \left(\forall p_0 < \frac{1}{20}\right)$$

$$H_{2c}(xy) : (\forall x \vee y \subset \{V, T\}) \cap (\forall r > \frac{1}{10}) \cap (\forall s \in \{\lceil s \rceil_1, \lceil s \rceil_2\}) \cap (\forall s \in \{\lfloor s \rfloor_n, \lfloor s \rfloor_{n-1}\})$$

Classification of software functions and applications followed the same procedure as the research question and first hypothesis; only different categories were selected, such as technical criteria, the visual critera, and SSBI applications. With this procedure, strong correlations were incorporated to prove the second hypothesis. This procedure was used for each separate possible correlation and defined the correlation's significance: 546 $((42 \cdot 2) \cdot 13)$ classifications were possible for software functions, 39 $(3 \cdot 13)$ for software applications, and 26 $(2 \cdot 13)$ correlations were possible.

To prove the third hypothesis, the same methods for classification and correlation from the second hypothesis were applicable. Nonetheless, the hypothesis was split by calculation. For every work experience category, educational level educational category, hobby category, and hobby name, a classification was used. Since educational levels were additionally usable as an ordinal data scale, correlations among educational levels were determined as well.

$$H_{3a} : (\forall f \subset \{R_2, R_3, R_4\}) \cap (\forall s \in \{\lceil s \rceil_1, \lceil s \rceil_2, \lceil s \rceil_3\}) \cap (\forall s \in \{\lfloor s \rfloor_n, \lfloor s \rfloor_{n-1}, \lfloor s \rfloor_{n-2}\}) \cap \left(\forall p_\alpha > \frac{1}{20}\right) \cap \left(\forall p_0 < \frac{1}{20}\right)$$

$$H_{3b} : (\forall x \vee y \subset R_{2b}) \cap (\forall r > \frac{1}{10}) \cap (\forall s \in \{\lceil s \rceil_1, \lceil s \rceil_2, \lceil s \rceil_3\}) \cap (\forall s \in \{\lfloor s \rfloor_n, \lfloor s \rfloor_{n-1}, \lfloor s \rfloor_{n-2}\})$$

For the third hypothesis, if compliant, the top and bottom three classifications and correlations were selected. By applying the classification and correlation procedures: 1859 $((4 + 18 + 18 + 18 + 85) \cdot 13)$ classifications were possible, and 39 $(3 \cdot 13)$ correlations were possible.

For all ordinal data scales, the top and bottom results and the total top and bottom ten results were measureable. Similarly, for each hypothesis and research question, classifications, correlations, and quadratic relations were subjected to the same constraints. To obtain the top and bottom results of each analysis' calculation method, the following definitions were usable:

$$x_{1a} : \ (\forall s \in \{\lceil s \rceil_1, \dots, \lceil s \rceil_{10}\}) \cap (\forall s \in \{\lfloor s \rfloor_n, \dots, \lfloor s \rfloor_{n-10}\}) \cap \left(\forall p_\alpha > \frac{1}{20}\right) \cap \left(\forall p_0 < \frac{1}{20}\right)$$

$$x_{2a} : \ (\forall r > \frac{1}{10}) \cap (\forall s \in \{\lceil s \rceil_1, \dots, \lceil s \rceil_{10}\}) \cap (\forall s \in \{\lfloor s \rfloor_n, \dots, \lfloor s \rfloor_{n-10}\})$$

$$x_{3a} : (\forall b(x) = \lfloor t \rfloor) \cap (\forall q > 2) \cap (\forall q \in \{\lceil q_1 \rceil, \dots, \lceil q_{10} \rceil\})$$

To identify each top and bottom result for each ordinal data scale, a selection must be defined. Therefore, the following definitions were usable for the ordinal data scale top and bottom values:

$$x_{1b} : (\forall x \subset f) \cap (\forall s \in \lceil s \rceil) \cap (\forall s \in \lfloor s \rfloor) \cap (\forall p > \frac{1}{20})$$

$$x_{2b} : \ (\forall x \subset f) \cap (\forall r > \frac{1}{10}) \cap (\forall s \in \lceil s \rceil) \cap (\forall s \in \lfloor s \rfloor)$$

$$x_{3b} : (\forall x \subset f) \cap (\forall b(x) = \lfloor t \rfloor) \cap (\forall q > 2) \cap (\forall q \in \lceil q \rceil)$$

A possible 2691 $((18 + 18 + 18 + 4 + 85 + 3 + 3 + 4 + 3 + 2 + 3 + 2 + 2 + 18 + 24) \cdot 13)$ classifications (x_1) were measurable and a possible 196 $(13 \cdot 13)$ correlations (x_2), and quadratic relations (x_3) were possible.

A further essential measurement definition was perception. In this research, each participant was asked several questions regarding their perceptions of the BI concept, their own abilities, their organization's abilities, and favorability on their organization's BI-related plan. Related questions resulted in ordinal data scales and categorical classes, and all calculation methods were usable:

$$Rx_1 : (\forall x \subset \{R_5, R_6, R_7, R_8, R_9, R_{10}, R_{11}\}) \cap (\forall s \in \lceil s \rceil) \cap (\forall s \in \lfloor s \rfloor) \cap \left(\forall p_\alpha > \frac{1}{20}\right) \cap \left(\forall p_0 < \frac{1}{20}\right)$$

$$Rx_2 : \ (\forall x \subset \{R_5, R_6, R_7, R_8, R_9, R_{10}, R_{11}\}) \cap (\forall r > \frac{1}{10}) \cap (\forall s \in \lceil s \rceil) \cap (\forall s \in \lfloor s \rfloor)$$

$$Rx_3 : (\forall x \subset \{R_5, R_6, R_7, R_8, R_9, R_{10}, R_{11}\}) \cap (\forall b(x) = \lfloor t \rfloor) \cap (\forall q > 2) \cap (\forall q \in \lceil q \rceil)$$

With these definitions, a possible 169 $((3 + 3 + 4 + 3) \cdot 13)$ classifications, 39 $(3 \cdot 13)$ correlations, and 39 $(3 \cdot 13)$ quadratic relations were present in the data model.

Perceptions were supported by text comments and used for field notes if participants wished to clarify. Text comments were analyzable by linking counted words within sentences. This analysis method can potentially extracting extra information from the participants, and field notes. Text analysis was able to further support the perceptional measurements. An extra calculation was required to support text analysis (see Table 13).

Table 13: Text analysis measurements

Name	Formula	Description
Sentence (Z)	$X \in z$	The collection of words within a sentence.
Word count	$n(x)$	The occurrence of the same word within the texts.
Linked (w)	$w = n(x) \in n(z)$	The occurrence of the same word in the same sentences.

$$w(x) : (n(x)_i \in z) \cap (\frac{\sum n(x)}{n} > 2)$$

Text analysis used a procedure to include linked words in sentences. To add a strength constraint, the mean word count was used. If the mean word count was above 2, the sentence was assumed sufficiently strong to be included in the analysis.

Field notes were registered during the research. Proving, disproving, or declaring a field note's significance was performed through the same classification, correlation, quadratic relation, and text analysis procedures. To have field notes suit calculations, relating selections were included, and some field notes required further drilled-down selections $f(f(x))$, intersecting the results of two selections.

Top and bottom results and field notes are integrated in the analysis chapter, and research question and hypotheses examination are integrated into the discussion chapter. Analysis concerning perceptions were assimilated into the top and bottom results and the research question's discussion. Researched perceptions had their separate ordinal data scales although not directly included in the hypotheses.

3.9 Validity and reliability

To further increase research results' validity and reliability, an expert panel was introduced. The panel included 13 BI field experts recruited from our personal network, online expertise blogs, our LinkedIn network, and related LinkedIn expertise groups. Experts took a survey about research findings and were asked to confirm any results on both the hypotheses and the research question's analysis. Since experts all have different forms and years of experience, they were asked what their work position, related educational level, and years of experience were. Regarding any questions, the number of experts confirming results was tallied for their cardinality on each given question's choice. Similarly, an "expertise equation" was introduced. The expertise equation was defined with the following formula; $W \cdot E \cdot Y$. Scores were defined as stated in Table 14.

Table 14: Expertise equation score

	Expert's notation	Integer
W = work position	Operational/analyst	1
W = work position	Project-based	2
W = work position	Scientist/innovator	3
E = educational level	None	0
E = educational level	Vocational/MBO niveau ½	1
E = educational level	Vocational/MBO niveau ¾	2
E = educational level	Associate Degree/HBO (first two years)	3
E = educational level	Bachelor's degree/HBO	4
E = educational level	Master's degree/WO	5
E = educational level	Docter of philosophy/Gepromoveerd/PhD/Post-doc	6
Y = experience	Years of experience (#)	$\#: D(1{,}50)$

For example, when an expert stated that they were a BI project manager (2), completed a related bachelor's degree (4), and had five years of BI experience (5), their score equaled 40 ($2 \cdot 4 \cdot 5$). Each choice made by that expert gained a score of 40. Expert opinions were thus analyzed in two ways, namely by the number of experts confirming a result and the expert equation calculation. Options with the highest count and highest expertise equation outcome are viewed as accepted.

To demonstrate this study's validity and reliability, the validity and reliability of each accepted result were calculated to determine how the claim was comparable to other claims. Hence, the research's accuracy was verified. Each included research calculation method contained a validation measure, and reliability was derived by the number of confirming sources (e.g., literature or experts). Calculations are available in Table 15.

Table 15: Validity and reliability calculations

Name	Formula	Description
Classification validity	$\upsilon_{\Delta} = \frac{\left(p(x) \in f(x)\right) + \left(p(x) \notin f(x)\right)}{n(p)}$	Average *p*-values of the experimental and control groups
Correlation validity	$\upsilon_{r} = \frac{r + (\left(J_{\frac{1}{4}} + J_{\frac{4}{4}}\right) + \left(J_{\frac{2}{4}} + J_{\frac{3}{4}}\right))}{n(r) + n(J)}$	Average of the Jaccard correlation coefficients with average of conventional correlation coefficients
Quadratic relation validity	$\upsilon_{q} = \frac{t + (\left(J_{\frac{1}{4}} + J_{\frac{3}{4}}\right) + \left(J_{\frac{2}{4}} + J_{\frac{4}{4}}\right))}{n(t) + n(J)}$	Average of the Jaccard correlation coefficients with average of quadratic trend coefficients
Declarations	$D : \{-1,0,1\}$	1 = result confirmed, 0 = result neutrality, and -1 = result rejection by sources
Sources	$C : \{S, L, J, E, B\}$	*S* = claim's validity measurements (e.g., valid or not valid), *L* = scientific literature recognition, *J* = expected Jaccard figures, *E* = expert choices, *B* = sentiment and urgency from blog topics (only three results; method described in analysis chapter)
Reliability percentage	$\mu(\lambda) = \frac{\Sigma D_i(C_i)}{n(D_i(C_i))}$	Percentage of sources confirming results

A validity and reliability integer was determined through the calculation methods illustrated in Table 15. This number indicates which claims are more valid or reliable in relation to other claims. The number of observations on which a claim's validity was based and that of sources determining its reliability were also provided.

4. Results

Results included relatively simple calculations in which no comparison with other categories or ordinal data scales were formed. Measurements are shown in Table 8 and categories in Table 5, 6, and 7. Calculations were arranged in groups. Counts were suitable for recorded perceptions, H3 categories (e.g., education, work experience, and hobbies), and additional research variables. MMM measurements were applicable to recorded perceptions, scores, and H3 categories. The research counts demonstrated the research's size, and differences in these amounts led to validity differences. Correspondingly, the MMM measurements also showed some validity information applicable in the conclusions since the more similar these values were, the more valid the results (Basu & DasGupta, 1997).

Table 16: Research counts

	Count	Unique count
Total observations	3901	508
Field notes	18	
Text analysis	41	
Assignments	372	
Visualizations	208	
BI opinions	117	
Hobbies	189	85
Hobby categories	18	
Work experiences	99	18
Educations	79	18
Participants	62	
Organizations	27	

In Table 16, the research counts show the number of elements mentioned emerging from the research. Elements were based on participants' characteristics, their survey answers, and assignments question answers. In addition, some elements originated from participants who only took the first survey and neglected the assignments (5). Some elements were probably counted even when left blank by participants, constituting a bias. As stated earlier, two different count types were available. The count characterized all available mentions, and the unique count indicated the individual mentions of the dataset element. Counted elements included the number of participants, the number of BI-opinions, the number of participant-produced visualizations, the number of text analyses, and field notes. The lowest number was the predefined hobby count, which was constituted by the hobby list. Furthermore, the largest number was the produced visualizations, as participants created an average of 2.5 visuals. Depending on the variable, the sample's minimum was reached in total assignments and observations, yet not in recruited participants and organizations (Krejcie & Morgan, 1970).

Table 17: MMM measurements from results (n = 117, 186, 208, 62)

	Mean	Median	Mode
Age	40.3	40	27
Spend time (in hours)	1.4	1.3	1
Strategic grade	7.5	7.5	7.5
Practical grade	7	7.5	9
Technical performance	6	6	6
Visual performance	-0.9	-1	-1
Participants' grade own their BI capabilities	5.9	6	7
Participants' grade on their organization's BI capabilities	6	6	6
Participant favorability grade concerning organization's BI-related plan	6.9	7	7

MMM measurements consisted of the mean, median, and mode. As stated previously, the closer the MMM measurements per ordinal data scale was, the more valid the result of this ordinal data scale. Furthermore, the mean score values demonstrated that the general participant answered strategic questions with only one fault. Likewise, they visualized two out of three visualization requiring questions properly. In terms of technical and visual scores, participants generated simple visualizations generally containing one understandability flaw.

While not measured physically, the participant's average performance resembled Sparks and Mccann's (2015) research. In their research, analytical culture (relatable to strategic score) was measured at 6.5, analytical capability (relatable to practical score) at 6.1, analytical maturity (relatable to technical score) at 6.0, and information quality (relatable to visual score) at 6.6. Nevertheless, Sparks and Mccann's (2015) research was conducted among industry managers and only through a survey. According to Peters et al. (2016), managers have traditionally been the target segment of BI systems. However, performance scores varied across industries, organizations, users' business positions, or other backgrounds, as executive support or related training influences users' participation (Elena, 2011; Kulkarni et al., 2017). According to Robertson (2020), BI implementation has been influenced by several factors, such as culture investments, available data, SSBI application choice, stakeholders, and managers' emphasis on analysis.

Moreover, participants' opinion MMM data were closely among each individual component, all around 6 or 7. Generally, participants gave themselves, their organization, and their organization's BI-related plan a minimum pass. Because their general perceptions were broadly and mildly positive, users had a degree of confidence in themselves and their organizations. According to Issa and Haddad (2008), knowledge sharing in organizations is enhanced by users trusting their organization's choices regarding information technology. This trust can develop into competitive advantages. Therefore, most users are willing to share information within organizations, as they largely trust their organization and colleagues and perceive knowledge sharing as a benefit to their organization.

*Table 18: Nominal modes of researched categories (*n *= 189, 62, 117)*

Hobby	Soccer
Hobby category	General inside
Experience category	Business
Education category	Business
Educational level	Bachelor
Gender	Male
Software	
Needed help	No
Previous training	No
Onsite research	Yes
Participants' grade on the BI concept	Yes
Participants' grade own their BI capabilities	Yes
Participants' grade on their organization's BI capabilities	Yes
Participant favorability grade concerning organization's BI-related plan	Yes

Although the modes specify the frequency from a given ordinal category, they can also be calculated for nominal categories. Modes for each category were outlined for all H3 categories, perceptions, and some additional research variables, as detailed in Table 18. All listed modes were not directly related without comparative analysis. Considering that 14 modes and only one measurement were generated, if a bias was present among a nominal mode, its effect was relatively small. If a bias was present among the measurement, its effect was relatively higher. Since only the modes were calculated for categories, the validity of these categories was debatable. Therefore, the category modes were not included in the reliability calculations since no mean or median could be obtained. Landes et al. (2013) reported that modes and counts are a form of limited nominal analysis. The Jaccard index, in which union and intersection sets are combined, can be used to analyze nominal results (Jaccard, 1912). However, this method was not used in this study, as participants' performance was mainly measured by ordinal data scales.

Table 19: SRI measurements from results (n = 62, 117, 208, 186)

	St.dev	Range	IQR
Age	13	45	23
Spend time	0.7	3.5	0.8
Strategic grade	1.4	6	3
Practical grade	2.2	9	3
Technical performance	1.3	7	2
Visual performance	1	5	2
Participants' grade own their BI capabilities	1.7	8	2
Participants' grade on their organization's BI capabilities	1.7	8	2
Participant favorability grade concerning organization's BI-related plan	1.6	8	7

As stated previously, SRI components consisted of the standard deviation, range, and IQR. SRI data are visible in Table 19. Because the mean and median were also functional for reliability and validity tests, the standard deviation, range, and IQR were also applicable to reliability and validity calculations. If calculated correctly, widely distributed measurement results reflect low reliability and validity. Hence, these measurements were further used in the conclusions (Harding et al., 2014). Accordingly, SRI measurements were calculated for each available score, perception, and other research variables.

Since a small group of SSBI software-skilled participants and IT personnel were represented in the research sample, their effects were minimal. Although their results were slightly superior, these participants were not excluded, as their sample proportion was negligible. Since this proportion of individuals having IT work experience was larger than individuals with specific with SSBI software skills, their results were individually measured. However, their influence was minimal (determined in field note 7).

5. Analysis

The analysis consists of two parts: top and bottom results for each ordinal data scale and top and bottom results for perceptions and field notes. Top and bottom ordinal data scale results were sorted between positive and negative effects defined per ordinal data scale and prioritized by the result's strength calculation. The categories were not included in chapters because many were available. Most results were already associated with an ordinal data scale, field note, hypothesis, or the research question. Furthermore, registered field notes were characterized in their text's context to accommodate its measurement to determine if the field note was claimed a proven state of reality. All available data, field notes, and perceptions were analyzed depending on their reliability and validity.

5.1 Top and bottom findings

The total and for each measurement top and bottom results derived from the research's ordinal data were determined in the analysis. For each top and bottom result, the positively and negatively influencing factors were assessed. The other scales were participants' age and research completion time. Ordinal data scales' definitions are explained in the methods chapter. Furthermore, for each of these measurements, the proposed calculations were carried out. Thus, for each classification, the delta mean, strength, standard deviation, and *p*-values were calculated; for each correlation, the correlation, strength, standard deviation, and slope were assessed; and for each quadratic relation, the trend coefficient and strength were determined.

5.1.1 Effectiveness score

Participants' effectiveness scores were determined by taking the averages of the strategic, practical, technical, and visual scores. The scores were influenced by all measurement methods except for negative correlations and mostly by positive correlations and all classifications. The necessary calculations were carried out for each measurement and are shown in Appendix M.A.

Positive

- High etiquette (label for metrics)
- High dimension (categorical analysis)
- High sortation
- Low over-scrolling
- Low label orientation
- Business education
- BI training
- High visualization method (proper technique was chosen)
- High relation (visualization with data from multiple tables)
- High education level
- High grade on own capabilities
- High or low research completion time
- Median score on strategic CSF
- High or low grade on own capabilities

Negative

- High undefined data (participant not employing a verification process)
- Low etiquette (label for metrics)
- No BI training
- Low sortation
- Onsite research
- Running as a hobby
- High grade on organization's BI abilities
- High over-scrolling
- Qlik Sense usage
- Participants requiring help (participants who were stuck at a question or technique)
- Median research completion time
- High or low score on strategic CSF
- Median grade on own capabilities

n = 508

A significant number of factors influenced participants' effectiveness scores. The strongest effects were users' etiquette usage for their defined metrics and appropriate use of dimensions and expressions, and information verification. Poorly performing participants frequently designed undeveloped measurements. A paradoxical result was represented by participants' grades on their own capabilities, as positive and negative effects were determined on this score. Furthermore, in agreement with Isaacs et al. (2014), users' visualization method invocation depends on different information purposes. Using the appropriate visualization method improves the intended information context to be communicated. Isaacs et al. (2014) also state that debugging and testing information are enhanced by creating appropriate accommodating data structures. Accordingly, the right dimension, expression, etiquette, and data relation usage improved users' performance in SSBI processes because understanding data structures allows users to focus on the intended informational context. It likewise further supported their BI process efficiency. Users correctly testing their introduced dimensions and expressions further improved their effectiveness. According to Law et al. (2021), users' judgment on correlational graphs is relatively poor because users are easily exposed to incorrect information. Law et al. (2021) further state that users generally trust the visualized or structured data without questioning their calculation methods, data origins, or the impact of randomness.

5.1.2 Efficiency score

Efficiency scores are represented by the number of visualizations participants produced during their research period. While all the mentioned methods affected the efficiency score, only positive classifications, positive correlations, and ∩-type relations were found. Calculations are available in Appendix M.B.

Positive

- High relation (visualization with data from multiple tables)
- Median strategic score

n = 124

Negative

- High or low strategic score
- High participant grade on organization's BI abilities
- High participant favorability grade concerning organization's BI plan

Only four effects on the efficiency score were established. No negative classification, positive correlation, or ∪-type relation was deemed strong enough to be included in the analysis. The strongest influence was identified in participants' ability to join data tables and use mixed data for their generated visualizations. Since all perceptional measurements were generally positively correlated, negative effects on both participants' grade on their organization's BI performance and their favorability about their organization's BI-related plan was expected. According to Çöltekin et al. (2010), users follow a hypothetically constructed path, and accurately following this path makes them more efficient at analytical reporting. In their study, they concluded that users with relevant expertise in analytics were faster due to shorter paths and accurate following. The same effect was not measured in this research's results.

5.1.3 Strategic score

The strategic score was characterized by strategic assignment questions in which the participant had to devise a simple strategy map for a particular organization. Each proposed measurement had an impact on the strategic score. Calculations can be accessed from Appendix M.C.

Positive

- High multi (two or more dimensions or expressions)
- High educational level
- High or low practical score
- Median efficiency score
- Middle-aged users
- High or low visual score
- High or low participant favorability grade concerning organization's BI-related plan
- High or low participant grade on own BI capability

n = 186

Negative

- Participants requiring help (participants who were stuck at a question or technique)
- Median practical score
- High or low efficiency score
- Young or old users
- Median visual score
- Median participant favorability grade concerning their organization's BI-related plan
- Median participant grade on their own BI capabilities.

A reasonably large number of quadratic relations existed in the strategic score, containing more fluctuating results compared to other ordinal data scales. Furthermore, no negative correlations were deemed strong enough to be included.

Platts and Tan (2004) define strategy as a broad concept compared to the data visualization concept. Strategy can be associated with every aspect of the organization and the amount of data visualization techniques are limited. Platts and Tan (2004) informally tested their framework and generally received positive feedback from field experts and managers. However, in their study, they found that organizations struggled to define similar frameworks for their respective organizations. Measuring strategic decisions and competitive advantages became therefore chaotic. Fluctuating patterns in the strategic score and perceptional grades were then anticipated and measured with quadratic relations.

Since multidimensional or expressional analysis positively influences the strategic score, users can improve BI functionality for their respective organizations. As discussed in Peters et al.'s (2016) study, they concluded that organizations using multidimensional or expressional supporting applications produced superior and tailored BI functionality for their competitive advantage.

Furthermore, according to Elbashir et al. (2008), an organizational strategy can be divided into upstream (suppliers), internal (efficiency), downstream (customers), and performance (competitive). In their study, BI had a positive impact on all aspects of organizational strategy. However, organizations tended to focus on internal efficiency; as might be assumed, internal data are easy to obtain, and their effects easy to measure.

5.1.4 Practical score

The practical score was defined by the open questions that participants answered by data visualizations. Positive and negative effects were established. Calculations are available in Appendix M.D.

Positive

- High visual score
- High sortation
- High effectiveness score
- High participant grade on own capabilities
- Median strategic scores
- Middle-aged users
- High or low educational level

n = 186

Negative

- No BI training
- Median educational level
- High or low strategic score
- Young or old users

The practical score was the most significant factor affecting the effectiveness score, as the practical score correlated 71% with the effectiveness score. Furthermore, the visual score was also correlated with the practical score. Moreover, no negative correlation was strong enough to be included for the practical score. Two educational factors affected the practical score because no BI training had an adverse impact, and educational level was positively correlated. The mentioned effects on education level and age can be attributed to individuals with different cognitive abilities between experience and knowledge. According to Grigorenko and Sternberg (2000), age, gender, and education are predictors of practical intelligence, analytical intelligence, and self-efficacy. In their study, they found that younger and higher educated individuals have higher levels of self-efficacy, whereas creative men perform less well. This effect was found to be stronger and more fluctuating for women. They also note that gender and age-homogenous groups scored higher across all forms of intelligence. Therefore, different cognitive ability patterns among the measured research results confirmed the same patterns were existent in this research.

5.1.5 Technical score

Technical scores were specified by the shared software functions used by research participants (see Table 3). Not all used measurement methods were applicable due to insignificant results for this ordinal data scale. Calculations are provided in Appendix M.E.

Positive

- High cluster
- Young or old users
- High or low participant grade on organization's BI capabilities

n = 208

Negative

- Logistical educational
- Middle-aged users
- Median participant grade on organization's BI capabilities

No correlation influenced the technical score, indicating that attempted correlations analyses were not significantly strong. Only a few effects on the technical score were found; most results were insignificant. Although some factors were significant, no direct relation between them could be established.

According to Law et al. (2021), when analytical software includes generated descriptions to help users' BI processes, such as information describing an algorithm's calculations, constraints, processes, and resources, it will result in more analytically critical users. Users are persuaded to consider BI processes' effectiveness, efficiency and their software, improving organizations' analytical culture. Furthermore, according to Isaacs et al. (2014) and Hung et al. (2016), the clustering of visualizations makes data more usable, as greater categorization is possible. However, it involves another layer of complexity for users to face. According to Landes et al. (2013), clustering helps pattern recognition, detect anomalies, spot similarities, and predict probabilities. These visualization techniques are necessary to achieve human intelligibility of clusters. Users who can integrate clustering can thus introduce pattern-discovery techniques. These users presumably have superior visual performance, although this has not been measured in the study. Furthermore, in this work, the "logistics" educational background was found to have a negative effect on the technical score. Although these results were validated, this effect can be assumed due to sample randomness, as literature shows otherwise. According to Adebambo and Toyin (2011), Brah and Lim (2006), Evangelista and Sweeney (2006), and Closs et al. (1997), IT processes, introduction, and resources predominantly have a positive effect on logistical effectiveness and efficiency. Users concerned with logistical processes were capable of using IT technology and analysis techniques.

5.1.6 Visual score

The visual score was based on participants' adherence to the data visualization criteria indicated in Table 4. Not all calculations to define results were included due to insignificant results, as ∪-type relations and negative correlations were not present. Measurements are available in Appendix M.F.

Positive

- High label (exact values in visualizations)
- High practical score
- High effectiveness score
- Middle-aged users
- Median participant favorability grade concerning organization's BI-related plan
- Median strategic score

n = 208

Negative

- High undefined data (participant not employing a verification process)
- High or low participant favorability grade concerning organization's BI-related plan
- Young or old users
- High or low strategic score

Although it was not the highest affecting component of the effectiveness score, the visual score still had a substantial effect on it. Furthermore, different software applications imply different visualization methods (Isaacs et al., 2014). Depending on the information context, the software's source code substantially influences participants' visual performance. Software's visualization method invocation usually depends on data type and adapts users' visualizations choices. Therefore, a correlation with the practical and effectiveness score was expected. The communicated information context is more understandable if users produce understandable visualizations (Isaacs et al., 2014). Furthermore, Cawthon and Vande Moere's (2007), North's (2006), and Behrisch et al.'s (2018) investigations concluded that information-retrieval effectiveness is mainly achieved by flat, logically ordered visualizations. Consequently, the visual score's criteria were designed to include this. Therefore, correlations between practical and effectiveness scores were expected and confirmed this result. Cawthon and Vande Moere (2007) also claim that users' information retrieval effectiveness is higher when users experience familiar visualization techniques. Therefore, the participants tend to create basic visualizations, such as bar charts (Talbot et al., 2014). As label usage was a positive factor, users who introduced them on their measurements or software that automatically produced them in their visualizations also obtained higher scores. According to Behrisch et al. (2018) and Law et al. (2021), notations about expressions improve the comprehensibility of visualizations because they give meaning to clusters, classes, and categories. However, expression notations are often ignored (Behrisch et al., 2018). Therefore, correlation with the practical score was expected because, if known, users who labeled their expressions correctly were aware of their BI processes or their processes in their software.

5.1.7 Age

Participants' age was requested in the first survey that they filled in before the research started. All proposed measurements were suitable for the age scale. However, not all measurements yielded significant results. Calculations are viewable in Appendix M.G.

Positive

- High participant grade on organization's BI capabilities
- High or low practical score
- High or low visual score
- Median technical score

n = 62

Negative

- Median practical score
- Median visual score
- High or low technical score

While there were only 62 participants that attended, no classification was deemed strong enough to be included, as this measure did not reach a hundred observations. However, significant results were expected in terms of participants' age, as some correlations and quadratic relations were strong enough.

Furthermore, technical and visual scores have had an intuitively adverse effect on participants' age, as both scores are technically oriented. Furthermore, according to Kulkarni et al. (2006) and Birkinshaw et al. (2019), an organization's analytical culture is often created by the organization's senior staff. Seniors are employed longer and gain managerial positions, or their years of experience enhances their colleagues' trust in their abilities and knowledge in the organization. In their research, they also discovered that BI systems' success is created through a top-down approach. Therefore, age expectedly affects the organization staff's perceptions of the organization's BI capabilities. Older users are more likely to be responsible for these processes and have more knowledge about the organization's history. They therefore have a better perspective in positive or negative organizational change.

According to Birkinshaw et al. (2019), age diversity in organizations is growing. People live and work longer due to economic changes and better health care. Younger managers tend to be self-centered and technologically and methodically oriented, while older managers tend to be socially oriented and endorse holistic views. This is partly due to changing biology and accumulated experience. As changes in age are constant, the research's measured oscillating patterns were expected and occurred. Hence, these findings are consistent.

5.1.8 Time

Participants' time spent in the research was recorded and was usable as an ordinal data scale. Therefore, the spent time was classifiable, correlated, or represented in a quadratic relation. Associated measurements are represented in Appendix M.H.

Positive

- Median effectiveness score
- High participant grade on organization BI capabilities
- High or low participant favorability grade concerning organization's BI-related plan

n = 62

Negative

- High or low effectiveness score

Similar to age data, no classification was included concerning participants' research completion time. Only one time variable was recorded per participant, and only 62 individuals participated. Negative correlations were assumed to be positive effects, as spending less time in research is considered valuable because results are produced more efficiently. Only negative correlations were determined, and these correlations were data on participant perceptions. However, as time is an efficiency component, no correlation on the efficiency score was found to be strong enough. Therefore, research completion time did not significantly influence participants' production speed. As previously stated by

Çöltekin et al. (2010), participants' speed depends on their respective expertise. This effect was not fully measured in this study, which was mostly carried out by inexperienced users.

5.1.9 Educational level

The educational level was defined by the stated courses declared by users in their survey. All of the proposed measurements were viable for the educational ordinal data scale. However, not all measurements yielded results. Related data can be found in Appendix M.I.

Positive

- High effectiveness score
- High strategic score
- Median practical score

Negative

- High or low practical score

n = 78

More results were expected for this ordinal data scale, as higher education is often more analytically lenient. Concerning the effectiveness score, the educational level was correlated with the strategic score, indicating that better-educated users are more aware of what needs to be measured. Likewise, no classification was significant, as only 78 educational courses were registered. According to Isaacs et al. (2014), performance in the software's processes varies across users' educational levels because differently schooled users exhibit different cognitive patterns. Research findings also state that higher educational levels influenced participants' performance positively, confirming the research finding.

5.1.10 Strategic parts

The strategic parts are the components on which participants were graded based on their strategic score. Specifically, it was composed by their CSF, KPI, and link. The results are presented in Appendix M.J.

Table 20: Strategic parts (n = (62, 62, 62, 117, 508, 186))

X	Type	*Y*
Link	∪	Participant grade organization plan
CSF	∩	Effectiveness
CSF	∪	Participant grade organization BI capabilities
CSF	∪	Participant favorability grade concerning organization BI-related plan
KPI	∪	Strategic score

Likewise, since only 62 individuals participated, the strategic parts were not valid enough to be classifiable, and no correlation was found to be strong enough. Nevertheless, some quadratic relations between valid ordinal data scales were identified. Two quadratic relations between strategic parts and the effectiveness score were present. Strategic parts were components of the strategic score, and the strategic score was a component of the effectiveness score. Therefore, adverse relations have been measured. Furthermore, other related ordinal data scales were perceptual data about participants' organizations. They all encompassed ∪-type relationships, as the strategic score implied the same relation. As noted in Peters et al.'s (2016) paper, organizations' strategic management is strengthened and enhanced by the manager's use of BI results. The effects measured in their work were not supported in this study, as there were no sufficiently strong correlations and classifications to support their proposition. On the contrary, Peters and collaborators explained that their findings on BI processes' strategic impact was measured indirectly. Hence, it was not similar to this research's findings.

5.1.11 Participants' grade on their own capabilities

Participants could rate their perceived BI performance both at the start and at the end of this study. Therefore, calculations could be carried out on these ordinal data, and classifications, correlations, and quadratic relations were produced. The calculations are presented in Appendix M.K.

Positive	*Negative*
▪ BI training ▪ Male gender ▪ Business education ▪ High and median effectiveness score ▪ High and median participant grade on organization's BI performance ▪ High practical score ▪ Median strategic score	▪ High cluster ▪ Education in communication and journalism ▪ Low effectiveness score ▪ High or low strategic score ▪ Low participant grade on organization's BI performance

n = 117

High numbers on this data indicate that users are convinced of their own abilities. Therefore, this is not a performance score; it is a perceptual ordinal data scale. All perceptual ordinal data scales were correlated with each other by 36%. If users had a positive perception of their capabilities, they were often also positive about other perceptual aspects. This indicates that when they claimed that they would perform well on BI processes, they were generally honest, especially in terms of their strategic score (Martijn et al., 1992).

The result implied a Dunning-Kruger effect, as a quadratic relation was measured between participants' confidence in their BI abilities and their effectiveness score. This effect was similarly measured by Aggarwal et al. (2015). They analyzed the general IT intelligence of a pharmaceutical company in India and found that users with critical views had more relative expertise. Confident users had dishonest perceptions and scored lower on their test results. However, their work measured overall IT intelligence, whereas this research involved SSBI performance. Furthermore, men who have been trained in information management and have a business background are often more confident in their abilities. Since training and business backgrounds are components of the third hypothesis, the analysis of the related claims is presented in the discussion chapter. Coutinho et al. (2020) studied the Dunning-Kruger effect in female students in a United Arab Emirate's college. They found that the Dunning-Kruger effect occurred in all their defined aspects and areas because poor performers lacked insights into their cognitive processes. Even when feedback was given, the Dunning-Kruger effect was still present. Since students in their sample originated from both Western (e.g., US, UK, and the Netherlands) and Eastern (e.g., UAE, India, and China) cultures, they also found differences between these cultures: since the latter tend to be more collectivized, the Dunning-Kruger effect is lower than in the former. They also found that analytical thinkers suffer less from this effect than more intuitive thinkers. Likewise, they further stated that individuals who perceive intelligence as static tend to suffer more from it than more dynamic thinkers.

According to Çöltekin et al. (2010), naive users perceive analytical software processes more by perceptual tendencies than by thematic relevance. Ignorant users explore factors that are of personal interest instead of considering their importance. Research results suggest that this effect also occurred in this study. As the effectiveness score was also positively correlated, Çöltekin et al.'s (2010) effect was adequately measured as expected. Therefore, when users trusted their own abilities, users' SSBI performance was average, whereas when they were not that convinced, they usually scored higher.

As regards gender, according to Coutinho et al. (2020), women tend to estimate their abilities more when confronted with a task and compare actual results with their estimates. Men tend to cognitively improvise, leading to misperceptions. According to Richardson (2016), women discount their abilities when working in mixed fields, whereas men struggle to recognize their shortcomings. Therefore, when referencing research results, men rated their abilities higher in this study, which confirms this research's finding.

According to Kulkarni et al. (2006), if the user believes there is a benefit, then this benefit will usually develop, meaning social exchange theory. Hence, the existence of a BI system can develop into a benefit due to user perception. If the BI system is present, the system will at least be used.

The negative effects of the communication and journalism educational background have been confirmed, as journalists are often more reserved. However, according to Hanitzsch (2007), journalists learn impartiality and objectivity to carry out their research. In practice, this brings about different outcomes, as news agencies tend to vary based on fact, speed, persuasion tactics, or political direction to attract viewers, readers, or listeners, and they are subjected to ideologies. Furthermore, journalists learn to adapt to qualitative research because it can be better communicated to the masses.

5.1.12 Participants' grade on organizations' BI performance

The proposed measurements were used to calculate the impact of users' trust on their organization's BI capabilities. Classifications, correlations, and quadratic relations resulted in positive and negative effects on participants' grades, as shown in Appendix M.L.

Positive

- Non-competitive sports outside
- Older users
- High participant grade on own capabilities
- High participant favorability grade concerning organization's BI-related plan
- High or low technical score
- High or low strategic CSF score
- High or low participant grade on own capabilities

n = 117

Negative

- High favorability grade concerning organization's BI-related plan
- Short research completion time
- Low efficiency score
- Median technical score
- Median strategic CSF score
- Median participant grade on own capabilities

The most influencing factor was the user's efficiency in producing visualizations, which was divided by participants' research completion time. Because of some inconsistencies in the results, participants' favorability on their organization's BI-related plan and their grade on their own capabilities were not included in resulting claims since positive, negative, and neutral results were all present. Furthermore, according to Kulkarni et al. (2007), when BI systems are deployed in the organization, employees are subjected to new biases. When historical knowledge about the organization becomes available, users can only use this data to study their assumptions. They may either be overwhelmed by available data or become overconfident despite deteriorating information quality. Furthermore, Law et al. (2021) argues that organizations acquire analytical software applications to improve BI processes. Although analytical software increases software utilization, it does not directly create or improve an organization's analytical culture. Users are encouraged to participate in the whole process rather than only its technical usage.

5.1.13 Participants favorability on organizations BI-related plan

Similar to other perceptual data, participants could declare whether they preferred their organization's BI-related plans, if known. Participants provided this data at the beginning and end of the research. The proposed measurements were applicable, and the resulting values are available in Appendix M.M.

Positive

- Master's degree users
- High participant's grade on organization's BI performance
- High efficiency score
- High or low score on strategic link
- High or low strategic score
- High or low score on strategic CSF
- Median visual score

n = 117

Negative

- Tableau usage
- Low dimension (categorical analysis)
- Median score on strategic link
- Median strategic score
- Median strategic CSF score
- High or low visual score

Users with a master's degree or higher tended to rate their organization's BI plans high. This is perhaps due to the fact that highly educated users are usually more involved in the development of these plans. A controversial result was the ordinal data scale's result on Tableau software usage. As the research's Tableau users were only able to directly influence this rate after the research, this result may have some randomness. Even so, Alberts (2017) proved that Tableau has a competitive advantages over Microsoft PowerBI. Microsoft PowerBI focuses on cost-effectiveness and Qlik Sense focuses on data discovery. This is due to Tableau's orientation towards the user's native process, thinking patterns, and biases

(Cynixit, 2020; DataFlair, n.d.). Since Tableau appeals to the user's native process, it has the potential to attract an inexperienced user better than its rivals. Furthermore, when users compared Tableau to their current organizational information environment, their perceptual rate tended to decrease. Moreover, a relatively large number of strategic parts influenced participants' perceptions of their organization's BI-related plan. This is possibly due to the strategic score since the strategic parts were measured independently.

Results indicated either positive or negative effects, and ordinal data scales were either perceptual, performance-related, or participant-property-related. Therefore, different strategies for using the results were possible. According to Helms and Nixon (2010), when organizations want to implement SSBI effectively and efficiently, the following four strategies should be adhered to: 1) investing in perceptual or participant property data's positive effects to increase support for SSBI application usage in the organization; 2) preventing perceptual or participant properties' ordinal data' negative effects, as, unlike positive effects, negative effects will make the organizational support decrease; 3) further developing positive effects on performance data, specifically, it is advisable for projects to maximize technical strengths to exploit the SSBI's effectiveness and efficiency of users; and 4) resolving negative influences on performance. Since positive performance effects require development projects, negative ones force structural adjustment projects to reduce or eliminate unsuitable factors.

Furthermore, all the results shown in this analysis are subjected to several biases. Some are known and mostly explained in the conclusion chapter; some may still be present. Since 13 ordinal data scales were evaluated, bias was likely limited. However, all data was calculated by three measurements and led to either positive or negative effects. Therefore, if bias was present in the measurements or conclusions, their impact was likely to be more significant.

5.2 Field notes

Field notes included patterns discovered by us during the study and registered for further analysis. Furthermore, field notes' patterns were affiliated or recognized in software application use, participants' assignments performance, participants' thinking in assessing the assignment, similarities among organizations and industries, and supporting activities. Although the percentile analysis did not measure a difference from the total mean, it did calculate the proportion of a particular occurrence within its total; formula: $p(x) = \frac{A^c}{\xi}$. Determining which measurement method to choose for which field note depended on the field note's context. For example, when a field note suggested that IT-related participants performed better, a classification analysis was performed. This method is utilized because performance between "IT" and "non-IT" groups was comparable. Almost all field notes required detailed filter selections in data to arrange the proposed grouping in the field note's phraseology. A field note was either proven, disproven, or declared insignificant, and it could include multiple calculation methods to prove its significance. Using multiple measurements can improve a field note's validity.

Table 21 describes field notes' settings, determinations, foundations (*N*), and appendix references to calculation results. Since full field notes' descriptions were too extended, they are provided in Appendix R.

Table 21: Field notes declarations

#	Setting	Determination	N	Appendix
1	*When importing data into Microsoft PowerBI, the sheets were not automatically selected, the selection options did not stand out, and they were not functional when they were not selected*	*Effects proven*	*41/208*	*N.A.*
2	*Qlik Sense did not automatically configure the measurement etiquettes when presenting the information. Other software can do this*	*Proven*	*91/208*	*N.B.*
3	*Data management in Tableau was perceived as unfriendly. The average user did not know the union types that Tableau presented*	*Disproven*	*41/208*	*N.A.*
4	*Field orientation in Tableau felt broken. Text-formatted numbers were not easily converted to numbers with the options presented by Tableau nor in its loading code*	*Disproven*	*36/208*	*N.C.*

5	*Dimensions and expressions were not always properly predicted, and participants experienced difficulties in finding the options to convert them in Tableau*	*Insignificant*	*8/208*	*N.L.*
6	*Multiple software functions relate to participants' perceptions*	*Insignificant*	*206/208*	*N.M.*
7	*Participants from technical sectors did better*	*Insignificant*	*179/208*	*N.F.*
8	*Most respondents were used to Microsoft Excel, and most organizations' data was centered on spreadsheets*	*Proven by participant statements*	*117*	*N.P.*
9	*Organizations do not invest time or budget in BI*	*Proven by participant statements*	*117*	*N.Q.*
10	*Onsite participants requested extra help or used extra help*	*Proven*	*90*	*N.E.*
11	*When research was carried out onsite, participants tended to complete it earlier*	*Insignificant*	*62*	*N.H.*
12	*Participants in independent research performed better*	*Proven*	*142/508*	*N.N.*
13	*Average scores of managers and leaders were lower than that of other participants*	*Insignificant*	*43/508*	*N.I.*
14	*Participants had more difficulty when they had to visualize with more than two dimensions or expressions*	*Insignificant*	*43/508*	*N.D.*
15	*Participants intended to invest more time in data visualization than in data preparation*	*Insignificant*	*42/508*	*N.G.*
16	*Older participants were more confident in their own as well as their organization's BI abilities and favored their organization's BI-related plan more*	*Proven*	*117*	*N.J.*
17	*Sportive participants were more subjected to the Dunning-Kruger effect in SSBI*	*Insignificant*	*152/508*	*N.K.*
18	*Participants who graded their own BI abilities, their organization's BI abilities, or their favorability for their organization's BI-related plan high tended to rank high for all these perceptual ordinal data*	*Proven*	*117*	*N.O.*

6. Discussion

Analysis' results were appropriate to the hypotheses and the research question. As they were distributed among the usable measures, each detail was examined individually. Furthermore, each outcome of the discussion was further examined by a combination of validity and reliability measurements, related literature, an expert panel, and textual analysis of related blogs to address the resulting claims' validity and reliability. The discussion is presented by the divided propositions resulting from the research question and hypotheses. This division is determined in the Proposition definitions and constraints chapter at 3.8.

6.1 Users can generally conduct BI processes in SSBI software (H1a).

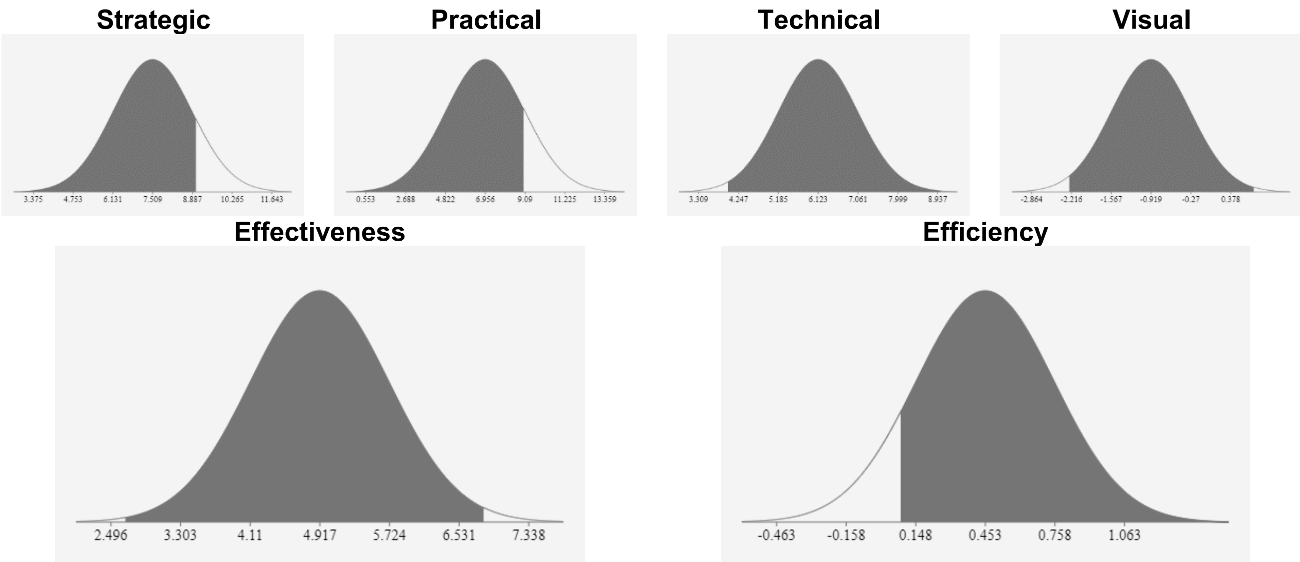
The user's workability of the SSBI concept determined whether users' exploration abilities were sufficient to ensure BI quality. It further determines whether their abilities were an adequate trust establishment for BI managers. This examination was carried out by taking the average, percentage, MMM measurements, and SRI measurements of each performance score, such as the strategic, practical, technical, visual, effectiveness, and efficiency ordinal data scales. Validity was therefore determined by low MMM and SRI measurements.

Table 22: H1a SSBI user workability

	Mean in domain	Percentile	MMM	SRI
Strategic performance	6/9	67%	0	1.6
Practical performance	7/9	78%	2.5	3.8
Technical performance	6/10	60%	0	3.7
Visual performance	-1/-6	79%	-0.1	2
Effectiveness performance	71/100	71%	0.6	2.8
Efficiency performance	2.4/4	60%	0.7	2

Consistent with the research results shown in Table 22, participants usually passed assignments in all categories, compliant with the Dutch standard ($\geq 55\%$). Technical and efficiency scores were only slightly above the Dutch standard. Participants' strategic and technical scores did not show any difference between their mean, median, and mode. The strategic, visual, and effectiveness scores were modestly unoccupied in unpopulated ranges and performed equal to or lower than 2.

Figure 3: Normal distributions H1a



Normal distributions for the strategic, practical, technical, visual, effectiveness, and efficiency scores, as performed by participants, are shown in Figure 3. Because distribution calculations ignore domain cut-offs, the mean values of the displayed normal distributions do not match the scores in Table 22. However, domain cut-offs are displayed as a transparent filling with a visible cut-off line.

When dividing participants' scores, the following statistics were obtained:

- 95% of participants were able to score six or higher on their strategic questions, implying that they correctly answered two out of three questions;
- 81% of participants were able to score six or higher on their practical questions, implying that they correctly answered two out of three questions with a visualization.
- 78% of participants were able to achieve a score of six or higher on the use of technical functions, indicating that they used at least six of the predefined technical criteria;
- 71% of participants were able to score six or higher on their visual criteria adherents, implying that they included at least six predefined visual criteria in their produced visualizations;
- 88% of participants were able to score four or higher on their effectiveness score, implying that 88% of participants passed the assignment according to the Dutch standard of >55%;
- 91% of participants were able to achieve a score of one or lower on their efficiency score, indicating that they could produce at least one visualization per hour.

As Weiler et al.'s (2019) research was conducted qualitatively, users' SSBI effectiveness has been underestimated and stagnant for years. This is due to a number of hurdles, such as users' uncertainty, their participation, over-complexity, and a lack of understanding of their intended strategy and expectations. Users assume that SSBI systems work like artificial intelligence command systems (e.g., Amazon Alexa) and expect almost flawless outputs. Certain environmental factors were additionally discussed as concluding factors, such as users' fear of automation, artificial intelligence, and system complexity. Likewise, if users do not participate in the decisions that lead to the SSBI application acquisition, users' uncertainty and willingness to participate in the BI processes is reduced. This can affecting the implementation's effectiveness.

Spahn et al. (2008) developed an ontological-based SSBI system and found that the more tailored the SSBI system to the users' area of expertise is (e.g., processes, categories, definitions, terms, visualizations, and models), the more effective users' SSBI system performance is. Therefore, this study's assignments and survey questions were built on generally understandable processes and familiar concepts, they were appropriately incorporated into the strategy and logic of this study, and the results described to participants. As expected, the influencing factors outlined in the literature were not measured and were consistent with the study of Sparks and Mccan (2015). As stated in the results chapter, the mean score in their study was similar to the mean found in this study. Similarly, in their research, they found a relatively high number of variations across sectors, which was comparable to this study's results.

The expert panel was given a statement to declare their user trust based on users' SSBI workability results: "New users have been to training, and their average grades are available to you. Their scores were: questions requiring visualization answers: 70/100; use of technical functions: 60/100; and data visualization methods: 75/100. Do these grades give you enough trust to allow users to work on internal BI processes?" Five experts answered "no," four "yes," and four "maybe." If the expertise equation was introduced, answer scores were "no" = 137, "yes" = 189, and "maybe" = 98. Therefore, experts' trust in users who use SSBI was either inconsequential or equivalent to slight confidence.

Consistent with all relevant research findings, it can be said that users can perform "simple" BI procedures when facing SSBI for the first time. There is an emphasis on "simple," as users mostly do well on relatively simple questions, and these questions make up the bulk of participants' scores. Therefore, users can be trusted with simple analytical tasks in SSBI software, and the BI manager should act as a supporter or an administrator when analysis requirements are particualrely challenging.

6.2 Information training, different environments, and user assistance change users' SSBI performance (H1b).

A classification analysis was conducted to determine whether training, environment, and user support affected participants' performance. In it, an experimental and a control group were identified along with participants' performance. All participant results were included because they all took part in either an experimental or control group.

Table 23: H1b classification

Ordinal data	Category	Class	Delta mean	Strength	*n*	St.dev	*t*	H_α *p*	H_0 *p*
Effectiveness score	Training	Yes	1.55	110.05	71	1.44	9.07	0.39	<0.01
Effectiveness score	Onsite	No	1.19	77.35	65	1.08	8.88	0.28	<0.01
Effectiveness score	Help	No	0.63	68.67	109	0.52	12.65	0.18	<0.01
Effectiveness score	Onsite	Yes	-0.49	69.58	142	0.60	9.73	0.23	<0.01
Effectiveness score	Help	Yes	-0.81	72.90	90	0.92	8.35	0.28	<0.01
Effectiveness score	Training	No	-0.87	111.36	128	0.98	10.04	0.36	<0.01
Total (*t*) or (absolute (*a*)) mean:			***a* = 0.92**	**84.99**	***t* = 199**	**0.92**	**9.79**	**0.29**	**<0.01**

The results of H1b's classification analysis are outlined in Table 22. All H_0 *p*-values were accepted, indicating that deviations were present. BI-related training significantly increased participants' performance, whereas onsite research and social support negatively affected participants' performance. However, the trained group had the highest standard deviation, and the lowest standard deviation was found in the help-requiring group. However, the group that did not require assistance had the highest *t*-value, indicating a significant deviation. In contrast, the H_α *p*-value gave the opposite result, as the trained group had a higher *p*-value than the environmental and social support groups. Since only one measurement was used and only three categories were included, if there was a bias, its impact was higher. However, various validity calculations were measured, which produced sufficient results.

Hung et al. (2016) identify both training and expert presence as net benefits in organizational BI processes in terms of user satisfaction and overall performance. In particular, an expert's presence produces substantial positive differences, whereas social environments are net losses because they introduce competitive barriers for users. Hence, although Hung et al.'s (2016) research refutes this study's results regarding experts' presence, it confirms its figures on training and social environments.

According to Williams and Williams (2003), organizations frequently design different training courses for their users to familiarize themselves with their newly obtained BI software. While this improves users' capabilities, in practice, training is often voluntary and leads to regular users forming a power user group, whereas casual users often renounce.

According to Popovič et al.'s (2010) case studies, organizations mainly focus on training activities for their users and managers to support any BI-related changes, thus neglecting process integrations, technical alignment, and additional support. However, training is not the only beneficial factor in SSBI implementations (Fogg, 2019). Therefore, competitive barriers can undermine user confidence, as users can question their capabilities, which increases their uncertainty.

Regarding the first hypothesis' the training, and social environment results, the expert panel was given three survey statements to request their views on them. The statement about training ("BI trained users performed better") included five responses: "totally disagree," "disagree," "neutral," "agree," and "totally agree." One expert remained neutral, eight agreed, and four totally agreed. When the expertise equation was added, "neutral" equaled 15, "agreed" equaled 172, and "totally agreed" equaled 231. Experts seemed to agree with this statement, and therefore, considered training to be advantageous. The second statement was, "Users perform better if they are in an environment with their colleagues," and it included the same five responses. One expert remained neutral, seven agreed, and five totally agreed. With the expertise equation, "neutral" = 5, "agreed" = 211, and "totally agreed" = 202. Experts thus think that social environments are an advantage for users, which contradicts research results. The third statement was, “Users perform better when a BI expert is present,” and it included the same five responses. One expert disagreed, four remained neutral, four agreed, and four totally agreed. When the expertise equation was introduced, “disagree” equaled 16, “neutral” 78, “agreed” 85, and “totally agreed” 243. As in the case of social environments, the expert panel agreed, in contrast to the classification results.

Based on research results, included literature, and the expert panel, training is a valid and reliable benefit for SSBI implementation success. It increases users’ knowledge and retains data integrity and satisfaction. However, the results on social environments and expert presence were not consistent due to differences in reliability sources, such as literature and expert opinions. More specific research on these factors is advised to determine any valid and reliable claims.

6.3 Users’ SSBI performance on functions differ (H2a).

Deciding on any outcome for the second hypothesis involved measuring performance differences in participants’ use of software functions and validity calculations. A classification analysis was used to carry out this research. Experimental and control groups were applied.

Table 24: H2a classification

Ordinal data	Category	Class	Delta mean	Strength	*n*	St.dev	t	H_α p	H_0 p
Effectiveness score	Etiquette	0	1.18	191.16	162	1.04	14.57	0.38	<0.01
Effectiveness score	Sorting	1	1.16	165.88	146	1.02	18.95	0.35	<0.01
Effectiveness score	Etiquette	-1	-1.40	123.20	88	1.54	8.53	0.41	<0.01
Effectiveness score	Undefined data	-1	-2.81	126.45	45	2.95	6.39	0.57	<0.01
Total (*t*) or (absolute (*a*)) mean:			***a* = 1.64**	**151.67**	***t* = 253**	**1.64**	**12.07**	**0.43**	**<0.01**

All H2a results had H_0 *p*-values less than 0.05, meaning that deviations existed. The analysis results (Table 23) indicate that participants’ etiquettes usage were the greatest determinant of SSBI quality produced by users. Both experimental and control groups were included in the highest positive and negative results. This indicates that software that created measurement labels for users, or users who created them, achieved higher quality in BI results. These findings also had high *t*-values. Users who could not define data or information either partly or fully in the visualization, scored much lower than the average user. Results on etiquette usage and sorting were relatively reliable and valid. The experimental and control groups had top positive and negative results, and gave sufficiently low standard deviations and high H_α *p*-values.

In agreement with Isaacs et al. (2014), Behrisch et al. (2018), and Law et al. (2021), measurement labels in the form of etiquettes contextualize data for users, thereby translating data into information for human interpretation. By effectively constructing these etiquettes, the retrieval of information from visualizations is improved. As reported by Raber et al. (2012), when these etiquettes are implemented, organizations should standardize their definitions and include them in the “master data” list. This research also recognized that etiquette usage is productive for information management. Furthermore, according to Landes et al. (2013) and Behrisch et al. (2018), sorting introduces another layer of potential pattern recognition, in which the retrieval of user information from visualizations is improved. When different sorting techniques change, certain hidden patterns may also be discovered. According to Raber et al. (2012), it is recommended to standardize effective sorting patterns with respect to relative business models, as these sorting patterns can be selected with an efficient method. Similar to this research’s results, the literature further confirmed the positive effects of sorting patterns. According to Çöltekin et al. (2007) and Cawthon and Vande Moere (2007), undefined data is generally the consequence of users not testing and verifying their processes’ results in the software or an excess of software-related frustration relating to their perceived available time. Raber et al. (2012) encourage organizations to frequently monitor and standardize their data quality processes to maximize potential information quality.

The expert panel was confronted with four statements to obtain their confirmation on this hypothesis. The first statement was about the effect of sorting: “Sorted tables or visualizations,” with an ordinal range of responses: “Only bad-performing users show this” (OB), “Predominantly bad-performing users show this” (B), “Occurs generally” (G), “Predominantly well-performing users show this” (W), and “Only well-performing users show this” (OW). Two experts chose G, 10 W, and one OW. If the expertise equation was included, G = 32, W = 154, and OW = 232. Therefore, experts seemed to agree on the positive effects of sorting. Regarding etiquette usage, they received the following condition: “Definition labels on metrics” with the same ordinal responses. Six G, three W, and four experts OW. With the expertise equation, G = 287, W = 47, and OW = 84. Experts therefore slightly agreed with this statement, although the majority remained neutral. In this research, undefined data was divided by missing dimensions or expressions. The expert panel was therefore asked two questions on the two different categories. Regarding dimensions, the expert panel was asked, “Dimensions used for which no information is displayed” with the same ordinal responses. Four chose OB, six B, two G, and one W. By introducing the expertise equation, OB = 72, B = 236, G = 40, and W = 60. Regarding expressions, the following outcome was presented to experts: “Expressions in which no information is displayed,” with the same responses. Two chose G, six B, and five OB. With the expertise equation, G = 72, B = 241, and OB = 105. Since the experts agreed on the negative effects of missing dimensions or expressions, experts predominately agreed with this statement.

Since all research-based propositions were approved by the literature and the expert panel, sorting by either the software or user and etiquette usage were determined positive effects on users’ SSBI performance. Undefined data was a verifiable negative effect on SSBI user performance. Hence, users who took these simple but information-enhancing aspects into account and tested their procedures frequently were well-suited for the SSBI concept.

6.4 Users perform differently in different SSBI applications (H2b).

The second hypothesis also implied performance differences in software applications used by participants. Compared to the previous hypotheses, value measurements were combined, and a similar classification analysis was performed. The results were associated with scientific literature, and guidance was requested from the expert panel.

Table 25: H2b classification

Ordinal data	Category	Class	Delta mean	Strength	*N*	St.dev	*t*	H_α *p*	H_0 *p*
Effectiveness score	Software	Tableau	1.28	88.32	69	1.18	9.01	0.32	<0.01
Practical score	Software	Tableau	0.52	29.64	57	0.42	9.35	0.10	<0.01
Practical score	Software	Qlik Sense	-0.68	38.76	57	0.78	6.58	0.19	<0.01
Effectiveness score	Software	Qlik Sense	-1.46	109.50	75	1.56	8.11	0.45	<0.01
Total (*t*) or (absolute (*a*)) mean:			***a* = 0.99**	**66.56**	***t* = 208**	**0.99**	**8.28**	**0.27**	**<0.01**

H_0 *p*-values less than 0.05 were found in all H2b results, indicating that deviations were present. The top and bottom results on software (displayed in Table 24) refer to effectiveness and practical data, as Tableau mainly had positive and Qlik Sense negative results. The highest disparities were found on both scores, despite the fact that the number of observations differed. As participants created visualizations with only one of the selected applications, lower numbers were similarly predictable. Furthermore, low standard deviation and H_α *p*-values resulted in Tableau's scores, while high standard deviation and H_α *p*-value resulted in Qlik Sense's effectiveness score. By using classification analysis, bias similarly stated in other hypotheses were present. However, since sufficient strength, standard deviation, and H_α *p*-value were established and adverse measurements among the experimental and control groups were present, this classification was valid and reliable.

As scientific research on software comparisons are generally performed and presented in web articles, bachelor theses, and online reviews. Specified scientific work based on performance differences in SSBI software is thus limited. Therefore, sources that can be perceived less scientific are provided. Since this research concerns inexperienced users, Tableau was expected to perform better (Dataflair, n.d.; Cynixit, 2020; Alberts, 2017). However, since Qlik Sense is based on the discovery of relatively integrable and combinable data, it lacks in visualization generation. Users need more experience to create visualizations and dashboards effectively due to a large code necessity. Furthermore, according to TrustRadius , there are user reviews for each selected SSBI application: Qlik Sense = 7.9/10 ($n = 692$), Microsoft PowerBI = 8.2/10 ($n = 750$), and Tableau = 8.2/10 ($n = 1644$). These review ratings originate from all kinds of users, such as casual users, power users, BI managers, and enthusiasts.

Gartner's (2020) research and reviews, Harms' (2018) work, and Amara et al.'s (2012) study contain analytical features, software performance, visualization features, data formatting features, data warehousing, code necessity, costs, filtering and sorting features that can be obtained and classified. Based on the researched participants using these features, weighing factors were introduced and the scores combined (available in Appendix O). In this analysis, Tableau was considered to be more compatible for inexperienced users, and Qlik Sense and Microsoft PowerBI were similar and just below Tableau.

The expert panel was presented with a visualization in which the following results of all SSBI applications were presented: Tableau = 1.25, Microsoft PowerBI = 0.30, and Qlik Sense = -1.45. Experts were asked the following question: "Do you agree with this result?" with possible answers being "Yes," "No," and "Maybe." Four experts chose "Yes," six "No," and three "Maybe." By including the expertise equation, "Yes" = 104, "No" = 283, and "Maybe" = 31. Experts were asked to answer a follow-up question: "Which of the three selected self-service business intelligence applications do you prefer?" with possible answers being "Microsoft PowerBI," "Tableau," and "Qlik Sense." Seven experts chose "Microsoft PowerBI," five "Tableau," and one "Qlik Sense." With the expertise equation, "Microsoft PowerBI" = 151, "Tableau" = 219, and "Qlik Sense" = 48. However, their objectivity may be debatable, as favorites may have been based on their predominant experience. Conflicting results were therefore also present in the expertise equation because results were not agreed upon. The popular SSBI application was Tableau; therefore, results were unconventional.

As related literature and reviews were consistent with research findings, it follows that Tableau performed best. Likewise, Qlik Sense performed worst out of the three selected applications for inexperienced users.

6.5 Users' technical and visual capabilities affect users' performance (H2c).

Users' technical and visual scores from their assignments can be associated with other ordinal data scales. The methods were performed to match efficiency, practical, technical, and visual-performance scores.

Table 26: H2c correlation

***X*-scale**	***Y*-scale**	**Correlation**	**Strength**	***N***	**Standard deviation**	**Slope**
Effectiveness	Technological	0.60	232.80	388	1.32	1.57
Effectiveness	Visual	0.59	228.92	388	0.95	1.82
Practical	Technological	0.18	37.44	208	1.32	-0.01
Practical	Visual	0.24	50.64	211	0.95	0.67
(Absolute (*a*)) mean:		***a* = 0.40**	**137.45**	**298.75**	**1.14**	**1.01**

Among effectiveness score effects, the highest correlation was identified as technological score, as shown in Table 25. Both measurements had high slopes, high strength values, high cardinality, achieving greater validity. Correlation between practical scores was lower, as both the technical and visual scores were part of the effectiveness score, which was anticipated. The practical score's greatest correlation was with the visual score, although both practical score's strength and cardinality number were relatively lower.

According to Behrisch et al. (2018), Law et al. (2021), Landes et al. (2013), and Peters et al. (2016), data visualization provides more functionality for organizations by improving pattern finding and human understandability. However, proper data visualization is introduced through made changes to the visualization properties by the user or indicated by the software's default processes (Isaacs et al., 2014). As reported by Elbashir et al. (2008) and Adebambo et al. (2011), data visualization helps users' overall processes, as data can be understood faster and miscommunication decreases. For enterprise knowledge management, timing is also important, and since accurate visualization in traditional BI is time-consuming, SSBI potentially presents faster results. Hence, rapid information production has to be abstract, quantitative, structured, atomic, and comprehensible to solve organizational problems (Dudycz, 2010; Cawthon & Vande Moere, 2007; Zheng, 2017). BI thus tends to focus on analytical processes to generate relevant trends and expectations and becomes a critical user skill. In accordance with the literature, it is thus expected that users' technological and visual performance are associated with effective and practical BI performance.

The Jaccard Index was used to further verify found correlations between the effectiveness, practical, technical, and visual scores. Fractions were created by dividing all scores into upper mean and lower mean groups. For example, high values in set A are compared with high values in set B, high values in set A are compared with low values in set B, low values in set A are compared with high values in set B, and low values in set A are compared with low values in set B. If there is a valid correlation, high-versus-high and low-versus-low comparisons will return a relatively high number. If a invalid correlation occurs, high-versus-low and low-versus-high comparisons will return a low number. All related performance scores were applied to this calculation method, and the results are in Appendix P.1. Since both the technical and visual scores are part of the effectiveness score, the correlations were confirmed to be valid, as all sets resulted as expected. However, the correlation on the practical score was more controversial because the correlation between the practical and the technical score was "FALSE." Only the highest values were properly correlated with the practical score, and results on visual score were "PARTIAL" because the lowest values did not correlate sufficiently.

Therefore, it can be claimed that users' technical and visual abilities both contribute to overall user performance. Although users' visual abilities were related to their practical abilities, the correlation between practical and technical scores was verified to be invalid. This was especially the case when users performed well. Further research into the potential correspondence between users' practical and technical BI capabilities is recommended to identify any potential relationships.

6.6 Users' SSBI performance change due to different educational courses, work experiences, and hobbies (H3a).

Users' personal backgrounds can be different, which can affect their BI performance. Although these differences can occur on many levels, classification was done by hobby names, hobby categories, work experiences, and educational courses to simplify results. This hypothesis' results were specific to individuals, training, and knowledge requirements. This may be relevant to SSBI implementation, as their differences change their effectiveness or efficiency. Highest and lowest resulting classifications were assessed against literature statements and expert panel questions to increase result validity.

Table 27: H3a classification

Ordinal data	Category	Class	Delta mean	Strength	*n*	St.dev	*t*	H_α *p*	H_0 *p*
Effectiveness score	Educational course	Business	1.98	108.90	55	1.91	7.69	0.54	<0.01
Effectiveness score	Work experience	Computer science	1.37	69.87	51	1.30	7.53	0.36	<0.01
Practical score	Work experience	Computer science	1.36	65.28	48	1.29	7.30	0.35	<0.01
Practical score	Hobby name	Running	-2.11	44.31	21	2.18	4.44	0.39	<0.01
Effectiveness score	Hobby category	Outdoor, non-competitive sports	-1.44	59.04	41	1.51	6.11	0.37	<0.01
Effectiveness score	Hobby name	Running	-2.84	68.16	24	2.91	4.78	0.55	<0.01
Total (*t*) or (absolute (*a*)) mean:			***a* = 1.85**	**69.36**	***t* = 388**	**1.85**	**6.31**	**0.43**	**<0.01**

All H3a results had H_0 p-values less than 0.05, indicating that deviations were present. Calculations largely emanated from effectiveness and practical scores, as they gave the highest results, as demonstrated in Table 26. According to research results, users with a background in business or computer science obtained favorable scores; in particular, business education made a profound difference. Conversely, non-competitive sports produced unfavorable results, especially among participants indicating running as their hobby. The greatest measurement strength and cardinality values were linked to business education. In contrast, the running hobby gave the weakest result on the practical score. High standard deviation and H_α p-values were in the running hobby, and lower standard deviation and H_α p-values were in the IT work experience.

Gottesman and Morey (2015) argue that there is no evidence that financial performance is affected by educational level. They also claim that managers' education affiliations affect organizations' development. For example, when managers have completed a technology educational course, the likelihood of the organization being technologically developed is higher. It was further determined that managers with a background in technology make wider use of theoretical models and course-related technologies. Since technological experience enhances development, high classification in computer work experience was expected. Job performance, perception, and satisfaction are also broadened when a significant amount of related experience is present (Quiñones et al., 1995).

In this study, almost all sports categories scored below average. According to Beek (2014), sportive individuals tend to focus on other types of learning than those required in SSBI software. Hence, sportive individuals adapt better to the opposite appropriate learning method required for BI performance. In Davenport's (2014) report, sports analysis is a heavily invested, albeit relatively slow, process. This is due to a lack of direct involvement, inadequate data collection, and localized organization. Lack of involvement can stem from a sportive individual's thinking, learning, and experiencing. Sportive individuals can therefore perceive experience existence different from what BI processes' require thinking patterns to necessitate (McCarthy, 1980).

As with previous hypotheses, the expert panel was asked to confirm the hypothesis results. Two related statements were presented; the first was, "Users with a business and computer science background perform better," with possible answers being "totally disagree," "disagree," "neutral," "agree," and "totally agree." Five experts remained neutral, two agreed, and six totally agreed. With the expertise equation, "neutral" = 187, "agree" = 36, and "totally agree" = 195. Experts thus agreed with this statement, but most remained neutral. Concerning the sports categories, the panel was presented the following statement: "Users with a sportive background perform worse," with the same possible answers. Four experts totally disagreed, one disagreed, six remained neutral, and one agreed. With the expertise equation, "totally disagree" = 107, "disagree" = 5, "neutral" = 258, and "agree" = 48. Compared to the previous question, experts also remained largely neutral on this statement. However, they more discreetly disagreed with this statement with the expert equation.

Since the literature and the expert panel largely agreed that business education and computer science backgrounds have a positive effect on SSBI performance, this hypothesis included plausible measurement results. Hence, it can be argued that these backgrounds positively affect SSBI implementations. Although scientific literature implies that sportive individuals are less likely to perform on BI processes, the validity of measurements is questionable due to low H_α p-values, relative low t-values, low strength, and high standard deviation. Furthermore, the expert panel did not believe that this hypothesis was valid.

6.7 Users' educational level improves SSBI performance (H3b).

Users' education level may imply that there are some BI-related qualities not found in lesser-educated users. Any results from this hypothesis' may narrow user selection, training, or knowledge acquisition on SSBI application usage or additional data analytics. The resulting correlation's strength and validity measurements were used to determine its legitimacy.

Table 28: H3b correlation

***X*-scale**	***Y*-scale**	**Correlation**	**Strength**	***n***	**Standard deviation**	**Slope**
Effectiveness	Educational level	0.23	89.24	388	3.32	0.36
Strategic	Educational level	0.15	27.90	186	1.39	0.31
(Absolute (*a*)) mean:		***a* = 0.19**	**58.57**	**287**	**2.36**	**0.34**

Although more education-related correlations have been established, most were too weak to determine sufficiently valid correlations. Although the correlation with the strategic score was only 15% and contained a low strength value, this correlation consisted of a relatively low standard deviation (Table 27). Consequently, both correlations had validity issues, although the correlation on the effectiveness score was stronger.

Correlations were further scrutinized with the Jaccard index to increase validity. It was necessary to define the averages for the strategic and effectiveness scores, and participants' education level. Strategic and effectiveness averages were characterized in H1a. However, the average education level had to be enumerated to describe an average. Therefore, "MBO/vocational" or lower level = 1, "Associate degree/Bachelor/HBO" = 2, and "Master/WO" level or higher = 3. By forming the average educational level, participants' average educational level was defined as 1.94, which was slightly below "Associate/Bachelor/HBO." For each correlation, high and low groups were defined using the same structure in H2c. These groups were applied to the Jaccard index calculations, and obtained calculations are available in Appendix P.2. Resulting figures show that the correlation between the education level and the effectiveness score has validity problems. The low and high group's effectiveness score yielded high results, contradicting a valid correlation. However, this problem only occurred in one of the four defined quartiles. Correlation between the educational level and the strategic score was thoroughly high because both quartile correlations with high versus high and low versus low reached 50%. Contrasting quartiles were determined below 10%. Therefore, the correlation between the strategic and educational levels was considered strong, whereas the correlation between effectiveness and education level was only partly correlated.

As stated in hypothesis part H3a, Gottesman and Morey (2010) found no evidence that educational level affects organizational financial performance. However, they claim that it affects organizations' development trajectory. Since higher education courses generally includes more required analytical-oriented courses, higher-educated individuals possess more analytical knowledge than others (Tsai et al., 2017; Sclater et al., 2016; Nguyen et al., 2020). Hence, those with higher education have an advantage when faced with analytical scenarios. Daniel (2014) also suggests that the use of highly qualified analytical procedures positively affects strategic management as well. It can contextualize and simplify the competitive environment. Furthermore, Kollom et al. (2021) argue that perceptual differences between organizations, cultures, individuals, and processes exist in applying analysis. Consequently, an organizational strategy and policy formulation is needed regardless of educational level. Hence, the literature is in favor of higher education to enhance strategic and analytical performance. While educational level correlates with the effectiveness and strategic scores, it does not correlate sufficiently with the practical scale, having a quadratic ∪-type relationship.

The expert panel was presented a statement on the strategic correlation. Only one question was chosen because describing the effectiveness score required more time and the strategic score was also part of the effectiveness score. The statement was, "Higher educated users discover suited metrics for success factors faster," with possible answers being "totally disagree," "disagree," "neutral," "agree," and "totally agree." Three experts disagreed, four remained neutral, four agreed, and two totally agreed. With the expertise equation, "disagreed" = 52, "neutral" = 76, "agreed" = 258, and "totally agreed" = 32. Hence, the expert panel agreed with this proposition, although not unanimously.

Considering the correlation between the effectiveness score and educational level having relatively acceptable validity measurements, its validity on the Jaccard index was more ambiguous. However, the correlation was still accepted, as relevant evidence confirmed this claim. Regarding the correlation between the strategy score and educational level, while the correlation coefficients and strength values were low, other validity calculations were sufficient, the Jaccard index validity was strong, the literature supported it, and the expert panel did so too.

6.8 Research question classification (RQa)

The research question included classifications in which the effectiveness, strategic, practical, technical, visual, efficiency, and visualization cardinality performance scores and ordinal data scales were compared with participant properties, software applications, software applications' functions, assignment questions, and participant perceptions. Since similar calculations were produced when discussing the hypotheses, comparable conclusions may follow, as some categories may outperform others. As some results were added later, the expert panel questions did not include questions for each measured inequality. Thus, the blog text-analysis on the subject's sentiment and urgency was carried out to improve the inequality's validity and reliability.

Table 29: RQ classification

Ordinal data	Category	Class	Delta mean	Strength	*n*	St.dev	*t*	H_α *p*	H_0 *p*
Effectiveness	Etiquette	0	1.18	191.16	162	1.10	13.65	0.52	<0.01
Effectiveness	Sorting	1	1.16	165.88	143	1.08	12.84	0.48	<0.01
Effectiveness	Dimension	1	0.66	126.06	191	0.58	15.73	0.30	<0.01
Effectiveness	Scrolling	0	0.65	122.20	188	0.57	15.64	0.29	<0.01
Effectiveness	Undefined data	0	0.60	120.00	200	0.52	16.32	0.27	<0.01
Effectiveness	Relation	1	1.11	118.77	107	1.03	11.15	0.40	<0.01
Effectiveness	Method	0	0.56	111.44	199	0.48	16.46	0.25	<0.01
Effectiveness	Training	Yes	1.55	110.05	71	1.47	8.89	0.46	<0.01
Effectiveness	Education category	Business	1.98	108.90	55	1.90	7.73	0.53	<0.01
Effectiveness	Label orientation	0	0.52	103.48	199	0.44	16.67	0.23	<0.01
Effectiveness	Software	Qlik Sense	-1.46	109.50	75	1.54	8.21	0.50	<0.01
Effectiveness	Training	No	-0.87	111.36	128	0.95	10.36	0.40	<0.01
Effectiveness	Etiquette	-1	-1.40	123.20	88	1.48	8.87	0.51	<0.01
Effectiveness	Undefined data	-1	-2.81	126.45	45	2.89	6.52	0.72	<0.01
Total (*t*) or (absolute (*a*)) mean:			***a* = 1.18**	**124.89**	***t* = 245**	**1.18**	**12.07**	**0.42**	**<0.01**

H_0 *p*-values less than 0.05 were found in all RQ classification results, indicating that deviations were present. All top measurements were determined on the effectiveness score because they yielded the largest strength numbers, as shown in Table 28. Since all participant visualizations were either part of an experimental or control group in technical or visual categories, these categories dominated calculations' strength values. Only three additional categories were present, such as "education category," "training," and "software." Furthermore, the resulting differences and standard deviations on negative classifications were higher than the positive classifications, and their strength was lower. Apart from "scrolling," "relation," "method," and "label orientation," which were discussed in this research question section, "Etiquette," "sorting," "dimension," and "undefined data" were analyzed in H2a, "software" in H2b, "training" in H1b, and "education category" in H3a.

According to Landes et al. (2013) and Isaacs et al. (2014), scrolling is one of the factors that hinders users' information retrieval because users focus on instant individual views when checking information. According to Chung (2009) and Behrisch et al. (2018), scrolling features are frequently used in application views because large amounts of information can be easily represented in short spaces. It encompasses an easy solution without considering the information quality on behalf of their users (Vlamis & Vlamis, 2011). Hence, the literature agreed with the idea that both SSBI users and BI managers should refrain from scrolling features.

According to Isaacs et al. (2014), data structures are often used to diagnose problems in reports, tables, visualizations, and dashboards. Data structures often include large amounts of data that can complicate organizations' information provision. However, these structures also allow managers to make decisions based on larger amounts of available data (Platts & Tan, 2004). These complex big-data structures are often centralized in the organization, allowing a single data source to be used by different applications, which saves time and money (Watson & Wixom, 2007; Peters et al., 2016). As reported by Law et al. (2021), users' overall data understanding and its possible structural relationships are recognized as insufficient. However, BI and data warehousing have been perfected in organizations, improving users' data apprehension (Watson & Wixom, 2007). With SSBI adoption, users are allowed to experiment with data combinations and thus develop organizations' ability to use information (Behrisch et al., 2018). If data structures are centralized, these structures are useful for information management. When SSBI is introduced, it is recommended to create a semantic layer to keep data centralized. However, users' data understanding can make it difficult for them to engage in this centralization. The literature related to centralization is therefore inconsequential, as users' data knowledge is generally lacking, although it has improved over time.

Using the right visualization method is often achieved by presenting the most information in its simplest form. This achieves the most effective human interpretation of the intended message because simplicity makes information more memorable (Behrisch et al., 2018; Kumar & Belwal, 2017). To a certain extent, visual styles determine what information is conveyed and influence decisions based on this portrayed information. This occurs as all visual types hide some data (Platts & Tan, 2004; Cawthon & Vande Moere, 2007). In contrast, viewers often try to find patterns they want to see, implying a visual confirmation bias. Furthermore, according to Isaacs et al. (2014), in SSBI, visualization methods are often indicted by the selected data type. As long as certain visual methods are consistently maintained, the possible beneficial information can be suppressed. Hence, literature encourages the exploitation of many suitable visualization methods. Althrough simple, distinctive, and viewer-adjusted methods increase the effectiveness and efficiency of information communication.

Label orientation is similar to etiquettes. Etiquettes define measurements, whereas labels identify the categories in which these measurements are presented. Since label orientation determines their full visibility, when these labels are hidden, the user is prevented from completely contextualizing their viewed information. According to Law et al. (2021), contextualized visual elements increase users' understanding of the intended message. Data specifications are needed to improve visualizations' communicative aspects, which, according to Behrisch et al. (2018), is often overlooked. According to the mentioned papers, label orientation should be such that the complete description can always be viewed to enhance visualizations' effectiveness.

Furthermore, a statement about scrolling was posed to the expert panel. Statements on the researched aspects were not all included for the expert panel, as the results for "relation," "method," and "label orientation" were added later. Therefore, urgency and sentiment analysis is included and explained in more detail in the following paragraph. The statement about scrolling was, "dashboards or visualizations in which scrolling is necessary," with possible answers being "only bad-performing users show this" (OB), "predominantly bad-performing users show this" (B), "occurs generally" (G), "predominantly well-performing users show this" (W), and "only well-performing users show this" (OW). One expert chose OB, seven B, three experts G, and two OW. With the expertise equation, OB = 12, B = 315, G = 62, and OW = 29. Thus, the expert panel accepted the proposition that scrolling features occur among lower-performing users.

Regarding "relation," "method," and "label orientation," sensitivity and urgency analysis was performed on online blog posts (PowerBI, Tableau, and Qlik communities) concerning related topics. These analyses examined language elements that can affect sentiment (e.g., "good," "worked," "not," or "problem") or urgency (e.g., "time," "need," or "!") and calculated the percentage between negative and positive indicators (supported by MonkeyLearn). Through this technique, online communities' problem-solving abilities and the potential frustrations that blogs with affiliation to research results may involve could be grasped. Inexperienced users may face similar issues. By combining online sentiment and urgency, this mechanism mimicked or simulated expert opinions. This research thus gained general BI expert judgments on these researched categories that could have been included in the expert survey.

The selected blogs had 24 topics referring to relational diagrams and data warehousing where 159 users had posted comments. Overall sentiment turned out to be positive, as it scored below average ($s = 0.684 < 0.748$), and urgency also reached positivity, as it scored below average ($u = 0.479 < 0.576$). BI developers were positive about data warehousing and relational diagramming, and emerging issues were less urgent for the selected SSBI applications. Therefore, it can be argued that online experts tended to be positive on the “relation” category. For “method,” 30 blog topics were acquired that referred to visualization method techniques, and 173 users had commented. The overall sentiment was neutral, as it was almost equal to the average ($s = 0.747 \approx 0.748$), and urgency was negative, as it scored above average ($u = 0.638 > 0.576$). Therefore, problems included a corresponding sentiment and higher frustration, which was not consistent with research findings. Furthermore, with regard to “label orientation,” 29 topics related to *x* and *y* axes labels were found, in which 115 users had commented. Text-analysis disclosed negative sentiment, as it scored above average ($s = 0.814 > 0.748$), and, likewise, a negative urgency was identified, as it scored above average ($u = 0.610 > 0.576$). Therefore, online experts concluded that “label orientation” was similarly negative, contradicting research findings.

Concerning the “scrolling” claim, the literature confirmed, the expert panel agreed, and its validity measurements were acceptable. The “relation” claim had high acceptability on its validity measurements and blog text analysis. However, the literature did not directly suggest that users’ interference in data structure developments was favorable. Although acceptability was still debated, this conclusion was still accepted, as, in total, results were favorable. Likewise, for the “method” claim, acceptance issues existed in the blog text analysis, as the blog text analysis resulted slightly negative. However, this claim was also accepted, as an overall consensus was reached. It can be concluded that scrolling by users or indiction by software negatively affects users’ results and can hinder SSBI implementation success. The “label orientation” results did well in validity measurements, and the literature was relatively neutral on this claim. However, the results following blogs’ text analysis were unacceptably low: hence, this claim was refuted.

6.9 Research question correlation (RQb)

The research question was also measureable by correlation methods, and only the highest correlations were selected. High correlations implied what abilities, perceptions, or participant characteristics determine SSBI performance and increase SSBI implementation success. When a correlation from an effectiveness or efficiency component was associated with its parent, these components were considered as strong influence. These influences were either on effectiveness or efficiency scores.

Table 30: RQ correlation

***X*-scale**	***Y*-scale**	**Correlation**	**Strength**	***n***	**Standard deviation**	**Slope**
Effectiveness	Practical	0.72	279.36	388	3.32	1.15
Effectiveness	Technological	0.60	232.80	388	1.32	1.57
Effectiveness	Visual	0.59	228.80	388	0.95	1.82
Effectiveness	Strategic	0.54	209.52	388	1.39	0.96
Effectiveness	Participants’ grades on own capabilities	0.47	182.36	388	1.73	0.38
(Absolute (*a*)) mean:		***a* = 0.60**	**230.83**	**388**	**1.83**	**1.23**

Like other research question calculations and hypotheses, all included ordinal data scales affected the effectiveness score, as shown in Table 29. The four components of the effectiveness score were all included, as expected. As a result, it can be seen which component contributed the most to users’ SSBI effectiveness. Users’ ability to conceptualize questions based on available data (practical score) was the most influential skill. However, users’ metrics’ development on competitive advantages (strategic score) was the least influential. The use of technical functions (technical score) and following data visualization principles (visual score) obtained similar scores and fell between the practical and strategic scores. All effectiveness components also obtained a relatively high slope. The practical score had a high standard deviation, while the visual score had the lowest. Furthermore, an additional calculation was deemed sufficiently strong to be included. This was the grade given by participants to their own perceived BI capabilities in relation to their effectiveness score. For this reason, when users claimed a BI skill, they were usually truthful. Compared to other correlations in Table 29, this result obtained the lowest score. However, relative to all possible correlations, it was approximately high. The correlations between the effectiveness score and the technological and visual scores were discussed in H2c. This subchapter focuses on the correlations between effectiveness, strategic, and practical scores.

According to Sharma and Djiaw (2011) and Çöltekin et al. (2010), while BI can, in part, measure the effectiveness and efficiency of business processes, it also involves processes themselves. Hence, BI can enhance users' understanding of their organization's processes, inputs, and outputs and can eliminate users' uncertainty (Platts & Tan, 2004). Therefore, it is often structured around Porter's (1985) value chain. Since nearly all BI-related users are at least familiar with reporting, generated results from BI are usually recognizable by users (Cawthon & Vande Moere, 2007). As SSBI can allow users to produce more familiar BI results faster, it will surely improve users' software satisfaction. If properly advised, users often know their capabilities (Peters et al., 2016; Behrisch et al., 2018). Therefore, when users are familiar with their organization's and BI's processes, they will perform effectively in SSBI applications.

Furthermore, BI is primarily designed to assist decision-makers, who are often found in managerial positions. Involved decisions can often be highly serious, as they determine the success or failure of an organization. Hence, a large amount of data can create some certainty when considering a decision's situations. Moreover, BI can monitor the impact of any made decision by organizations' performance figures (Kumar & Belwal, 2017). Therefore, it is indirectly linked to organizational strategic performance. However, according to Elbashir et al. (2008), BI's use in organizational strategy and its impact varies. Organizations tend to focus more on internal processes because data is easier to obtain, and a manager's influence is more direct. Conversely, BI can be used to define customer and supplier processes. Therefore, a strategy is partly influenced by BI usage because the insights that BI can generate lead to more effective and efficient decision-making if used regularly.

Naive users are more likely to focus on personal rather than topical relevance when using analytical software (Çöltekin et al., 2010). Perceived benefit, overconfidence, and experience influence BI usage in different ways (Kulkarni et al., 2006). Although not in a strong way, users' age is correlated to BI performance as well because younger users are more technology and methodically oriented. Younger were likewise expected to have higher confidence in their abilities (Birkinshaw et al., 2019). Influencing perceptions may be alleviated by expertise and competitive barriers. BI knowledge leads to critical insights into analytical results, and competitive barriers can lead users to over- or underestimate their capabilities (Law et al., 2021). BI effectiveness can thus be linked to perceptions. However, they may have several origins, such as, the perception of competitive barriers in their social environment and users' estimation of their own abilities. This can emerge from their experience, or lack of it.

The Jaccard index was used to determine correlations' reliability. Averages needed to be defined for each ordinal data scale, and included averages were given in the results chapter. Calculations are available in Appendix P.3. The correlation between the practical and effectiveness scores was considered reliable because both high and low groups reached comparably higher values than other correlations, resulting in "TRUE." However, effectiveness score's correlations between the strategic and participant grades on their own abilities resulted in "PARTIAL" and "FALSE". This is because in both correlations only the upper quartiles correlated. Peculiarities were present in the correlation between the effectiveness and strategy scores, and therefore this correlation's reliability was refuted.

As for the correlation between the effectiveness and practical scores, the resulting Jaccard index confirmed this correlation in all quartiles, the literature generally agreed, and validity measurements were comparably acceptable, this correlation was accepted. However, this result is valid for users that are familiar with software and organization's processes. While the correlation between effectiveness and the strategic score led to false reliability in the Jaccard index, this correlation was still accepted. Acceptance was determined, as the literature clearly agreed and validity measurements were favorable. Although the literature suggested that numerous perceptual factors affected participants' confidence, it was determined that the correlation between the effectiveness and participants' grade on their own BI capabilities was insupportable. Validity measurements revealed complications and the Jaccard index implied unreliability in some quarters.

6.10 Research question quadratic relations (RQc)

Quadratic relationships characterize ∪- and ∩-type relations, which imply that the median range do not fit the highs and lows of the measurement. Specific abilities, perceptions, or participant properties that involved this trend can complicate any practical implication. They would tend to drift from traditional correlations, suggesting a balance or an extreme.

Table 31: RQ quadratic relations

***X*-scale**	***Y*-scale**	**Type**	**Trend difference**	***n***	**Strength**
Visual	Age	∩	0.22	208	195.41
Effectiveness	CSF	∪	0.12	388	187.12
Strategic	Practical	∪	0.14	208	147.31
Strategic	Age	∩	0.26	186	127.83
Effectiveness	Participant grade on own BI abilities	∪	0.09	388	101.85
	Mean:		**0.17**	**275.60**	**151.90**

Quadratic relationships largely emerged across age, effectiveness, and strategic parts, as can be seen in Table 30. These correlations were present between visual and strategic scores. The correlation between age and the strategic score included the lowest cardinality, as results were collected from strategic tasks. Correlation between the effectiveness score and participants' grade on their own abilities implied that a Dunning-Kruger effect was measured in this research. Users have substantial trust in their abilities were either an expert or too oblivious to their knowledge or experience.

With improved healthcare and more educated young individuals, organizations are becoming increasingly diverse by age (Birkinshaw et al., 2019; Grigorenko & Sternberg, 2000). Younger individuals tend to be more methodical and technically focused and have higher self-efficacy levels. An organization's technical and visual abilities are, in part, determined by the ability to keep up with technical changes. As seniors often run organizational management due to their experience, these adjustments are often experienced with difficulty (Kulkarni et al., 2006). Furthermore, younger individuals are more reflective and can thereby rely more on visual learning. Older individuals rely more on their accumulated experience and holistic perspectives (Lindenberger & Baltes, 1994). Hence, younger and older individuals both have advantages and disadvantages when visual performance is essential.

According to Peters et al. (2016), BI performance is indirectly linked to strategic performance. Organizations can apply BI to make their decisions more effective. However, Elbashir et al. (2011) state that an organization's strategic performance is primarily fixed on internal procedures because this data is easier to obtain. However, a strategy can be divided into several facets, such as customer, supplier, and competitor orientations. Likewise, the market in which organizations operate is subjected to changes with which organizations must comply, and data can increase their speed in implementing them them (Guarda et al., 2013; Platts & Tan, 2004). BI usage can also introduce other barriers within organizations, such as colleague competition, tampering with any competitive advantage, and knowledge sharing. Therefore, organizations' users should trust each other, and organizations' loyalty and perceived loyalty can reform this trust (Issa & Haddad, 2007).

The BI concept is generally developed to assess performance and monitor activity within companies (Negash & Gray, 2008). However, strategy is a broad concept, and the visualization concept is relatively narrow. Therefore, BI is expected to be widely applicable in these areas. Since BI processes are indirectly associated with strategic performance, it is expected that users learning with uncertainty will achieve better BI results. Therefore, this relationship may be attributable to the measured Dunning-Kruger effect, in which experience also improves practical and strategic performances (Çöltekin et al., 2010; North, 2006). However, in both strategic and practical performance, confirmation bias is possible, and this likely occurs when relatively poor performance in both categories is noted. Therefore, due to the imaginable Dunning-Kruger effects and confirmation bias, this fluctuating pattern is something to be expected.

Furthermore, strategic decisions in organizations are traditionally determined by leaders or seniors. As a result, strategic dilemmas are often resolved with a top-down approach. A functional and analytical culture is therefore orchestrated by organizations' strategic top; the implementation of analytical software itself does not change organizations' culture (Law et al., 2021; Durand & Coeurderoy, 2001). According to Platts & Tan (2004) and Elbashir et al. (2011), organizations have traditionally focused their strategy on internal processes, while a more comprehensive strategic framework is needed for sustainable growth. This type of framework must make quick decisions and implement technological changes promptly, in which younger individuals tend to perform better. However, complications can arise because methodical strategy depends on IT and the work environment. These dependencies diversify as the number of innovations increases and the workplace evolves more and more heterogeneously.

A multitude of biases is possible with analytical dilemmas. Confirmation bias, overconfidence, and the Dunning-Kruger effect have implications when expertise is needed (Coutinho et al., 2020; Gibbs et al., 2017; Dunning, 2011). As reported by Aggarwal et al. (2015) and Gibbs et al. (2016), the Dunning-Kruger effect has been measured in several facets of computer science, and this effect is likely to be present in this research. According to Çöltekin et al. (2010), naive users examine new systems to help themselves personally rather than exploring them with thematic relevance, partly because of the Dunning-Kruger effect. When users are trained, they gain more knowledge on related topics and become increasingly critical and experienced. Since a ∪-type relationship has been established between effectiveness score and participants' grade on their own BI abilities, the Dunning-Kruger effect is implicitly identified in this research.

Equivalent to other correlation-based research questions and hypotheses' propositions, the Jaccard index was used to determine the correlation's validity and reliability. Since previous Jaccard usages included conventional correlations, a more specific approach was used to evaluate the ∪- and ∩-type correlations. For instance, the high values in set A and set B are correlated, the high values in set A and the low values in set B are not correlated, the low values in set A and the high values of set B are correlated, and the low values of set A and set B are not correlated. Adequate quadratic relationships were established between visual performance and age, effectiveness and CSF scores, and the effectiveness score and participants' grades on their own BI abilities (TRUE). However, correlations between strategic score and participants' grades on their own BI abilities were found to be insufficiently correlated (FALSE). This was because associated groups resulted as almost equal. Correlation between strategic and practical scores was partly significant because only one group resulted as deficient (PARTIAL).

Since validity measurements, associated literature, and the Jaccard index correlations returned favorably, the quadratic relationship between the visual score and age was confirmed. This was also the case for the quadratic relationship between the effectiveness score and participants' grade on their own BI abilities. These results were acceptable and the claim was confirmed, implying a proven Dunning-Kruger effect. As literature suggested that many possible causes determined the quadratic relationship between the effectiveness and CSF scores, this quadratic relationship remained accepted. This was accepted, as sufficient validity and an appropriate Jaccard index pattern was present. The quadratic relationship between the strategic score and participants' age was assessed as insignificant. Its validity measurement and literature evaluation were considered satisfactory, although its Jaccard index pattern did not achieve significance; hence, this claim was disputed.

In this chapter, all propositions have been evaluated and scrutinized for their validity and reliability. Twenty claims were accepted, one was determined contextually, and eight were deemed insignificant. All claims are further discussed and summarized in the conclusion chapter.

7. Conclusion

7.1 Answering propositions

This chapter summarizes the findings illustrated in the discussion chapter, answers the research question and hypotheses, analyzes the research's overall validity and reliability, examines the research's bias and limitations, and provides research recommendations. As the discussion chapter debated the researched claims' validity and reliability on multiple lines, these results were summarized and answered based on the discussion's evidence. Therefore, the discussion's parts are presented in Table 31 and show each accepted, inconsequential, and contextual conclusion.

Table 32: Proposition parts

Proposition	#	Accepted	Inconsequential	Contextual
Hypothesis 1	H1a			All performance data
	H1b	Training	Expert presence, environment with colleagues or expert	
Hypothesis 2	H2a	Etiquette, sorting, undefined data		
	H2b	Tableau, Qlik Sense		
	H2c	Technical and visual abilities	Practical abilities	
Hypothesis 3	H3a	Business and computer science backgrounds	Sportive backgrounds	
	H3b	Effectivity, strategic abilities in education		
Research question	RQa	Scrolling, relational structures, visualization methods	Label orientation	
	RQb	Practical, strategic	Participant grade on own capabilities	
	RQc	(Visual-age), (effectivity-grade own capabilities), (effectivity-CSF)	(strategic-age), (strategic-practical)	

- **Result averages (H1a):** the research's average performance scores exceeded 60%. Whether users have an acceptable performance to participate in their organization's full BI processes varies contextually for each organization, department, data warehouse, or requirements. This is contextual due to that relating BI importance or skills may differ.
- **Environment and support (H1b):** user training was determined to have a great positive effect on users' SSBI performance in all defined quality descriptions. However, expert presence and a social environment were equally inconsistent. More insufficient validity and reliability results were obtained on these lines.
- **Software functions (H2a):** discussed software functions were considered valid and reliable effects. This implied that the use of measurement etiquettes and sorting patterns represented positive effects. Undefined data, with which users do not test the quality of their intended measurements, represented a negative effect.
- **Software (H2b):** Tableau was determined to be the most suitable SSBI software package for inexperienced users, and Qlik Sense the least suited. However, the expert panel confirmed that Microsoft PowerBI is probably the most popular. The expert panel included BI field managers, and while Microsoft PowerBI has a relatively low cost, its popularity probably stems from their personal accumulated experiences.
- **Technical and visual abilities (H2c):** users' technical and visual capabilities affected their overall SSBI abilities, and their impact was remarkable. Moreover, as results fluctuated more, those among practical scores were negligible.
- **Personal backgrounds (H3a):** personal backgrounds related to education and work experience largely derived from the expected high-scoring backgrounds. Business and computer science backgrounds therefore scored highly.

- **Educational level (H3b):** users' educational level has predominantly been correlated with SSBI performance, especially with reference to their strategic abilities. This was confirmed by strong evidence.
- **Highest classified capabilities (RQa):** high resulting user abilities were determined to be the ability to keep information in one glimpse, the understanding and creation data relations, the suitable selection of visualization methods. Proper label orientation was considered inconsequential, as validity and reliability were insufficient.
- **Highest correlated capabilities (RQb):** All effectiveness components were correlated sufficiently to users' abilities to perform BI processes in SSBI applications. However, participants' grades on their own BI abilities were considered insignificant since their correlation did not result in a sufficient Jaccard correlation pattern.
- **Highest extremes or balances (RQc):** High-scoring balances were found in visual score and age, effectiveness, and CSF scores. This indicated that middle-aged users had superior visual performance, and average-performing users performed well on identifying competitive advantages. Furthermore, an extreme was established when the Dunning-Kruger effect was measured. This implied that when users were ignorant about SSBI, they tended to be overconfident and score lower than others.

By enumerating each supported and unsupported result, it was possible to answer the hypotheses and research question. The hypotheses and research question are provided in Table 32.

Table 33: Propositions

Hypothesis 1	Users can conduct general BI processes in SSBI software to produce decision-support information in an environment with their peers with limited help functions and training.
Hypothesis 2	Among SSBI software, users experience differences in its usability to produce decision-support information.
Hypothesis 3	Differences in users' in SSBI applications skills depend on educational background, work experience, and hobbies.
Research question	What user analytical capabilities are determinants for successful organizational SSBI implementations?

- **Hypothesis 1:** users' capabilities to perform general BI processes are contextually different for each analytic report or dashboard. This study demonstrated that users can create relatively simple visualizations or tables. This signifies "simple" by having one dimension and one measurement aggregation ("sum," "avg," "min," "max," or "count") for each involved visualization. User training is considered an excellent benefit for SSBI-related performance.
- **Hypothesis 2:** various software features yield positive or negative results compared to others. A number of software functions are used correctly by inexperienced users to create their visualizations or tables or to increase information quality. Similarly, some software functions cause inability to create visualizations properly or reduce information quality due to negative results. Likewise, different produced quality levels were measured for the included SSBI applications. As a result, Tableau is the best suited for inexperienced users, and Qlik Sense the worst.
- **Hypothesis 3:** out of all background definitions included in this study, only those that were expected returned favorable results. Business and computer science backgrounds are identified as SSBI performance-enhancing, and education level correlates with users' abilities. Higher education mainly corresponds to BI's strategic aspects.
- **Research question:** the answer to the research question is a summary of the results in Table 31. SSBI performance-enhancing capabilities are the following: 1) users' ability to introduce or control measurement labels while sorting patterns and data relationships in tables and visualizations; 2) users' ability to verify whether included dimensions or expressions and visualization methods produce the intended data or information; 3) users' familiarity with Tableau; 4) superior general technical and visual abilities; 5) practical insight in data and

information; 6) skills related to business education and computer science experience; 7) the capacity to summarize information, in which scrolling is reduced; 8) the ability to reach higher education; 9) the ability to create strategic insights; and 10) critical-thinking skills with regard to information representation and processes.

The previous bulletin list is considered the answer to the research question. Yet, more potential questions remain unanswered, possibly because included data contained bias, and the number of propositions were limited. Some implicit biases were identified in the conclusion chapter, and further research suggestions were put forward to verify result reliability due to bias.

7.2 Validity and reliability

To assess the research's validity and reliability, the calculations provided in Table 15 were performed for each claim to examine their relative validity and reliability. Cardinality is provided to demonstrate general validity and reliability's establishment.

Table 34: General validity and reliability

Proposition	Measure	Claim	Mean validity	Reliability percentage	$n(\upsilon)$	$n(\lambda)$
H1a	Classification	Training	0.38	0.82	62	22
H2a	Classification	Etiquette	0.40	0.69	208	26
H2a	Classification	Sorting	0.45	0.86	208	27
H2a	Classification	Undefined data	0.50	0.88	208	33
H2b	Classification	Tableau	0.21	0.50	208	48
H2b	Classification	Qlik Sense	0.32	0.67	208	46
H2c	Correlation	Technical abilities	0.38	0.86	208	14
H2c	Correlation	Visual abilities	0.42	0.81	208	31
H3a	Classification	Business education	0.87	0.65	62	23
H3a	Classification	Computer science work experience	0.83	0.63	62	27
H3b	Correlation	Educational level vs. effectiveness	0.14	0.53	388	15
H3b	Correlation	Educational level vs. strategic abilities	0.57	0.58	186	12
RQa	Classification	Scrolling	0.32	0.68	208	22
RQa	Classification	Relational structures	0.35	0.65	208	20
RQa	Classification	Choice visualization method	0.27	0.71	208	24
RQb	Correlation	Practical abilities	0.61	0.72	388	19
RQb	Correlation	Strategic abilities	0.35	0.56	388	18
RQc	Quadratic	Visual abilities vs. age	0.81	0.74	208	19
RQc	Quadratic	Effectiveness vs. strategic CSF	0.21	0.76	388	17
RQc	Quadratic	Effectiveness vs. participant grade on own BI capabilities (Dunning-Kruger)	0.22	0.73	388	15
		Mean:	**0.41**	**0.67**	**210.19**	**22.76**

The validity and reliability of each claim, which can be seen in Table 33, are presented together with their establishment. Claims that arose from educational levels, and business and computer science background classifications were least established in terms of validity. Only a few of these results from each participant were generated. Still, the educational business background had the highest average validity. The highest reliability was that of the claim on "unidentified data," which included users validating their metrics and categories. Among classifications, the least valid and reliable measurement was the one relative to the claim on Tableau. Tableau turned out to be the one with the lowest percentages, but this measurement was robustly established for the reliability calculation. The correlation between users' educational level and effectiveness score turned out to be the weakest in terms of validity and reliability. Both numbers gave the lowest results for this calculation method. However, this claim included the best established validity. Likewise was the correlation between practical and strategic scores and the quadratic relationship between strategic CSFs and participants' grades on their own BI abilities, whose validity was evaluated with 388 results. The least established reliability was determined to be the correlation between users' educational level and their strategic abilities, as only 12 sources were included. Among the conventional correlations, that between the practical score and their effectiveness score was deemed to be the most valid. However, this correlation was generally weaker than valid results related to other calculation methods. Given all included results, the quadratic relationship between users' visual abilities and age was considered the most credible claim. The correlation between users' educational level and effectiveness score was considered the least credible. This research is generally valid. Average H_α p-values and correlation coefficients were set at 0.41, and all H_0 p-values resulted lower than 0.05. This study is also considered largely reliable. About two-thirds of included sources confirm resulting claims. Moreover, the validity establishment calculation was supported with the same cardinality as the research claims.

7.3 Biases and limitations

This study presents biases, some of which were discussed in the results and discussion chapters because they were observed during the research. Possibly, more deviations emerged and went undetected during the study's implementation. The following paragraphs describe some of the noted and unforeseen prejudices and limitations caused by the research process. Biases and limitations encompassed both measurements and participating entities.

In some measurements, not enough results were obtained. For example, for trained individuals, measurements could only be detailed per participant. Since only 62 individuals participated, no more than 100 observations could be reached. This implied an extension neglect. An extension neglect occurs when the sample size may not be enough to satirize data or be representable for the targeted population (non-response figures are provided in Appendix Q). Furthermore, as for the sample size, the sampling approach also contained explicit biases and limitations. In terms of organization and participant selection, a referral effect and localized entities were opted for to increase the sample size during a challenging recruiting period. As stated in the methods chapter, the sampling approach required attendance from participants or organizational representatives. This might have differed due to their unique wishes, requirements, geographic positioning, onsite, or offsite research conduction.

Regarding software selection, to simplify the research for its feasibility and increase its validity, only three SSBI applications were incorporated. Similarly, only one SSBI application per manufacturer was included. Although the most popular applications were used, a bias was present regarding the potential effects that could have been measured if other applications, such as Domo, Sisence, or YellowFin, had been included. Furthermore, the results will not be valid for programmable BI, such as R and Python. The research is also not valid for centralized BI environments. Centralized environments are predefined information systems for IT department's data managers, in which users do not have to directly perform analytical processes themselves. Likewise, this research is not suitable for semi-tailored packages, such as Microsoft Excel, MySQL Workbench, or ERP systems with BI modules. These applications do not contain SSBI as a primary focus. Although most software packages remain the same for long periods of time, software changes in included SSBI applications may affect the software due to developer updates. In this study, it was observed that Qlik Sense changed its offer plans and included a preprogrammed trend line option; however, participants did not use it. Tableau's method to combine data tables was also revised.

To classify all possible backgrounds for the third hypothesis, lists were sourced online and served as inspiration for used categories. However, for hobby categories, the list stemmed from a Wikipedia entry. However, the list was further tweaked to include specific categories, such as splitting "competitive" into "competitive sport" and "non-competitive sport" with "in" and "outside" affiliations, and including "gaming," "music," and "pets." A fitting bias is still present regarding the number of included categories. This is possible because over-fitting may have reduced their effectiveness of the categorization. Likewise, under-fitting may have led to the inclusion of unrelated concepts in unaffiliated categories.

Since the created assignments required one or two hours from participants, some of them felt discouraged. Participant may not always have been willing to invest this amount of time in completing their research participation. Furthermore, as multiple assignment options were available due to three included SSBI applications and four datasets, participants may have received several different difficulty levels compared to their equals. Hence, participants' assignment experiences differed. Moreover, the assignments and their grading were produced and performed only by us. His personal inclinations may thus have been involved in the assignment’s development and grade processing.

Since grades and other data were semi-automatically collected in the database and the input validation was limited, unwanted participants’ data inputs that could be accepted were possible. Some invalid results may have been included in the calculations. This limitation was to some extent present and was resolved where it was found.

Concerning the calculations, biases were widely present among the strength measurements. Strength calculations were tweaked from industry standards, and additional calculations were predefined widely distributed adaptations. The strength calculation that was performed for classifications and correlations was carried out by multiplying the delta or coefficient with its cardinality. This was Kendall’s τ coefficient, and its system on ties was ignored, only high concordants were selected, and suitability for the delta mean and numbers was not a standardized practice. Regarding quadratic relations, their strength calculation was determined by the trend’s fitting and skewness. The probability of a bias is approximately high because this formula is relatively complex and combines multiple standards, such as the R-squared model, the Pearsons Skewness model, and Kendall's τ coefficient. Similarly, including the factor for comparison with other strength calculations is not a common practice. Regarding the included calculation’s attribution to the respected propositions, biases may be present since the calculation’s attribution depended on the proposition’s textual interpretation.

The resulting claims were mostly assessed against the literature and with the help of experts and blog-post analysis. Claims’ associated literature was mostly consistent with their resulting effects since most of the literature was searched with claims’ related phraseology. Therefore, the probability of matching literature is remarkable, indicating a potential confirmation bias. Experts were also included and expressed their opinions on research resulting claims via an online form. Since experts completed this form anonymously, the likelihood for them to hold back or lie about the claims or their field expertise existed, either intentionally or not. Furthermore, since the expert’s form took only a few minutes, the busiest experts might have been discouraged from participating. Moreover, as some claims obtained from RQa were late additions, the corresponding questions were not included in the expert panel’s form. A text-analysis from associated blog posts was therefore introduced to assess sentiment and urgency on related topics. It can be assumed that blogs’ covered subjects may not always be attributable to researched claims. As in the expert panel, the contained expertise was not directly evaluated, and these “experts” may not be representative of this research.

Since all established biases and limitations might have influenced this research, some effects were thought to be greater than others. In particular, biases and limitations associated with the research’s relatively large non-response bias, the software selection, and the sentiment and urgency analysis of blog posts were considered substantial.

7.4 Suggested implications and recommendations

Claims produced by this research may have several implications. For instance, advice may suit HR recruiters and their selection methods and trainers, trainings, or training material selections, user preferences, or dashboard and report-producing methods. Specifically, suggested changes may apply to software functions, approaches for advising companies or consultants, and public or organizational knowledge bases. Research claims may suggest investing, adapting, transforming, solving, avoiding, or developing certain processes, technologies, tactics, or plans regarding SSBI and its implementations.

- Organizations are encouraged to invest in or develop SSBI user training. Training measurably increases user performance in developing decision-support information in SSBI applications, especially for its practical use. Appropriate selection or recruitment of SSBI-trained users can increase the likelihood of information accuracy and information-generating efficiency.
- The inclusion of measurement etiquettes and sorting patterns in compiled user reports or dashboards is recommended. As with software manufacturers, it is advisable to automate etiquette and sorting implementation to increase users’ visual understanding while still working

on visualizations. It is further recommended to include organizational knowledge base entries related to etiquette usage and sorting patterns. The user can then view the mechanics and their uses and include etiquettes and sorting patterns, thus getting the needed instructions. Consultants and trainers are also encouraged to incorporate these benefits into their training and counseling.

- This research confirmed that users who validated their included categories and metrics achieved greater information quality than those who did not. For this reason, it is recommended that users be allowed to add a control process in their BI processes. Including a verification process in knowledge bases and training is likewise encouraged, as it is assumed to improve SSBI's effectiveness.
- As both users' technical and visual capabilities improve their performance in SSBI applications, it is recommended that organizations invest in users' capabilities. Investing in users' capabilities improves information accuracy and quality. Users who perform well in these measurement scores generally performed better in total. Distributing knowledge about relational diagramming to combine data and selecting proper visualization methods is also encouraged. This can be achieved through training or by applying a technical BI-related knowledge base. When consultants are recruited to assist the organization, they are encouraged to further educate recruiting organizations about these capabilities. If HR departments are required to hire information-producing individuals, it is recommended to test the potential user's relative technical and visual abilities along the research's findings lines. This can potentially improve organizations to hire the most suitable candidate.
- Users with educational business backgrounds tended to perform better in this research. As a result, BI users are advised to take business courses in their organizational areas. Likewise, it is advised for HR departments to recruit users with an associated business educational background. Organizations are likewise encouraged to publish their business processes, strategies, resources, and financial performance for their users. Users will then be able to further educate themselves about their organization status from a business perspective.
- Likewise, among users with educational business backgrounds, those with computer science work experience tended to produce better results. It is recommended to allow users to experiment with various IT applications and to recruit users with relatively high and varied application experiences. Installing demo-systems for users to try and discover SSBI applications is also recommended, and it is suggested that users improve their relevant IT experience.
- Participants' strategic performance correlates with their educational level and overall performance. Enabling users to take strategic courses or increase their educational levels would help them become better suited to analyzing organizations' BI needs or determining where BI's results are most effective. This effect will also be further enhanced by letting HR departments hire highly educated users. Given that a quadratic relationship was established between participants' ability to create competitive advantages and their age, middle-aged users' recruitment will also strengthen organizations' strategic performance.
- Keeping information to a minimum and in a glance is essential for adequate communication. Although scrolling features are an easy solution for presenting large amounts of information, they hinder information communication effectiveness. Scrolling features should thus be avoided. Training or consulting users on how to avoid them or software developers limiting these features can increase the representation quality of produced information in or from SSBI applications.
- The research's most reliable result revealed that middle-aged users perform better visually. Therefore, it is recommended to train, recruit, or appoint middle-aged users in positions that produce or advise on SSBI. Middle-aged users tend to produce visually-superior visualizations and are better able to interpret these visualizations.
- As the Dunning-Kruger effect was demonstrated in this research, low-performing SSBI users tended to overestimate their performance. They were not acquainted with the knowledge and skills required and were ignorant about their deficiencies. Therefore, the Dunning-Kruger effect can interfere with the production, quality, accuracy, and interpretation of organizations' information and should be avoided. Furthermore, if they increase their related knowledge, they

will be more self-critical, and their perception will become more reliable. Therefore, training, consulting, or hiring trained users will reduce the Dunning-Kruger effect.

The recommendations largely resulted in training investments, process adaptations, hiring or selecting guidelines, designing knowledge bases, avoiding certain perceptual habits, and supporting middle-aged users. The implementation of these recommendations will undoubtedly increase SSBI implementation success.

7.5 Research suggestions

By proposing future research ideas, knowledge about out-of-scope research directions, results without mentioned biases, and confirmation on the stated recommendations can be obtained. Some suggestions are provided in the following paragraphs. All suggestions can strengthen this research or conceptual SSBI implementations as a whole.

Many out-of-scope ideas are present in this research. Well-established out-of-scope ideas are mainly seen in Figure 2. In this table, some concepts were included, and some were dropped. The excluded research directions outline two proposed orientations, such as the following: 1) largely inexperienced users were in the research sample. Therefore, a study investigating the long-term user experience that develops out of SSBI applications usage is recommended to provide insights into the long-term impacts of SSBI implementations and how return on investment can be determined; 2) since this research extensively focuses on SSBI's business impacts, analyzing SSBI's impact on the technical IT landscape, data availability, accessibility, and governance practices can help specify the possible and required technical implementation methods for SSBI.

Given the wide variety of biases in this study, a similar investigation in which these biases are not present may lead to different results. Thus, research measuring the same effects, although with different calculation methods, can reinforce this study's findings and reliability and alleviate biases. Likewise, since this research included a limited sample, comparable research including the same calculations but with a larger sample may improve this research's validity. However, only if the same results emerge.

Recommendations often encouraged training, adjustments in SSBI user selection processes, and warnings about particular practices. Measuring the effects when recommendations are implemented or when awareness is raised reinforces the research's results. Therefore, conducting research with experimental and control groups about trained or selected individuals strengthens the research's reliability. However, only if the same positive effects are measured in the experimental group. Similar research can be conducted in which awareness of the Dunning-Kruger effect is raised within an experimental group to measure this awareness's effects.

7.6 Research method acknowledgement

The research methods used in this study were inspired by Aggerwal et al. (2015). In their research, they analyzed users' IT intelligence at an Indian pharmaceutical company, in which they provided assignments to their participants to measure it. Furthermore, time-tracking software provided us with a surveillance opportunity. This research encouraged participants to collaborate on their analytical processes. Moreover, by partially using groups within organizations and a referral effect, the research could rely on a larger sample size to support the study. This is in contrast to what could have been obtained through an approach when only we directly contact potential participants. Nonetheless, personal qualities were still measurable. Likewise, according to Moran (1981), psychological research requires large sample sizes to generate stable claims. When a sufficient sample is reached, this research method can arrange a pragmatic approach for practically experienced problems.

8. References

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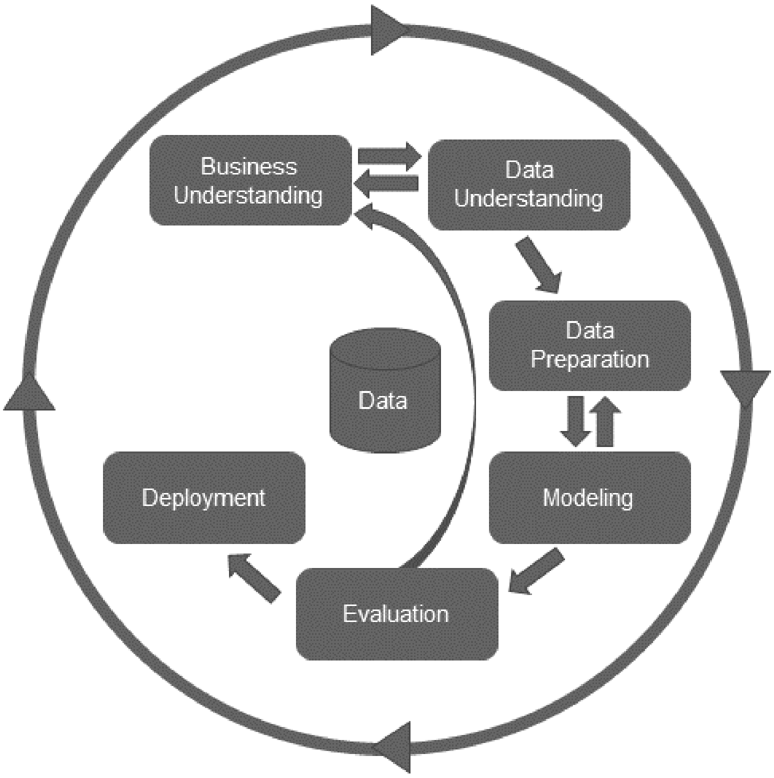
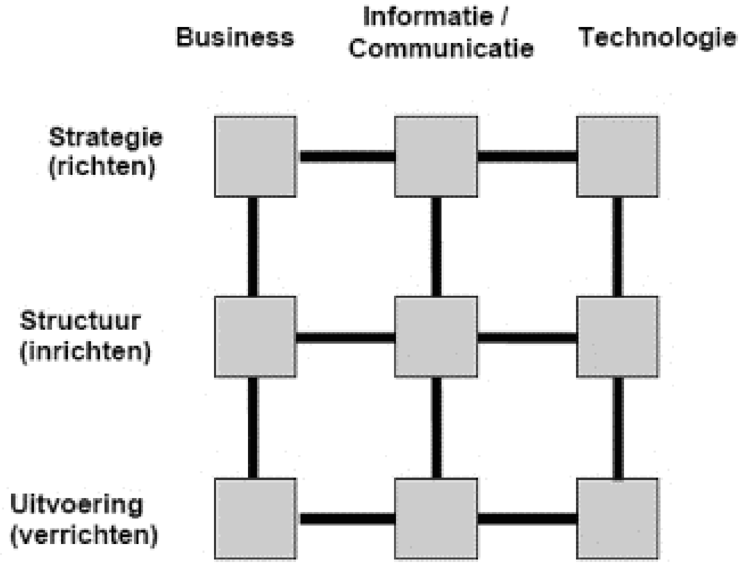
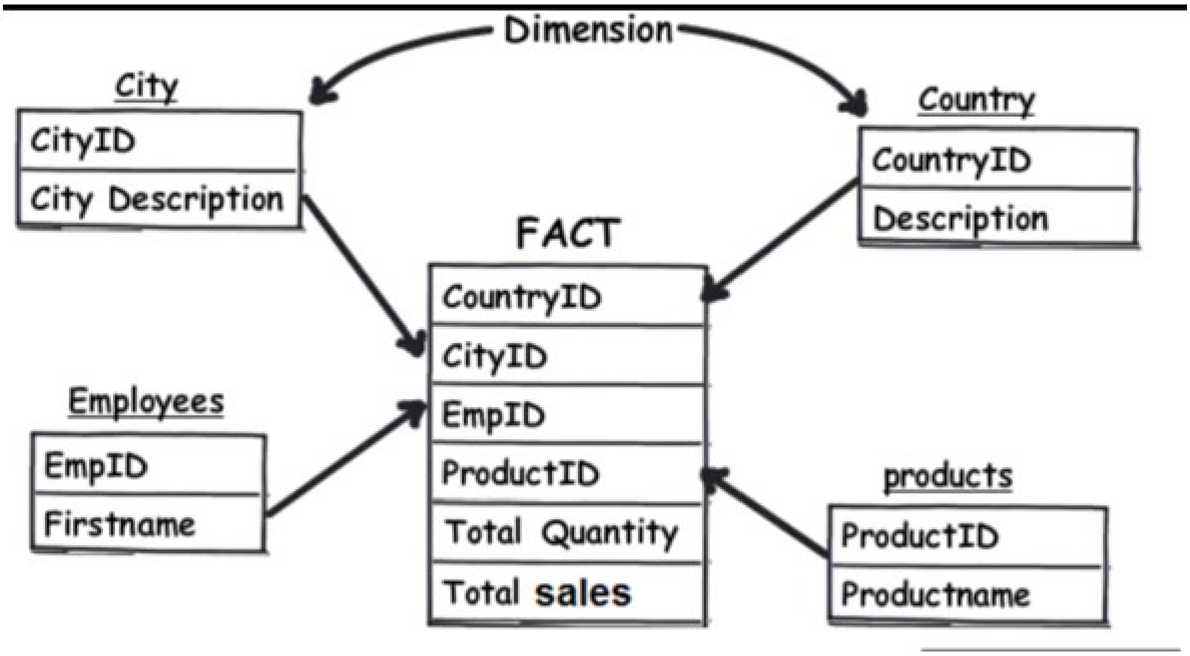
Appendix A


Business Understanding
Data Understanding
Data Preparation
Data
Deployment
Modeling
Evaluation

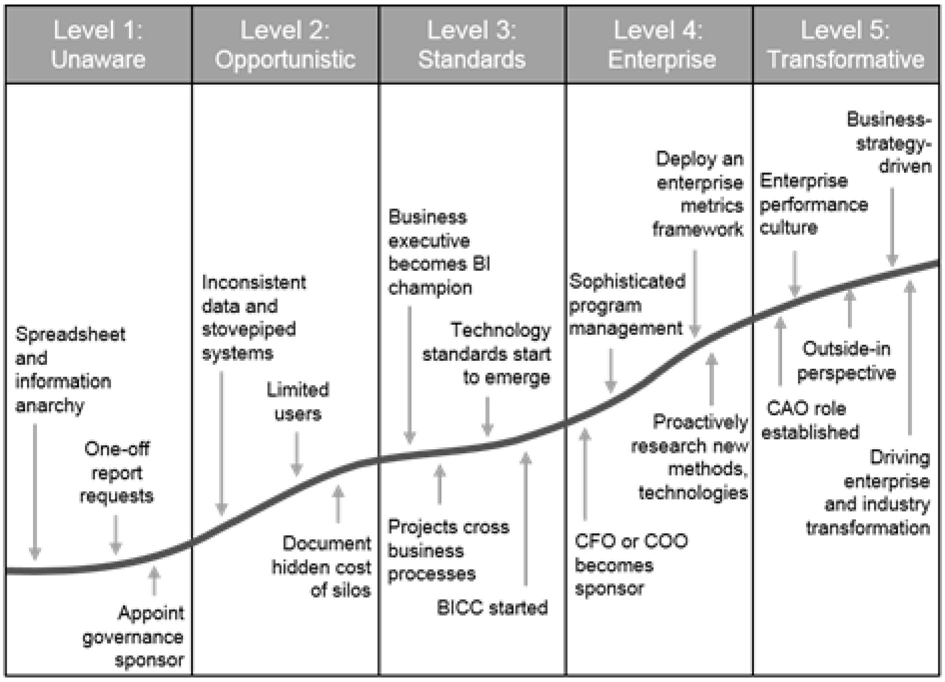
Appendix B


Business
Informatie /
Communicatie
Technologie
Strategie
(richten)
Structuur
(inrichten)
Uitvoering
(verrichten)

Appendix C


Dimension
City
CityID
City Description
Country
CountryID
Description
FACT
CountryID
CityID
EmpID
ProductID
Total Quantity
Total sales
Employees
EmpID
Firstname
products
ProductID
Productname

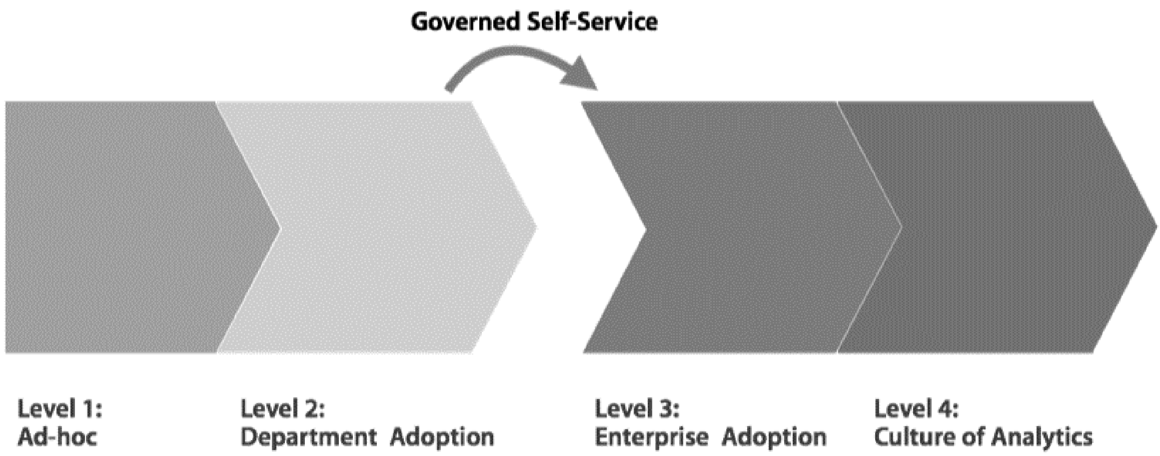
Appendix D



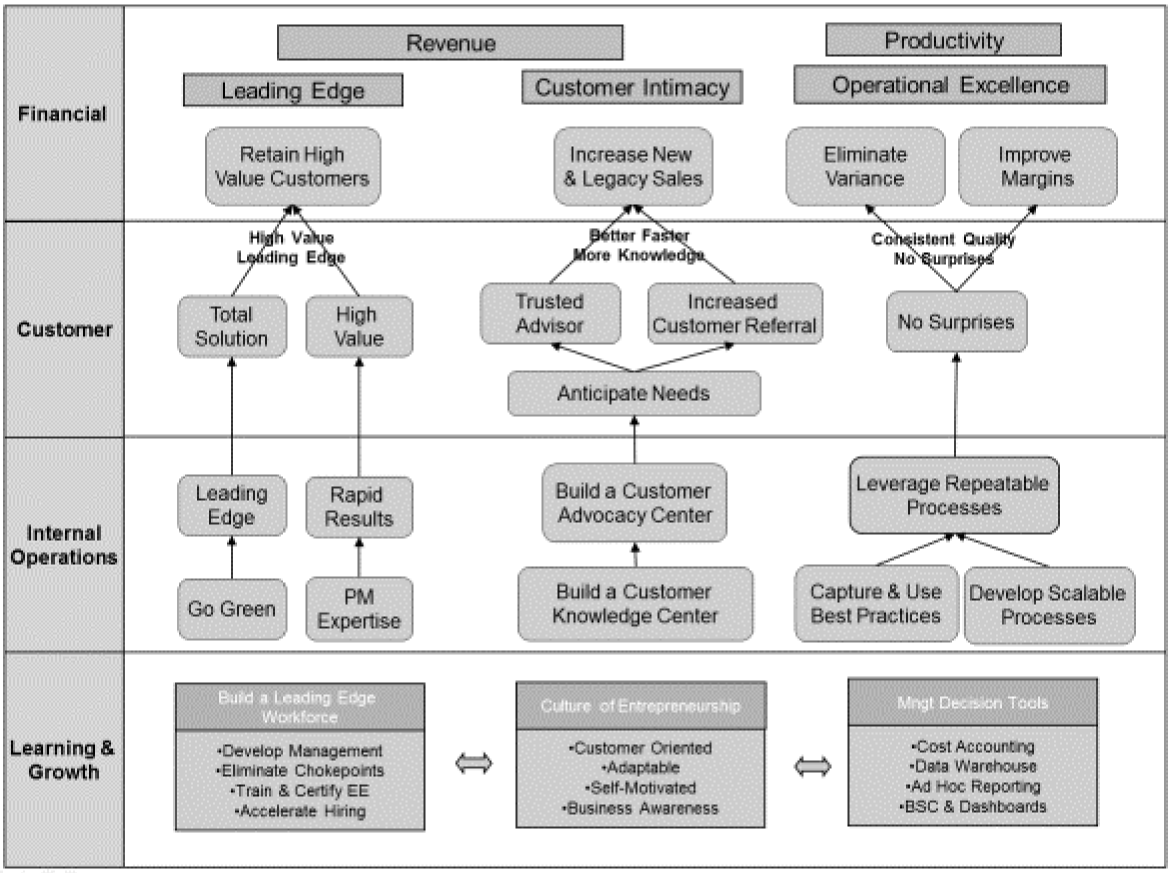
BI = Business intelligence
BICC = BI competency center

Appendix E

Self-Service Analytics Maturity Model



Appendix F


Financial
Revenue
Productivity
Leading Edge
Customer Intimacy
Operational Excellence
Retain High Value Customers
Increase New & Legacy Sales
Eliminate Variance
Improve Margins
High Value Leading Edge
Better Faster More Knowledge
Consistent Quality No Surprises
Customer
Total Solution
High Value
Trusted Advisor
Increased Customer Referral
No Surprises
Anticipate Needs
Internal Operations
Leading Edge
Rapid Results
Build a Customer Advocacy Center
Leverage Repeatable Processes
Go Green
PM Expertise
Build a Customer Knowledge Center
Capture & Use Best Practices
Develop Scalable Processes
Learning & Growth
Build a Leading Edge Workforce
•Develop Management
•Eliminate Chokepoints
•Train & Certify EE
•Accelerate Hiring
Culture of Entrepreneurship
•Customer Oriented
•Adaptable
•Self-Motivated
•Business Awareness
Mngt Decision Tools
•Cost Accounting
•Data Warehouse
•Ad Hoc Reporting
•BSC & Dashboards

Appendix G

- Agriculture
- Architecture
- Biological and Biomedical Sciences
- Business
- Communications and Journalism
- Computer Sciences
- Culinary Arts and Personal Services
- Education
- Engineering
- Legal
- Liberal Arts and Humanities
- Mechanic and Repair Technologies
- Medical and Health Professions
- Physical Sciences
- Psychology
- Transportation and Distribution
- Visual and Performing Arts

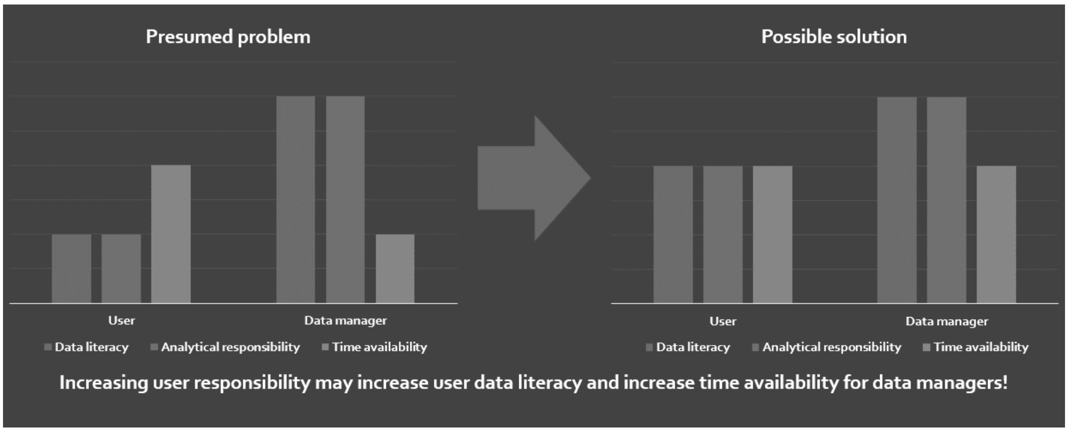
Complete cross-list: https://bit.ly/2t47MSg

Appendix H

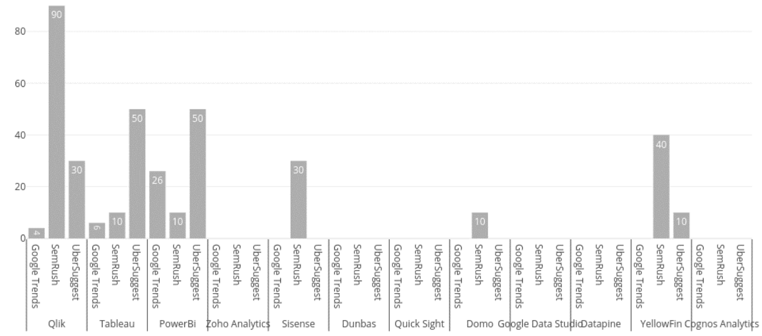
- General hobbies
  - Indoors
  - Outdoors
- Collection hobbies
  - Indoors
  - Outdoors
  - In/outside
- Sport-competitive hobbies
  - Indoors
  - Outdoors
  - In/outside
- Observation hobbies
  - Indoors
  - Outdoors
- Music hobbies
- Gaming hobbies
- Sport-non-competitive hobbies
  - Indoors
  - Outdoors
  - In/outside

Complete cross-list: https://bit.ly/2tUpBmN

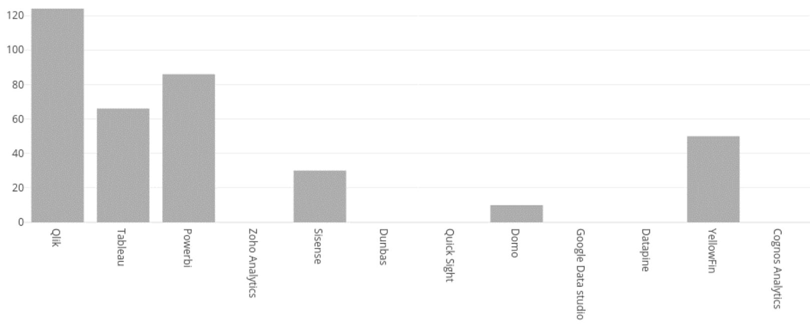
Appendix I


Presumed problem
User
Data manager
Data literacy
Analytical responsibility
Time availability
Possible solution
User
Data manager
Data literacy
Analytical responsibility
Time availability
Increasing user responsibility may increase user data literacy and increase time availability for data managers!

Appendix J

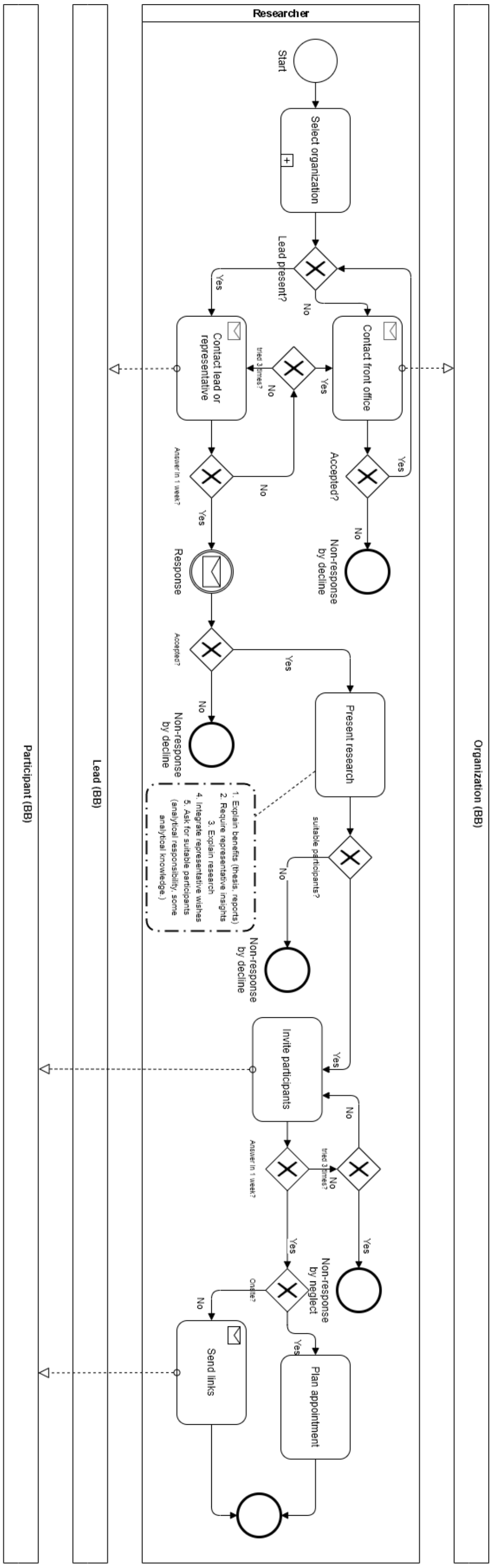


0
20
40
60
80
90
30
6
10
50
26
10
50
30
10
40
10
Google Trends
SemRush
UberSuggest
Qlik
Tableau
PowerBi
Zoho Analytics
Sisense
Dunbas
Quick Sight
Domo
Google Data Studio
Datapine
YellowFin
Cognos Analytics



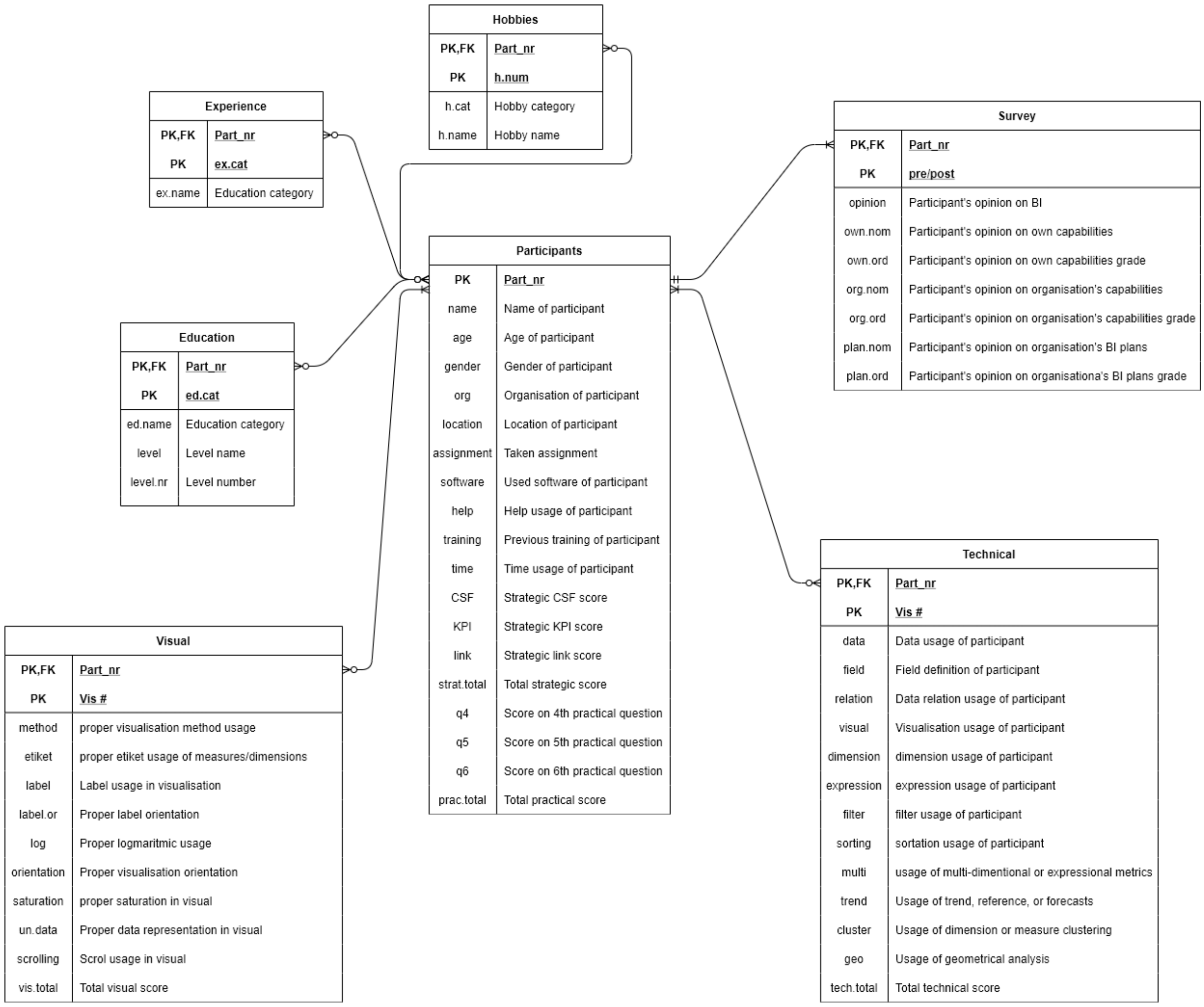
0
20
40
60
80
100
120
Qlik
Tableau
Powerbi
Zoho Analytics
Sisense
Dunbas
Quick Sight
Domo
Google Data studio
Datapine
YellowFin
Cognos Analytics

Appendix K



Researcher
Start
Select organization
Lead present?
Yes
No
Contact lead or representative
tried 3 times?
Contact front office
Yes
No
Accepted?
Yes
No
Non-response by decline
Answer in 1 week?
No
Yes
Response
Accepted?
Yes
No
Non-response by decline
Present research
1. Explain benefits (thesis, reports)
2. Require representative insights
3. Explain research
4. Integrate representative wishes
5. Ask for suitable participants (analytical responsibility, some analytical knowledge)
suitable participants?
No
Non-response by decline
Yes
Invite participants
No
Answer in 1 week?
tried 3 times?
No
Yes
Yes
Non-response by neglect
Online?
No
Yes
Send links
Plan appointment
Participant (BB)
Lead (BB)
Organization (BB)

Appendix L


Hobbies
PK,FK Part_nr
PK h.num
h.cat Hobby category
h.name Hobby name
Experience
PK,FK Part_nr
PK ex.cat
ex.name Education category
Survey
PK,FK Part_nr
PK pre/post
opinion Participant's opinion on BI
own.nom Participant's opinion on own capabilities
own.ord Participant's opinion on own capabilities grade
org.nom Participant's opinion on organisation's capabilities
org.ord Participant's opinion on organisation's capabilities grade
plan.nom Participant's opinion on organisation's BI plans
plan.ord Participant's opinion on organisationa's BI plans grade
Participants
PK Part_nr
name Name of participant
age Age of participant
gender Gender of participant
org Organisation of participant
location Location of participant
assignment Taken assignment
software Used software of participant
help Help usage of participant
training Previous training of participant
time Time usage of participant
CSF Strategic CSF score
KPI Strategic KPI score
link Strategic link score
strat.total Total strategic score
q4 Score on 4th practical question
q5 Score on 5th practical question
q6 Score on 6th practical question
prac.total Total practical score
Education
PK,FK Part_nr
PK ed.cat
ed.name Education category
level Level name
level.nr Level number
Visual
PK,FK Part_nr
PK Vis #
method proper visualisation method usage
etiket proper etiket usage of measures/dimensions
label Label usage in visualisation
label.or Proper label orientation
log Proper logmaritmic usage
orientation Proper visualisation orientation
saturation proper saturation in visual
un.data Proper data representation in visual
scrolling Scrol usage in visual
vis.total Total visual score
Technical
PK,FK Part_nr
PK Vis #
data Data usage of participant
field Field definition of participant
relation Data relation usage of participant
visual Visualisation usage of participant
dimension dimension usage of participant
expression expression usage of participant
filter filter usage of participant
sorting sortation usage of participant
multi usage of multi-dimentional or expressional metrics
trend Usage of trend, reference, or forecasts
cluster Usage of dimension or measure clustering
geo Usage of geometrical analysis
tech.total Total technical score

Appendix M

Appendix M.A

Table 35: Effectiveness score

Category	Classification (Class)	Delta mean	Strength	*n*	St.dev	*p*-value
Etiquette	0	1.18	191.16	162	1.08	0.46
Sorting	1	1.16	165.88	143	1.08	0.48
Dimension	1	0.66	126.06	191	0.58	0.30
Scrolling	0	0.65	122.20	188	0.57	0.29
Undefined data	0	0.60	120.00	200	0.52	0.27
Data relation	1	1.11	118.77	107	1.03	0.39
Visualization method	0	0.56	111.44	199	0.48	0.25
Training	Yes	1.55	110.05	71	1.47	0.46
Education category	Business	1.98	108.90	55	1.90	0.52
Label orientation	0	0.52	103.48	199	0.44	0.23
Undefined data	-1	-2.81	126.45	45	2.88	0.72
Etiquette	-1	-1.40	123.20	88	1.47	0.51
Training	No	-0.87	111.36	128	0.94	0.39
Software	Qlik Sense	-1.46	109.50	75	1.53	0.49
Sorting	0	-1.65	99.00	60	1.72	0.49
Help	Yes	-0.81	72.90	90	0.88	0.31
Scrolling	-1	-0.97	70.81	73	1.04	0.33
Onsite research	Yes	-0.49	69.58	142	0.56	0.25
Hobby category	Running	-2.84	68.16	24	2.91	0.53
Participant opinion on organization's BI capabilities	Yes	-0.40	68.00	170	0.47	0.23
y	**Correlation**	**Correlation**	**Strength**	***n***	**St.dev**	**Slope**
Participant grade on own BI capabilities		0.47	182.36	388	1.73	0.38
Educational level		0.23	89.24	388	3.32	0.36
y	**Quadratic relation**		**Type**	***n***	**Coefficient**	**Strength**
CSF			∪	62	0.3	187.11
Participant grade on own BI capabilities			∩	117	1.9	96.02
Completion time			∩	62	0.2	93.97

Appendix M.B

Table 36: Efficiency score

Category	Classification (Class)	Delta mean	Strength	*n*	St.dev	*p*-value
Data relation	1	0.73	79.00	208	0.49	0.23
y	**Correlation**	**Correlation**	**Strength**	***n***	**St.dev**	**Slope**
Participant grade on organization's BI capabilities		-0.24	49.92	117	0.61	-0.07
Participant favorability grade concerning		-0.19	39.52	117	0.61	-0.03

organization's BI related plan						
y	**Quadratic relation**		**Type**	***n***	**Coefficient**	**Strength**
Strategic score			∪	186	1.16	67.83

Appendix M.C

Table 37: Strategic score

Cateogy	**Classification (Class)**	**Delta mean**	**Strength**	***n***	**St.dev**	***p*-value**
Multi	1	0.50	46.50	93	0.46	0.24
Help	Yes	-0.39	30.42	78	0.42	0.20
y	**Correlation**	**Correlation**	**Strength**	***n***	**St.dev**	**Slope**
Education level		0.15	27.90	186	1.39	0.31
y	**Quadratic relation**		**Type**	***n***	**Coefficient**	**Strength**
Practical score			∪	186	1.09	147.31
Efficiency			∩	124	0.19	51.77
Age			∩	62	0.90	127.83
Visual score			∪	208	-0.40	92.34
Participant favorability grade concerning organization's BI related plan			∪	117	0.34	67.83
Participant grade on own BI capabilities			∪	117	0.22	56.55

Appendix M.D

Table 38: Practical score

Category	**Classification (Class)**	**Delta mean**	**Strength**	***n***	**St.dev**	***p*-value**
Sorting	1	0.60	95.40	159	0.51	0.22
Training	No	-0.51	56.61	111	0.59	0.22
y	**Correlation**	**Correlation**	**Strength**	***n***	**St.dev**	**Slope**
Effectiveness score		0.72	279.36	388	3.32	1.15
Participant grade on own BI capabilities		0.39	71.37	183	2.15	0.29
Visual score		0.24	50.64	211	0.95	0.67
y	**Quadratic relation**		**Type**	***n***	**Coefficient**	**Strength**
Strategic score			∩	186	1.09	147.31
Education level			∪	78	0.08	33.07
Age			∩	62	6.5	73.90

Appendix M.E

Table 39: Technical score

Category	**Classification (Class)**	**Delta mean**	**Strength**	***n***	**St.dev**	***p*-value**
Clustered visualizations	1	1.73	77.85	45	1.55	0.27

Education category	Transport/Logistical	-0.79	15.01	19	0.96	0.11
y	**Quadratic relation**		**Type**	***n***	**Coefficient**	**Strength**
Participant grade on own BI capabilities			∪	117	0.58	45.24
Age			∪	62	0.7	54.21

Appendix M.F

Table 40: Visual score

Category	Classification (Class)	Delta mean	Strength	*n*	St.dev	*p*-value
Etiquette	0	0.36	58.32	162	0.34	0.31
Undefined data	-1	-1.44	64.80	45	1.45	0.70
y	**Correlation**	**Correlation**	**Strength**	***n***	**St.dev**	**Slope**
Effectiveness score		0.59	228.92	388	0.95	1.82
Practical score		0.24	50.64	211	0.95	0.67
y	**Quadratic relation**		**Type**	***n***	**Coefficient**	**Strength**
Age			∩	62	8.8	195.41
Strategic score			∩	186	-0.4	92.34
Participant favorability grade concerning organization's BI related plan			∩	117	1.16	66.38

Appendix M.G

Table 22: Age

y	Correlation	Correlation	Strength	*n*	St.dev	Slope
Participant grade on organization's BI capabilities		0.27	31.59	117	1.69	2.2
y	**Quadratic relation**		**Type**	***n***	**Coefficient**	**Strength**
Visual score			∪	208	8.8	195.41
Technical score			∩	208	0.7	54.21
Practical score			∪	186	6.5	73.90

Appendix M.H

Table 23 - Time

y	Correlation	Correlation	Strength	*n*	St.dev	Slope
Participant grade on organization's BI capabilities		-0.28	32.76	117	1.69	-0.15
Participant favorability grade concerning		-0.23	26.91	117	1.58	-0.43

organization's BI related plan						
y	**Quadratic relation**		**Type**	***n***	**Coefficient**	**Strength**
Effectiveness score			∪	508	0.2	93.97

Appendix M.I

Table 24: level

y	Correlation	Correlation	Strength	*n*	St.dev	Slope
Strategic score		0.15	27.90	186	1.39	0.31
Effectiveness score		0.23	89.24	388	3.32	0.36
y	**Quadratic relation**		**Type**	***n***	**Coefficient**	**Strength**
Practical score			∩	186	0.8	33.07

Appendix M.J

Table 25: Strategic parts

X	*Y*	Quadratic relation	Type	*n*	Coefficient	Strength
Link	Participant favorability grade concerning organization's BI related plan		∪	117	0.43	79.11
CSF	Effectiveness score		∩	508	0.3	187.11
CSF	Participant grade on organization's BI capabilities		∪	117	0.16	55.15
CSF	Participant favorability grade concerning organization's BI related plan		∪	117	0.24	43.26
KPI	Strategic score		∪	186	0.7	32.30

Appendix M.K

Table 26: Own capability

Category	Classification (Class)	Delta mean	Strength	*n*	St.dev	*p*-value
Training	Yes	0.61	24.40	40	0.57	0.20
Gender	Male	0.30	23.10	77	0.21	0.07
Education category	Business	0.62	17.36	28	0.53	0.10
Cluster	1	-0.61	18.30	30	0.64	0.19
Education category	Communication/journalism	-2.37	16.38	7	2.81	0.25
y	**Correlation**	**Correlation**	**Strength**	***n***	**St.dev**	**Slope**
Effectiveness score		0.47	182.36	388	1.73	0.38
Participant grade on organization's BI capabilities		0.40	46.80	117	1.69	0.26

Practical score		0.39	71.37	183	2.15	0.29
y	**Quadratic relation**		**Type**	***n***	**Coefficient**	**Strength**
Effectiveness score			∩	508	1.9	96.02
Strategic score			∩	186	0.22	56.55
Participant grade on organization's BI capabilities			∪	117	2.99	38.21

Appendix M.L

Table 27: Grade organization's capability

Category	Classification (Class)	Delta mean	Strength	*n*	St.dev	*p*-value
Hobby category	Sport non-competitive outside	0.79	16.59	21	0.62	0.07
Participant opinion on favorability on organization's BI related plan	Yes	-0.27	16.67	61	0.43	0.09
y	**Correlation**	**Correlation**	**Strength**	***n***	**St.dev**	**Slope**
Age		0.27	31.59	117	1.69	2.2
Time		-0.28	32.76	117	1.69	-0.15
Efficiency score		-0.24	49.92	208	0.61	-0.07
Participant favorability grade concerning organization's BI related plan		0.45	52.65	117	1.58	0.48
Own capability		0.40	46.80	117	1.69	0.26
y	**Quadratic relation**		**Type**	***n***	**Coefficient**	**Strength**
Technical score			∪	208	0.58	45.24
Strategic CSF			∪	62	0.24	43.26
Own capability			∪	117	2.99	38.21

Appendix M.M

Table 28: Favorability organization's BI-related plan

Category	Classification (Class)	Delta mean	Strength	*n*	St.dev	*p*-value
Level	Master's degree	0.63	17.64	28	0.57	0.13
Software	Tableau	-0.73	27.01	37	0.78	0.20
Dimension	0	-1.34	18.76	14	1.42	0.19
y	**Correlation**	**Correlation**	**Strength**	***n***	**St.dev**	**Slope**
Participant grade on organization's BI capabilities		0.45	52.65	117	1.58	0.30
Time		-0.23	26.91	117	1.58	-0.43
y	**Quadratic relation**		**Type**	***n***	**Coefficient**	**Strength**
Link			∩	62	0.43	79.11
Strategic score			∩	186	0.34	67.83
Visual score			∪	208	1.16	66.38
CSF			∩	62	0.16	55.15

Appendix N

Appendix N.A

Table 29: PowerBI data management

Ordinal data	Category	Selection	Classification (Class)	Delta mean	Strength	*n*	St.dev	*p*-value
Technical	Software	Field, data, relation	PowerBI	-0.24	4.08	17	0.99	0.23
Technical	Software	Field, data, relation	Tableau	0.34	4.76	14	0.91	0.31
Technical	Software	Field, data, relation	Qlik Sense	-0.06	0.60	10	0.67	0.05

Appendix N.B

Table 30: Qlik Sense etiquette

Ordinal data	Category	Selection	Classification (Class)	Percentage	Strength	*n*	St.dev	*p*-value
Technical	Software	Etiquette = -1	PowerBI	4.40%	8.32	4	45.6	0.80
Technical	Software	Etiquette = -1	Tableau	17.78%	33.28	16	32.22	0.36
Technical	Software	Etiquette = -1	Qlik Sense	79.02%	147.68	71	29.02	0.58

Appendix N.C

Table 31: Tableau field orientation

Ordinal data	Category	Selection	Classification (Class)	Delta mean	Strength	*n*	St.dev	*p*-value
Technical	Software	Field = 1	PowerBI	0.02	0.72	36	1.43	0.01
Technical	Software	Field = 1	Tableau	0.44	15.40	35	1.12	0.26
Technical	Software	Field = 1	Qlik Sense	-0.34	11.22	33	1.24	0.25

Appendix N.D

Table 32: Multi-measurement

Ordinal data	Category	Selection	Classification (Class)	Percentage	Strength	*n*	St.dev	*p*-value
Effectiveness	Multi	ass. = 4, qst. 6	0	76.92%	1.60	26	2.73	0.13
Effectiveness	Multi	ass. = 4, qst. 6	1	23.08%	0.48	26	3.46	0.44
Efficiency	Multi	ass. = 4, qst. 6	0	76.92%	4.69	26	0.65	0.16
Efficiency	Multi	ass. = 4, qst. 6	1	23.08%	9.03	26	1.95	0.51
Effectiveness	Multi	ass. = 2, qst. 6	0	66.67%	1.38	15	1.86	0.12
Effectiveness	Multi	ass. = 2, qst. 6	1	33.33%	0.69	15	1.64	0.23
Efficiency	Multi	ass. = 2, qst. 6	0	66.67%	6.08	15	0.43	0.29
Efficiency	Multi	ass. = 2, qst. 6	1	33.33%	4.33	15	0.53	0.54

Effectiveness	Multi	ass. = 1, qst. 4	0	86.05%	1.78	43	3.33	0.03
Effectiveness	Multi	ass. = 1, qst. 4	1	13.95%	0.29	43	1.91	0.28
Efficiency	Multi	ass. = 1, qst. 4	0	86.05%	2.58	43	0.19	0.08
Efficiency	Multi	ass. = 1, qst. 4	1	13.59%	0.83	43	0.09	0.48

Appendix N.E

Table 33: Onsite help-functions

Ordinal data	**Category**	**Selection**	**Classification (Class)**	**Delta mean**	**Strength**	***n***	**St.dev**	***p*-value**
Effectiveness	Help	Onsite	Yes	-0.32	28.80	90	3.22	0.08
Effectiveness	Help	Onsite	No	0.43	20.64	48	2.32	0.10
Effectiveness	Help		No	0.00	0.00	0	2.89	1
Effectiveness	Help	Onsite	Yes	0.13	12.30	95	0.33	0.03
Effectiveness	Help	Onsite	No	0.27	13.40	50	0.30	0.08
Effectiveness	Help		Yes	0.00	0.00	0	0	1
Effectiveness	Help		No	0.02	1.61	81	0.61	0.03

Appendix N.F

Table 34: Technical backgrounds

X	***Y***	**Selection**	**Correlation**	**Strength**	***n***	**St.dev**	**Slope**
Effectiveness score	Strategic score	Engineering, Computer science, Maintenance	0.72	14.30	20	2.87	2.41
Effectiveness score	Practical score	Engineering, Computer science, Maintenance	0.56	11.23	20	1.69	2.33
Effectiveness score	Technical score	Engineering, Computer science, Maintenance	0.89	17.73	20	2.87	1.74
Effectiveness score	Visual score	Engineering, Computer science, Maintenance	0.73	14.72	20	2.87	2.32
Effectiveness score	Efficiency score	Engineering, Computer science, Maintenance	0.19	3.80	20	0.97	-0.05
Efficiency score	Strategic score	Engineering, Computer science, Maintenance	0.48	9.60	20	0.97	0.30
Efficiency score	Practical score	Engineering, Computer science,	-0.21	4.20	20	0.97	-0.16

		Maintenance					
Efficiency score	Technical score	Engineering, Computer science, Maintenance	0.15	3.00	20	0.97	0.57
Efficiency score	Visual score	Engineering, Computer science, Maintenance	0.04	0.80	20	0.97	0.09
Effectiveness score	Strategic score	Reverse selection	0.56	100.24	179	3.45	0.95
Effectiveness score	Practical score	Reverse selection	0.73	130.67	179	3.45	1.22
Effectiveness score	Technical score	Reverse selection	0.59	105.61	179	0.45	1.59
Effectiveness score	Visual score	Reverse selection	0.59	105.61	179	3.45	2.01
Effectiveness score	Efficiency score	Reverse selection	0.01	1.79	179	0.62	0.00
Efficiency score	Strategic score	Reverse selection	0.01	1.79	179	0.62	-0.03
Efficiency score	Practical score	Reverse selection	-0.04	7.16	179	0.62	-0.11
Efficiency score	Technical score	Reverse selection	0.06	10.74	179	0.62	0.29
Efficiency score	Visual score	Reverse selection	0.00	0.00	179	0.62	0.04

Appendix N.G

Table 35: Participant's focus

X	*Y*	Selection	Correlation	Strength	*n*	St.dev	Slope
Visual score	Time	Data, field, relation	-0.03	1.05	35	1.00	0.11
Visual score	Time		0.02	0.82	41	2.80	0.67

Appendix N.H

Table 36: Onsite research completion time

Ordinal data	Category	Classification (Class)	Delta mean	Strength	*n*	St.dev	*p*-value
Effectiveness	Avg(Time)		0.08	11.36	142	2.89	0.02
Effectiveness	Avg(Time)	Onsite	-0.13	7.93	61	3.13	0.03
Efficiency	Avg(Time)		0.47	2.32	5	0.62	0.02
Efficiency	Avg(Time)	Onsite	0.41	5.72	14	0.32	0.01

Appendix N.I

Table 37: Manager's performance

Ordinal data	Classification (Class)	Delta mean	Strength	*n*	St.dev	*p*-value
Strategic score	Manager participants	0.18	3.24	18	1.14	0.10

Practical score	Manager participants	-0.13	2.34	18	2.06	0.04
Technical score	Manager participants	0.00	0.00	18	1.41	0.00
Visual score	Manager participants	-0.22	3.87	18	0.93	0.18
Time	Manager participants	0.04	0.72	18	0.54	0.04
Strategic score		-0.09	3.87	43	1.50	0.05
Practical score		0.06	2.58	43	2.23	0.02
Technical score		0.01	0.43	43	1.29	0.01
Visual score		0.09	3.87	43	0.95	0.07
Time		-0.02	0.86	43	0.78	0.02

Appendix N.J

Table 38: SSBI perceptions among age

X	***Y***	**Correlation**	**Strength**	***n***	**St.dev**	**Slope**
Age	Participant grade on their own BI capability	0.11	12.87	117	1.74	0.97
Age	Participant grade on their organization’s BI capability	0.27	31.59	117	1.70	2.20
Age	Participant favorability grade concerning their organization’s BI-related plan	0.09	10.53	117	1.59	0.40

Appendix N.K

Table 39: Dunning-Kurger effec in sports

X	***Y***	**Selection**	**Type**	**Coefficient**	**Strength**	***n***
Effectiveness score	Participant grade on their own BI capability	All sport categories	∪	3.20	42.70	152
Effectiveness score	Participant grade on their organization’s BI capability	All sport categories	---			
Effectiveness score	Participant favorability grade concerning their organization’s BI-related plan	All sport categories	---			
Efficiency score	Participant grade on their own BI capability	All sport categories	/			
Efficiency score	Participant grade on their organization’s BI capability	All sport categories	\			
Efficiency score	Participant favorability grade concerning their organization’s BI-related plan	All sport categories	∩	0.01	12.44	86
Effectiveness score	Participant grade on their own BI capability		∪	2.50	56.29	93
Effectiveness score	Participant grade on their organization’s BI capability		∪	2.90	39.26	93
Effectiveness score	Participant favorability grade concerning their organization’s BI-related plan		∪	0.03	51.02	93
Efficiency score	Participant grade on their own BI capability		∩	0.02	7.61	93
Efficiency score	Participant grade on their organization’s BI capability		\			

Efficiency score	Participant favorability grade concerning their organization's BI-related plan		∩	0.14	21.32	93

Appendix N.L

Table 40: Dimensions and expressions in Tableau

Ordinal data	Category	Selections	Classification (Class)	Delta mean	Strength	*n*	St.dev	*p*-value
Technical score	Software	Dim = 0, exp = 0	PowerBI	0.58	1.16	2	1.41	0.04
Technical score	Software	Dim = 0, exp = 0	Tableau	-0.41	0.82	2	0	0.61
Technical score	Software	Dim = 0, exp = 0	Qlik Sense	-0.04	0.32	8	0.52	0.46
Technical score	Software		PowerBI	-1.00	1.00	1	0	0.68
Technical score	Software		Tableau	-	-	0	-	-
Technical score	Software		Qlik Sense	0.50	1.00	2	0.71	0.38

Appendix N.M.1

Table 41: software function usage amidst perceptions (Classification)

Ordinal data	Category	Classification (Class)	Delta mean	Strength	n	St.dev	p-value
Technical score	Participant opinion on SSBI concept	Yes	0.00	0.00	0	1.32	1
Technical score	Participant opinion on SSBI concept	Maybe	-0.09	3.87	43	1.23	0.06
Technical score	Participant opinion on SSBI concept	No	0.70	10.50	15	1.93	0.40
Technical score	Participant opinion on their own BI capability	Yes	0.03	5.28	176	1.28	0.02
Technical score	Participant opinion on their own BI capability	Maybe	-0.02	1.62	81	1.43	0.01
Technical score	Participant opinion on their own BI capability	No	-0.62	14.88	24	1.40	0.36
Technical score	Participant opinion on their organization's BI capability	Confident	0.21	8.61	41	1.36	0.13
Technical score	Participant opinion on their organization's BI capability	Yes	-0.07	11.90	170	1.34	0.04
Technical score	Participant opinion on their organization's BI capability	Maybe	0.08	6.32	79	1.28	0.05
Technical score	Participant opinion on their organization's BI capability	No	0.82	4.92	6	1.60	0.46
Technical score	Participant opinion on favorability on their organization's BI-related plan	Yes	-0.01	1.42	142	1.33	0.01
Technical score	Participant opinion on favorability on their organization's BI-related plan	Maybe	-0.15	16.20	108	1.44	0.09
Technical score	Participant opinion on favorability on their organization's BI-related plan	No	0.19	5.13	27	1.04	0.11

Appendix N.M.2

Table 42: software function usage on perceptions (Correlations)

X	*Y*	Correlation	Strength	*n*	St.dev	Slope
Technical score	Participant grade on their own BI capability	0.04	8.32	208	1.32	-0.03
Technical score	Participant grade on their organization's BI capability	-0.02	4.16	208	1.32	-0.03
Technical score	Participant grade on favorability on their organization's BI-related plan	0.03	6.24	208	1.32	0.04

Appendix N.N

Table 43: Onsite performance

Ordinal data	Category	Classification (Class)	Delta mean	Strength	*n*	St.dev	*p*-value
Effectiveness score	Onsite	Yes	-0.49	168.98	345	3.13	0.12
Effectiveness score	Onsite	No	1.19	31.85	27	2.89	0.28
Effectiveness score	Onsite	Yes	0.12	18.00	150	0.32	0.01
Effectiveness score	Onsite	No	0.27	17.53	65	0.61	0.02

Appendix N.O

Table 44: Correlation perceptions

X	*Y*	Correlation	Strength	*n*	St.dev	Slope
Participant grade on their own BI capability	Participant grade on their organization's BI capability	0.40	46.80	117	1.70	0.26
Participant grade on their own BI capability	Participant grade on favorability on their organization's BI-related plan	0.23	26.91	117	1.59	0.15
Participant grade on their organization's BI capability	Participant grade on favorability on their organization's BI-related plan	0.45	52.65	117	1.59	0.15
Mean:		0.36	42.12	117	1.63	0.19

Appendix N.P

Table 45: Text analysis spreadsheet usage

Terms (Dutch)	Terms translated	Strength	*n*
SSBI-software-ervaring in eigen analyses in Excel	SSBI software experience in own Excel analysis	2,67	16
maken en plannen analytische dashboards in Cognos	Making and planning analytical dashboards in Cognos	2,4	12
Goed gebruik van analytische automatiseringspakket vind ik inzichtelijk	Good use of analytical ERP system I find insightful	2,29	7
In het verleden BI in Excel gedaan, gewerkt en gebruikt	In the past, used and worked with BI in Excel	2,17	13

Aardig ervaring in data analyses en draaitabellen in Excel	Quite a lot of experience with pivot tables in Excel.	1,86	13
Daarnaast organisatie-automatiseringspakketdata inzichtelijk bekeken	In addition, organizational ERP system data insightfully viewed	1,67	10
Excel strength:		4,84	29
Other strength (Cognos & ERP):		4,69	19

Appendix N.Q

Table 46: Text analysis BI investment

Terms (Dutch)	**Terms translated**	**Strength**	***n***
We hebben goede bedrijfsgegevens voor de informatievoorziening	We have good business data for information provision	2.75	11
Maken en plannen analytische dashboards in Cognos	Making and planning analytical dashboards in Cognos	2.40	12
Daarnaast doen we goede data gedreven beslissingen met data	Besides we're base decisions well on data.	2.00	12
Denk organisaties goed ken; afwijzen en negeren	I think when I know organizations well; turning down and ignoring	1.83	11
Gaan gebruiksvriendelijke analyse data gebruiken	Are going to use user-friendly data analytics	1.80	9
Analytische kennis ervan is aanwezig	Analytical knowledge of it is present	1.75	7
Daarnaast gebruiken we allemaal analyse tools	Besides we're using all anlaytical tools	1.60	8
Schat organisaties investeringen hierin afwijzen	Estimate organization's investments in this are turned down	1.40	7
Analyses gebruiken voor baseren van bijvoorbeeld besluitvorming	Using analytics for basing decision support for example	1.20	6
Not-invest strength:		3.32	18
Invest strength:		13.50	65

Appendix O

Table 41: Software comparison

	Weigth	Tableau	Qlik Sense	Microsoft PowerBI
Analytical Features	3	12 (4)	6 (2)	9 (3)
Visualization Features	5	15 (3)	15 (3)	10 (2)
Data formatting features	4	4 (1)	12 (3)	12 (3)
Data warehousing features	2	4 (2)	8 (4)	6 (3)
Code necessity	7	28 (4)	7 (1)	14 (2)
Costs	1	1 (1)	3 (3)	4 (4)
Fitler & Sortation Features	6	18 (3)	24 (4)	18 (3)
Total:		**82**	**75**	**73**
Mean:		**11.71**	**10.71**	**10.43**

Appendix P

Appendix P.1

Table 42: Jaccard grouping coefficient – H2c

	Practical v. Technical	Practical v. Visual	Effectiveness v. Technical	Effectiveness v. Visual
> v. >	0.35	0.37	0.32	0.32
> v. <	0.24	**0.15**	0.27	0.21
< v. >	0.29	0.23	0.21	0.16
< v. <	**0.19**	0.18	0.31	0.29
Reliability:	**FALSE**	**PARTIAL**	**TRUE**	**TRUE**

Appendix P.2

Table 43: Jaccard grouping coefficient - H3b

	Educational level v. Effectiveness	Educational level v. Strategic
> v. >	0.31	0.55
> v. <	0.29	0.05
< v. >	**0.32**	0.02
< v. <	0.35	0.50
Reliability:	**PARTIAL**	**TRUE**

Appendix P.3

Table 44: Jaccard grouping coefficient - RQb

	Practical v. Effectiveness	Strategic v. Effectiveness	Own capability grade v. Effectiveness
> v. >	0.39	0.37	0.34
> v. <	0.02	0.00	0.08
< v. >	0.16	**0.27**	**0.34**
< v. <	0.29	0.05	0.26
Reliability:	**TRUE**	**PARTIAL**	**PARTIAL**

Appendix P.4

Table 45: Jaccard grouping coefficient - RQc

	A v. V	**E v. C**	**S v. P**	**S v. A**	**E v. G**
> v. >	0.84	0.35	**0.18**	**0.16**	0.34
> v. <	0	0.13	0.15	0.16	0.08
< v. >	0.56	0.29	0.39	0.32	0.34
< v. <	0	0.11	0.19	**0.27**	0.26
Reliability:	**TRUE**	**TRUE**	**PARTIAL**	**FALSE**	**TRUE**

$A = Age$
$V = Visual\ score$
$E = Effectiveness\ score$
$C = CSF$
$S = Strategic\ score$
$P = Practical\ score$
$G = Participant's\ grade\ own\ capabilities$

Appendix Q

Table 46: Non-response bias

	Participants	***N* (part)**	**Organizations**	***N* (org)**
Reject	30.52%	29	9.68%	12
Neglect	4.21%	4	68.55%	85
Accept	65.53%	62	21.77%	27
Total:		*95*		*124*

Appendix R

F1: "When importing data into Microsoft PowerBI, the sheets were not automatically selected, the selection options did not stand out, and they were not functional when they were not selected" (effect was proven, n = 41/208). If the alleged software processes are not adjusted for users, they can increase user frustration by disrupting users' paths; furthermore, users are likely unfamiliar, and Microsoft PowerBI has possibly not been adjusted to users' intuition (Çöltekin et al., 2010; Cawthon & Vande Moere, 2007; Behrisch et al., 2018). If Microsoft PowerBI's algorithms are further illustrated to their users, this circumstance can be alleviated (Law et al., 2021). This field note could not precisely be confirmed with the recorded data. However, since this circumstance occurred when users conducted data warehouse management in the different software applications, it was possible to determine each application's data warehousing performance. Therefore, by classifying the included software in the technical score, while the "relation," "data," and "field" categories were selected, it could be concluded that Microsoft PowerBI's performance was insufficient, Tableau's performance superior, and Qlik Sense average. Therefore, this field note was not verified, but its possible effects were. Calculations are available in Appendix N.A. All p-values were verified, although the strength values were minimal. Only the delta measurement determined the difference. However, there were only minor variations. According to Cynixit (2020), Microsoft PowerBI focuses on cost-effectiveness concerning its competitors. Therefore, focusing on human intuitive processes and their reasoning abilities may not be relevant to their developers.

F2: "Qlik Sense did not automatically configure the measurement etiquettes when presenting the information. Other software can do this" (proven, n = 91/208). Measurement etiquette is defined by either software- or user-made labels for actionable measurements in visualizations. Etiquettes improve the understandability of information for visualizations' audiences and enhance contextual communication and information retrieval potential (Isaacs et al., 2014; Landes et al., 2013; North, 2006; Behrisch et al., 2018; Law et al., 2021). Introducing the appropriate label provides visualizations with the desired interpretation and specificity. To accomplish any calculations to prove this field note, a percentile analysis in software, technical score, etiquette usage, and experimental group selections was conducted. Therefore, the division of the software between etiquette usage was representable. This field note was proven with a relatively high margin. Qlik Sense scored high due to its negative effect on etiquettes usage. Furthermore, Microsoft PowerBI received a considerably low score. Calculations are accessible in Appendix N.B. Since calculations were performed with percentages, the resulting standard deviation was relatively high. Although Microsoft PowerBI scored low, its strength was also relatively low; hence, the results for Microsoft PowerBI were of limited validity. Furthermore, according to Data Flair (n.d.) and PwC's (2017) introductory manual of Qlik Sense, several processes have been added to encourage their users' use of etiquettes. As Qlik Sense's default etiquette copies its measurement's code, it is not intuitive for viewers. PwC further add that etiquettes are obliged to be corrected from its initial commencement, indicating the same circumstance as measured in this research.

F3: "Data management in Tableau was perceived as unfriendly. The average user did not know the union types that Tableau presented" (disproven, n = 41/208). This field note was similar to the first and second ones. On the other hand, it concerned differences of Tableau and data relations between the user tables. Unlike other software, Tableau requires users to define union types in relationships and have limited field orientation definitions, also not permanently functional. According to Isaacs et al. (2014), software's data management is the main approach to diagnosing any problems experienced by the user or the fact that the software is not programmed for. Unfriendly data management increases users' potential frustration with their software, as it potentially derails their intuitive path (Çöltekin et al., 2010; Cawthon & Vande Moere, 2007; Behrisch et al., 2018). Because this field note was not proven, users' data management performance in Tableau did not reflect any dysfunction. This field note was rejected by the same data as the first field note (Appendix N.A). Since Tableau's data management is broadly adjustable by users, it led to user satisfaction with the software (Peters et al., 2016). Tableau was designed for intuitive user processes; hence, this was an expected result, as Tableau will feel familiar to their users (Law et al., 2021; Cawthon & Vande Moere, 2007; Alberts, 2017).

F4: "Field orientation in Tableau felt broken. Text-formatted numbers were not easily converted to numbers with the options presented by Tableau nor in its loading code" (Disproven, n = 36/208). Field orientation's relevance is due to the user's ability to understand and measure data. Visualization measurements are structured in whole numbers, with decimals, currencies, and more, and when numbers are text-oriented, they are not usable calculations. Hence, it is essential for it to be suitable for information-producing users (Isaacs et al., 2014; Landes et al., 2013; Cawthon & Vande Moere, 2007; Behrisch et al., 2018). The same classification method, technical score, and control and experimental groups were chosen to demonstrate this field note. However, only the "field" category was selected. This field note was refuted and only partially insignificant because Tableau achieved a comparably high result in the "field" category, and Qlik Sense a relatively low one. The numbers are available in Appendix N.C. Furthermore, the results on Microsoft PowerBI were considered insignificant due to relatively low strength and p-value. Because Tableau focuses on native user processes, their high performance was expected for this field note, which was therefore disproven (Law et al., 2021; Alberts, 2017).

F5: "Dimensions and expressions were not always properly predicted, and participants experienced difficulties in finding the options to convert them in Tableau" (insignificant, n = 8/208). The used software can classify the results in this study due to these errors, and the project manager's choice to deploy SSBI may change or change the software manufacturer's preference for distributing updates or upgrades. Furthermore, according to Peters et al. (2016), SSBI software following a common data structure increases the data's centralization. The data types determine the software's visualization method invocation, whereby some data is visible and some is not, and, usually, every visualization method hides some patterns (Isaacs et al., 2014; Behrisch et al., 2018). Technical score differences in visualizations classifying improper dimension or expression usage between software were assessed to calculate the impact of predicting data fields. This field note was determined to be insignificant due to invalidity; two p-values resulted below 0.05, and all strength values were deficient. The resulting calculations are presented in Appendix N.L. If the validity measures were to be neglected, this field note was still declared insignificant because the results were unreliable. According to Law et al. (2021), a user upholds specific native and learned processes when exploring software. While algorithms make decisions on their behalf, describing the algorithm decisions to the user enhances their understanding of the software.

F6: "Multiple software functions relate to participants' perceptions" (insignificant, n = 206/208). Differences in the use of the software may be related to users' perceptional views on SSBI. Hence, various technical performances can presumably be experienced. For example, the user may experience familiarity with the functions, the software may not drill-down into data, users may be too confident in their abilities, the organization may not sustain new technological innovations, excessive data diversity may be present, or users may experience social exchange theory, in which users believe in the software's benefits, and therefore use it (Cawthon & Vande Moere, 2007; North, 2006; Kulkarni et al., 2006; Birkinshaw et al., 2019). The measuring of this field note was achievable with classifications and correlations. The classifications are presented in Appendix N.M.1, and the correlations are available in Appendix N.M.2. When validity was ignored, this field note was still insignificant because the results were unreliable. As such, the software functions likely did not change any user perceptions.

F7: "Participants from technical sectors did better" (insignificant, n = 179/208). Intuitively and routinely, technology-oriented individuals were perceived as more efficient in many IT-related processes. Furthermore, if technology-oriented individuals performed better, it was possible to select users to adopt SSBI more cost-effectively. If the user is unsure of their software, they are more hesitant and more sensitive to errors (Çöltekin et al., 2010; Behrisch et al., 2018). Furthermore, organizational factors are represented because specific training and experience increase the organization's trust, build the organization's technological market position, increase diversity in organizations, and improve the user's insight into the cognitive processes associated with SSBI software (Kulkarni et al., 2006; Birkinshaw et al., 2019; Coutinho et al., 2020). The numbers are available in Appendix N.F. This field note was declared insignificant because most of the calculations resulted in too low strength values, especially in the correlated efficiency scores.

F8: “Most respondents were used to Microsoft Excel, and most organizations' data was centered on spreadsheets” (proven by participant statements, n = 117). Most organizations structure data around Microsoft Excel spreadsheets. However, spreadsheets are designed for quick calculations, not for managing business processes and enterprise information provision. Furthermore, users’ pattern recognition is more advantageous in flat square visuals, highlighting, and centered views (Peters et al., 2016; North, 2006; Behrisch et al., 2018). When Microsoft Excel is used this way, an organization's data management is often chaotic and unstructured, and the organization increases its dependency on spreadsheets. If the user perceives that business intelligence processes depend on spreadsheet applications, the former can be measured through text analysis in the participant’s recorded text comments from the research’s survey. This field note was perceptually proven, as the data was derived from the participants’ explanations; not assignment data. The linked word count in sentences and their strength values are available in Appendix N.P. Users perceived that BI processes were predominantly carried out in spreadsheets, although some participants stated that they did so in the past and have currently moved to proper analytical software, indicating spreadsheet usage for BI processes is decreasing. Although the user’s familiarity with spreadsheets increased user satisfaction, spreadsheets require excessive time to perform the same BI process in spreadsheets, reduces user satisfaction, and lowers user productivity (Law et al., 2021).

F9: “Organizations do not invest time or budget in BI” (disproven by participant statements, n = 117). SSBI implementation projects are often counterintuitively time-consuming and costly. When organizations are willing to invest in BI, users’ confidence in their organization’s ability to support BI, the kind of shadow-applications present, and under-usage of organizations’ data can affect users’ perceptions of the SSBI concept. Since BI is a form of knowledge management, BI systems are a technique for learning and improving an organization's strategic and process performance (Peters et al., 2016; Lee & Widener, 2016; Elbashir et al., 2008). According to Law et al. (2021), a comprehensive user understanding of data is still lacking, and as users are generally accustomed to their current information-providing processes, their business processes depend on them. There may be mistrust between users, they may be diverse, and organizations may seek to improve their BI environment (Kulkarni et al., 2006; Birkinshaw et al., 2019). To improve a BI environment, certain best practices are available, such as improving aesthetics, maintaining familiarity with the process, and demonstrating unforeseen information. According to Kulkarni et al. (2006) and Platts and Tan (2004), the mere implementation of a BI system or BI process framework already increases the potential for implementation success through social exchange theory. Calculating if users perceive their organization’s willingness to invest in BI processes can increase an organization’s understanding of user support for SSBI implementation decisions. A textual analysis of the added comments in participants’ surveys was performed to analyze this field note. Based on the text analysis strength, it was possible to make a claim about users’ associated perceptions. This field note was refuted because users indicated that their organizations were willing to invest in BI. This did not mean that investments were always successful, as described in the introduction. Calculations are available in Appendix N.Q. Since this claim was based on perceptions rather than participants’ assignments, it referred to users’ general views rather than observations. As global SSBI investments grow, it is predictable that organizations are willing to spend on BI (Lennerholt et al., 2018; Mudzana & Maharaj, 2017). However, as approximately 70% to 80% of invested projects fail, users are also expected to view organizational investments negatively (Mudzana & Maharaj, 2017; Watson & Wixom, 2007).

F10: “Onsite participants requested extra help or used extra help” (proven, n = 90). The work environment in which participants can conduct research may differ, and these differences can affect their performance. Furthermore, social environments, possibly with professionals, can create pressure from colleagues, or establish a false sense of security due to an expert's presence, as participants can easily ask questions about the assignment, even if the response may not be relevant (Cawthon & Vande Moere, 2007; North, 2006; Coutinho et al., 2020; Behrisch et al., 2018). A classification of the efficiency score in the “help” category was initiated to measure this field note. For in-group analysis, the “onsite” category was used as a filter selection. This field note analysis confirmed its validity and was proven, as results indicated that when research was conducted onsite: either independent participants perform better due to fewer distractions or environmental familiarity; or participants in office environments and in the presence of an expert are less inclined to think analytically, are under social pressure, experience a competitive barrier with their colleagues, or feel relieved by the expert (Elbashir et al., 2008; Kulkarni et al., 2006; Hung et al., 2016). Calculations are presented in Appendix N.E. Furthermore, most research results of this field note's analysis were considered insignificant due to a lack of data. However, a sufficient number were accepted and were sufficiently favorable to claim this field note proven.

F11: "When research was carried out onsite, participants tended to complete it earlier" (insignificant, *n* = 62). As stated in the description of the previous field note, the expert and colleague's work environment or social pressure can impact the user's performance (Çöltekin et al., 2010; Birkinshaw, 2019). However, this explanation can also even be overwhelming for the participant (Cawthon & Vande Moere, 2007; North, 2006; Behrisch et al., 2018; Kulkarni et al., 2006; Law et al., 2021). Whether the earlier completion time resulted at onsite environments was analyzed with a classification analysis. The analysis concluded that this field note was not significant due to insufficient strength and *p*-values. Calculations are outlined in Appendix N.H. When significance values were to be neglected, this field notation would be proven because the efficiency and effectiveness scores from the onsite participants were lower.

F12: "Participants in independent research performed better" (proven, *n* = 142/508). Environmental conditions may influence participants' results. Designing more successive environments can influence decisions about implementing SSBI software or distributing tasks among SSBI users. Participants that performed research onsite maintained their processes in the software, which reduced frustration, maintained their intuition in assignment interpretation, cultivated a thematic focus, and operated in a familiar environment (Çöltekin et al., 2010; Peters et al., 2016; Behrisch et al., 2018). However, the participants had no additional barriers to competition, no direct contact to contextualize their assignments, or no immediate response channel (Kulkarni et al., 2006; Law et al., 2021; Coutinho et al., 2020; Birkinshaw et al., 2019; Hung et al., 2016). The calculation of this field note was performed by classifying experimental and control "onsite" category groups and compared by effectiveness and efficiency scores, which resulted in four distinct groups that provided performance in a variety of environments. This field note is only proven on the effectiveness score; the main performance score. The associated measurements are shown in Appendix N.N. Therefore, users conducting SSBI processes independently performed better because they were likely less distracted and not under peer pressure or had a better-suited environment.

F13: "Average scores of managers and leaders were lower than that of other participants" (insignificant, *n* = 43/508). Since managers and leaders are individuals who often seek information, as it is necessary to carry out their responsibilities, their performance may differ from the average user. Managers often request BI results to monitor strategic and operational performance (Peters et al., 2016; Elbashir et al., 2008; Birkinshaw et al., 2019; Platts & Tan, 2004). Furthermore, if managers and leaders are more aware of BI processes and their operations, they tend to invest more time and resources to improve their information systems and their associated processes (Sparks & McCann, 2015; Kulkarni et al., 2006; Peters et al., 2016; Adebambo et al., 2011). Managers' and leaders' performance measurements were gathered through the analysis dashboard used for the research results. This dashboard showed the average values of all ordinal data. By creating non-manager and manager groups through their stated work experience on LinkedIn, their effectiveness and efficiency could be calculated for each group. However, classification was calculated manually. This field note was claimed to be insignificant, as all the recorded strength values were insufficient, and most *p*-values were too low. Data are available in Appendix N.I. However, if significance was omitted, this field note was only partially true, depending on the specific score. Managers and leaders scored higher on the strategic score and completed the research slightly faster. Conversely, they scored low on practical and visual scores. Technical scores tended to be similar. According to Law et al. (2021), Çöltikin et al. (2010), Coutinho et al. (2020), and Grigorenko and Sternberg (2000), users' performance depends on the time they spend on the software, the expertise learned, their theoretical perception, their thinking patterns, and their difference in demographics. Therefore, performance was also individualized, as only small differences were measured.

F14: “Participants had more difficulty when they had to visualize with more than two dimensions or expressions” (insignificant, n = 43/508). Multidimensional or expressional measurements are important, depending on the hypothesis to be proven or the use of multi-layered visualizations (Isaacs et al., 2014; Peters et al., 2016; Behrisch et al., 2018; Landes et al., 2013). Multi-layered visualizations create an unsupervised learning method and can cluster and highlight any found anomalies or groups (Behrisch et al., 2018). A percentile analysis was performed on the effectiveness score, the efficiency score, and the chosen “multi” category to measure this field note. In this calculation, a selection assignment 4, question 6; assignment 2, question 6; and assignment 1, question 4 formed the control and experimental groups and included multidimensional and expressional measures. This field note was considered insignificant, partly due to very low strength and p-values. Figures are shown in Appendix N.D. If significance had to be ignored, this field note was proven because most participants’ visualizations did mostly not include a multi-measurable layers, and most participants experienced difficulty implementing them. According to Law et al. (2021), Isaacs et al. (2014), and Cawthon and Vande Moere (2007), educational factors, software explanations, and user knowledge affect users' abilities to use complex visualizations; hence, this field note may result in mixed validity of results.

F15: “Participants intended to invest more time in data visualization than in data preparation” (insignificant, n = 42/208). If researchers or project managers know the generally perceived focus that the average user has, they can identify which knowledge-sharing processes need to be centralized (Peters et al., 2016). According to Law et al. (2021), users’ general data understandability was determined to be poor, and to improve it, SSBI software manufacturers can support it by describing their algorithms, introduce familiarity, learning the right data, invoking visualization methods, and helping users focus (Çöltekin et al., 2010; Isaacs et al., 2014; Cawthon & Vande Moere, 2007). Calculations are provided in Appendix N.G. The field note was declared insignificant because the figures consisted of low correlations and high standard deviation values. If significance data was ignored, this field note was proven because the visual score was slightly higher on the inverse selection, which was expected because users were more familiar with data visualization (Cawthon & Vande Moere, 2007).

F16: “Older participants were more confident in their own as well as their organization’s BI abilities and favored their organization's BI-related plan more” (proven, n = 117). Particular perceptions can vary between ages, and organizations’ seniors often create analytical cultures due to their organizational experience and the occupation of strategic positions (Peters et al., 2016; Çöltekin et al., 2010; Kulkarni et al., 2006; Cawthon & Vande Moere, 2007; Birkinshaw et al., 2019). However, since SSBI suffers from a Dunning-Kruger effect, which is more common in older and higher-ranking individuals, the assumption that self-introduction of an application is enough to induce organizational change results often in the struggle to keep up with technology change, as most applications are more complex than estimated (Kulkarni et al., 2006; Çöltekin et al., 2010; Law et al., 2021). If this field note was proven, then the enhancement of SSBI software deployment support can be improved by adjusting the software’s rollout to vary on age. To conclude this field note, comparing age data with different perceptual data, confirmed that older adults are more positive on the topic. The relevant measurements are presented in Appendix N.J. While significance was relatively low, all perceptual data gave positive results and were therefore relatively reliable. Therefore, younger users tended to have more critical views regarding SSBI, and older users tended to accept SSBI faster due to either not understanding the concept or a greater ability to put this subject into perspective or trust the skills of others, which was confirmed by associated literature.

F17: “Sportive participants were more subjected to the Dunning-Kruger effect in SSBI” (insignificant, n = 152/508). As stated in the literature review, the Dunning-Kruger effect is a phenomenon that occurs when people have high confidence in their abilities; however, when expertise is necessary, an individual suffering from a Dunning-Kruger effect will perform poorly compared to other individuals. This overconfidence results from ignorance of expertise they are not aware of yet (Aggarwal et al., 2015). Therefore, sports can affect users’ perception of SSBI, and when selecting SSBI, users will probably be more efficient when knowing the validity of this field note. Differences in the quadratic relationship between sportive and not sportive individuals on efficiency and effectiveness scores were established to support this field note proposition, which was declared insignificant due to insufficient reliability.

Measurements are available in Appendix N.K. If its reliability was ignored, sportive individuals included a higher ∪-type relationship between effectiveness score and grade on their own capabilities, which concerned the most consequential data. Conversely, other measurements had unfavorable results. In other studies, this effect is positively measured because sportive individuals regularly have excessive confidence in their abilities, especially in competitive sports (Coutinho et al., 2020; Sullivan et al., 2019; Simons, 2013).

F18: "Participants who graded their own BI abilities, their organization's BI abilities, or their favorability for their organization's BI-related plan high tended to rank high for all these perceptual ordinal data" (proven, n = 117). According to Martijn et al. (1992), positive and negative perceptions can be transferred to other graded aspects if done by the same individual. Testing whether the general user was positive about the concept of SSBI and if the general perception was included in this study can prove if a user was willing to invest in BI. To calculate this field note, all perceptual ordinal data was correlated, for which the general correlation coefficient could be detected. This field note was shown to have a common correlation coefficient, measured at 36%, a wide margin. Calculations are available in Appendix N.O. When users were generally positive about SSBI, they were generally also positive about their organization's performance. Since the average for each perceptual ordinal data scale was around six, users were largely satisfied (Basu & DasGupta, 1997).