AN EVALUATION FRAMEWORK FOR BUSINESS INTELLIGENCE VISUALIZATION

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An Evaluation Framework for Business Intelligence Visualization

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ABSTRACT

Nowadays, data visualization is becoming an essential part of data analysis. Business Intelligence Visualization (BIV) is a powerful tool that helps modern business flows faster and smoother than ever before. However, studies on BIV evaluation are severely lacking; most evaluation studies for BIV is guided by general principles of usability, which have limited aspects covered for customers' needs. The purpose of this research is to develop a framework that evaluates BIV, including decision-making experience. First, we did a literature review for good understanding of research progress on related fields, and established a conceptual framework. Second, we performed a user study that implemented this framework with a set of questionnaires to demonstrate how our framework can be used in real business. Our result proved that this framework can catch differences among different designs of BIV from the users' standpoints. This can help design BIV and promote better decision-makings on business affairs.

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LIST OF ABBREVIATIONS

2D/2-D ....2 Dimensional

3D/3-D ....3 Dimensional

BI..Business Intelligence

BIV...Business Intelligence Visualization

DM ....Decision-Making

HCI...Human-Computer Interaction

MIMO ....Multi-In Multi-Out

US ....United States of America

UX/UE ....User’s experience

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1. INTRODUCTION

With the development of technologies and processes, most organizations are forced to deal with more and more data from various fields. In order to take advantage of using these data in a proper way, the tools for visualizing data have also developed dramatically. The boom in big data analytics has triggered broad use of information visualization in a variety of domains, ranging from finance to sports to politics (S. Liu et al., 2014). Visualization is an interdisciplinary field, which deals with the graphical representation of data (C. N. Knaflic, 2015). This is a powerful means of presenting compelling stories of data to individuals who are visually oriented.

One of the fields taking advantages from visualization is marketing and business management, which helps modern business flow faster and smoother than ever before. Business processes are one of the most important assets of organizations today, because they determine their success or failure in global markets (A. Nowak, et al., 2012). Business Analytics or Business Intelligence (BI) is becoming more needed by the top management of any organization to visualize, analyze and prepare strategic planning for the future (M. S. Gounder et al., 2016). The stakes are high for organizations to develop successful BI implementations (Jourdan, Z. et al., 2008). Winning companies, such as Continental Airlines, have seen investments in BI generate increases in revenue and produce cost savings equivalent to a 1000% Return-On-Investment (ROI) (H. J. Watson et al., 2009). On the other hand, losing companies have spent more resources than their competitors with a smaller ROI, while watching their market share and customer base continuously shrink (Gessner & Volonino, 2005). Obviously, BI has become an incredibly important component in modern business.

With the flood of data produced by today's information systems, measures must be taken to enable business decision-makers to extract the information contained in the data (David P. Tegarden, 1999). As a part of the modern BI movement that emphasizes self-service, visualization has been rising rapidly in the BI and analytics industry for the past a few years (Parenteau et al., 2016). While discussing visualization, we have to address that data visualization and information visualization are two sides of a concept, and are often used interchangeably. Also, M. C. Kim *et al.* have found in 2016, "while investigating scientific grounds and concepts such as interactivity and cognitive aspects is more prominent in information visualization than in data visualization. Developing and improving data processing techniques have been more frequently in data visualization than in information visualization" (M. C. Kim et al., 2016). In business field, we are mainly focusing on user's perspective because most users are not specialized in computing or data-processing. Therefore, we are mainly discussing information visualization in the article.

Information visualization helps people understand the significance of data by summarizing and presenting a huge amount of data in a simple and easy-to-understand format in order to communicate the information clearly and effectively (Ossama Embarak, 2018). With the wide application of BI in the market, based on Maslow's Hierarchy of Needs, users' needs will not just stay at the minimum functionality. In another words, the demand of better visualization methods is stronger than ever before. Most of the client/ users of BIV do not have a technical background and are not aware of technical details of the system. If we can improve the visualization design to enhance user experience, it will boost users' ability to obtain information and make decisions. Thus, a human-centric evaluation framework is obviously vital to business visualization.

In addition, one extra goal of BIV is to nudge business decision-making. Compared with visualization in other fields, BIV values more on the role of visualization in promoting decisions. Thus, it is necessary to assess the decision-making experience in the fields of BIV evaluation. There are also some other valuable aspects which are not covered by previous research, but important to a successful design of BIV, such loyalty, trust, interactivity, etc. However, there remain several questions about the research and application in BIV evaluation. The main goal of BIV is to promote business decision-making process, which is essential for any evaluation of business intelligence visualization. But based on what we have discovered, the current research on evaluation of BIV barely cover the decision-making quality. Moreover, the current studies for visualization about user's experience mainly focus on usability, but lack other aspects. In summary, it is necessary to propose a new evaluation framework that takes business needs into the consideration.

Specifically speaking, we first investigate the necessary aspects in BIV evaluations that may have influence on user experience and decision-making. Then, we introduce an evaluation framework that will evaluate BIV from three big dimensions: BIV attractiveness, decision-making experience, tasks and interactivity. These evaluations are influenced by four main factors: user's background, data characteristics, interactions, and interface design. This framework aims to cover most of the significant points in evaluating business intelligence visualization, and brings us a multi-dimensional evaluation that fits modern BIV. Moreover, we have conducted a user study, which followed the guidance of our framework, to evaluate different BIV designs. We believe that this research will help guide BIV design in the future.

2. LITERATURE REVIEW

In 1989, BI was first used as an umbrella term by Howard Dresner, but it was not until the late 1990s that this term was widely used. BIV is considered to be the core component of business intelligence, yet the research in this area is still in its early stage. For example, most studies on user experience of BIV focus on usability, but the experience of decision making (such as decision quality and decision complexity) is also an important indicator of BIV. However, limited research has been conducted on these aspects about BIV (Dinko Bačić & Adam Fadlalla, 2016).

2.1. Concepts related to BIV

In the era of big data, visualization, a clear way of visual communication, has emerged rapidly. Visualization is an interdisciplinary field that summarizes and presents data with simple and easy-to-understand designs, so as to convey information clearly and effectively (Embarak, 2018). When discussing visualization, we have to address that data visualization and information visualization are two sides of this concept, and they are often used interchangeably. However, when investigating scientific grounds and concepts, the mind and behavior of users, such as interactivity and cognitive aspects, are more prominent in information visualization than in data visualization; "developing and improving data processing techniques have been more common in data visualization than in information visualization" (Kim et al., 2016). In this research, we mainly focus on user's perspective to assess the visualization of business intelligence, rather than techniques in computing or data-processing. Therefore, in the article, we mainly discuss information visualization.

Information Visualization is an important means to analyze and interpret a large amount of information. It uses computers to interactively display unstructured and non-geometric abstract data sets (Nahum et al., n.d.). The function of information visualization is to provide people with a powerful analytic tool, so that people can make full use of their own visual and cognitive abilities to observe and analyze information, thus discover the relationship patterns of information (Nahum et al., n.d.). Currently, information visualization technology has been widely applied in Internet, medicine, biology, industry, agriculture, military affairs, political relations, entertainment information and business information (Barlowe et al., 2011; Didimo et al., 2011).

Business intelligence (BI) is the process of collecting, managing and analyzing business information, and its purpose is to promote the decision-making of enterprises (Dedić & Stanier, 2016; Eriksson & Ferwerda, 2021). Business intelligence has been widely used in banking, insurance, securities and retail industries. BI suppliers vigorously promote their visualization functions, which prove the importance of BIV to modern organizations, since BIV is considered to be the core component of business intelligence (Bačić & Fadlalla, 2016; Mohan, 2016). BIV uses computer-supported interactive visual representations to shows the complex relationships, potential information and development trends among original multidimensional business data, which promote better data, business, and behavior understanding and enhance the insight of decision making on business processes (Bačić & Fadlalla, 2016). Besides usability, aesthetics, pleasure and interactivity, the most important thing for BIV design is to provide decision support. Whether BIV can better reflect this design philosophy should be examined by user experience.

2.2. User's Experience of BIV

User experience has a long history that can be tracked back to late 1800s or early 1900s. The term UX was brought to wider knowledge by Donald Norman in the mid-1990s (Norman et al., 1995). UX involves all aspects of users' interaction with a product or service (Alben, 1996). ISO 9241–210 defines UX as the users' perceptions and responses when interacting with a product, system or service (Iso & Standard, 2010). Users' demands, subjective evaluation and emotional feelings during this process are considered as the core of positive experience (Kremer & Lindemann, 2015). Providing excellent user experience can at least prevent the loss of existing users (Jang & Han, 2022). With the continuous improvement of people's needs, UX has gradually become a crucial factor for product or service success, and has also become a hot issue in the field of HCI, design and business (Ntoa et al., 2021). Existing research indicates that it is necessary to define the corresponding elements or dimensions of UX according to the objects to be investigated (Jang & Han, 2022).

In visualization field, there has been research conducted about visualization UX. These studies covered usability, aesthetics, interactivity, user tasks, etc. Usability can be described as the capacity of a system to provide a condition for its users to perform the tasks safely, effectively, and efficiently while enjoying the experience (Lee et al, 2019). Stefania Passera has concluded that visualization helps improving usability on contracts. Helena Dudycz has validated the usability of visualization as it pertains to semantic searches in the analysis of economic and financial indicators (Dudycz, 2015). Khawaja et al have researched how to measure cognitive load in behave for usability evaluation (Khawaja et al., 2014). In 2006, De Angeli et al proposed that not only usability is important to UX, but also interaction and aesthetics(De Angeli et al., 2006). Wright et al proposed a guideline about the aesthetics and UX-centered design (Wright et al., 2008). And in 2009, Filonik and Baur have discussed how to measure aesthetics in information visualization (Filonik & Baur, 2009). Some other studies have been conducted in interaction and interactivity, such as the survey proposed in 2011 by Khan and Khan (M. Khan &

Khan, 2011). Sherry Koshman has conducted a study about user interaction in visualization system which helps to understand better the novice/expert paradigm when testing a visualized interface design for information retrieval (Koshman, 2005). Buja et al have discussed about interactions on high-dimensional data visualization (Buja et al., 1996). In order to perform a study the user task is also an important component in experimental design. Amar and Stasko proposed a task-based framework for evaluation of information visualizations (R. Amar & Stasko, 2004). Lee et al have performed taxonomy about tasks in graph visualization which concluded from various research (B. Lee et al., 2006). Yi et al. also performed research in order to analyze interactions in information visualization (Yi et al., 2007). Even there are such fields being researched, while we focus on the UX, we find that most of the existing studies only cover usability. Saket et al. also noticed this in 2016 and proposed several other important aspects for UX in visualization (Saket et al., 2016). Thus, we believe that it is necessary to expand UX evaluation in BIV to somewhere beyond usability.

In order to improve the productivity and efficiency of enterprises, user experience of BIV has become a new field of increasing interest to scholars. Although there are few existing studies on UX of BIV, this field is attempting to facilitate humans' interactions with visualization and to develop easy-to-use visual intelligent systems for decision-making (Attar-Khorasani & Chalmeta, 2022). However, current UX studies about BIV mainly focus on usability evaluation. Specifically, Chung and Leung (Chung & Leung, 2007) compared a visualization prototype (SNV) with traditional method (Web browsing and searching) on the analysis of business stakeholder information. Results showed that the information presented on SNV was more useful for analyzing than on the Web site, and SNV was perceived to be more capable in helping effective analysis and decision-making. Yun et al. (Yun et al., 2021) developed a novel visual decision support system (DSS) based on different data-mining techniques. The indicator of evaluation is the number counts of user's positive or negative evaluation on this system. Researchers collected the users' brief comments on this system. The results indicated that Concept Lattice-based method achieves the best performance, since this method received the highest positive evaluation rate among all the methods. Ltifi et al. (Ltifi et al., 2020) tried to combine visualizations with data-mining techniques to promote decision making in a newly developed visual intelligent decision support system (VIDSS). The result of user study demonstrated that VIDSS have good rating scores on usability. Basole et al. (Basole et al., 2016) evaluated the usability and usefulness of three visualization methods (list, matrix, network) for ecosystem analysis. List was considered the easiest to learn but the least useful. Network was rated the highest in virtually all ratings. Matrix was rated the most difficult to learn, but relatively useful for ecosystem analysis. Bačić and Fadlalla (Bačić & Fadlalla, 2016)proposed some BIV elements suggested as independent variables for UX studies on BIV, which expanded research ideas in this area. Their study presented BIV elements according to visual mental abilities in Non-Verbal Intelligence Quotient (NVIQ): exploration, interaction, business acumen and relevant data, analytics and statistics, representation, perception, cognition, cognitive effort, memory and storytelling. All these BIV elements should be regarded as significant factors that affect decision-making performance. However, for designers and UX researchers, if these BIV elements are considered as independent variables, they are too abstract and difficult to manipulate and the design problems cannot be identified directly and quickly.

2.3. Tasks

During our analysis through these articles, we have noticed that in order to evaluate BIV, a series of well-designed user tasks is important and necessary. The tasks may bring influence on the result of evaluation. We wish to have a representative landscape of the current user tasks literature in the BI or visualization research, in order to evaluate the roles that tasks played in BIV.

Through the literature review of BI and visualization we have conducted, some articles discuss tasks used in their research about visualization or BI. However, in this section, we have removed those articles that do not discuss tasks or do not involve user study. After this selection, 9 of the articles that have been noticed due to their outstanding research outcome in user's task (Appendix B). We have recorded and analyzed the metrics that were used in these studies, and believe it will boost our research.

The most common way to categorize tasks is to separate them with minimum elements. As far as we have observed, the researchers who have put their eyes on tasks. For example, B Lee et al. (2006) and J Stasko and R. Catrambone (2000) discovered their own categorization. The metrics proposed are not exactly the same, which means it might be somehow related to the usage scenario. During our study, we believe the common tasks which can be widely used across all visualizations do not perfectly fit business visualization, therefore, we need to propose our own tasks.

The advantage of dividing tasks into minimum objects is about the possibility to combine the tasks and make complex user story to describe the scenario in daily lives. In the articles proposed by B Lee et al. (2006) they have showed us how to combine the minimum tasks into high level complex tasks. They focused on graph visualization and the complex tasks they have proposed are graph related, which includes topology-based tasks, attribute-based tasks, browsing tasks, overview tasks, and high-level tasks. We can borrow their research approach in the business field, to let our task set closer to the daily usage in business. In addition, we can add qualitative metric into our framework which may come out from interviews, etc.

For the research of user tasks in BI, we can trace it back to 1999. In Tegarden's article (1999), he has mentioned: "As Cognitive Fit Theory suggests, we need to match the problem representation (visualization technique) to the problem-solving task. To help address this state of affairs, taxonomy of business problem domains, problem solving tasks, and visualization techniques would be useful." It is obviously that they have noticed the importance of user tasks during the evaluation process. But somehow due to the limitation they were unable to give a solid answer to this question.

Based on the research described above, we conclude that the current research for evaluating BIV is not sufficient. We need to develop a new framework aiming better evaluation for BIV.

2.4. Motivation

First of all, according to Maslow's hierarchy of needs, levels of needs are constantly improving, so users will not just stick to basic functions, but also pursue a satisfying experience (Yu & Wu, 2010). The business success of products depends more and more on a pleasant user experience. Most users of BIV do not have enough technical background and do not know the technical details of the system, so the quality of a user's experience with BIV system can have a critical impact on the work efficiency of decision makers. A satisfactory user experience provided by the BIV system can boost work performances of decision makers and bring obvious competitive advantages for companies.

Second, research on BIV evaluation mostly focuses on usability. However, good usability is not enough to create a good UX, because usability is only one part of the user experience. User experience includes all aspects of users' interaction with products or services. The dimensions of UX contain pragmatic aspects and hedonic aspects (Hassenzahl et al., 2010), that is, from traditional usability to aesthetics, appeal, and pleasure, etc. (Adikari et al., 2011; Kremer & Lindemann, 2015). Users' needs and their subjective and emotional evaluation of interaction are considered as the core of positive experience (Kremer & Lindemann, 2015). UX should also customize elements according to the characteristics of products or services (Jang & Han, 2022). UX of BIV lacks many valuable factors of user experience, such as trust, aesthetics, emotion, interactivity, loyalty etc., which are very important for the successful design of BIV.

Thirdly, the current research on BIV evaluation rarely covers decision performance. The existing BIV research indicators of decision-making performance are only the accuracy and speed of decision-making tasks, but not involve decision difficulty, time pressure, perceived information quality, decision-making quality, decision confidence, satisfaction and so on (Hwang, 1994; Visinescu et al., 2017); In addition, decision-making style of users will also affect the decision-making performance in BIV (Adnan et al., 2008). All these factors can help BIV design be more dedicated. The main goal of BIV is to nudge business decision-making. Compared with visualization in other fields, BIV values more on the role of visualization in promoting decisions. Thus, it is essential to assess the decision-making experience in the fields of BIV evaluation.

According to the above analysis, a UX evaluation framework for BIV is urgently required. This structured framework should basically contain the important components of BIV UX research and relationships among them. By using UXBIV, designers and developers of BIV can know how to study user experience of BIV. The independent variables include factors or elements that may affect the UX of BIV; the dependent variables involve dimensions of UX reflect the changes of independent variables; The framework also comprises user study design (selected tasks, methods and a paradigm) for use experience of BIV. Meanwhile, we also provide a case study based on UXBIV to promote the understanding and application of this framework. We hope that UXBIV can meet the needs of intelligent analysis industry, promote BIV design and customer loyalty, and enhance the competitiveness and influence of BI development companies.

3. FRAMEWORK

3.1. Method

The development of UXBIV framework came in three different steps through literature study:

- Search phase: we have obtained various articles through Web of Science and Google Scholar, based on the scope of BIV, UX, decision-making, and visualization evaluation (e.g. visualization AND user experience, visualization AND evaluation, visualization OR evaluation AND framework, etc.)
- Screen phase: when an article has been found, we conducted a screening on the article, and categorized it into several different interested areas based on their research goals.
- Identifying: we further processed these articles, and label all other interested areas covered by the articles.

After these steps, we have gained a set of literatures (Table 1) that can be used to build our framework:

Table 1. Articles reviewed based on interested areas (contains overlap)

Visualization Techniques	Business Intelligence	Visualization Design	UX	Evaluation	Framework	survey
115	30	20	51	43	13	12

The findings are used to create UXBIV evaluation framework. This framework compiled from all the interested areas based on existing research. We will introduce our findings in the following sections.

3.2. Independent Variables of BIV Evaluation

In this section we're discussing what we need to evaluate. UX is a subjective term that evaluates user's feelings from different aspects. However, BIV is an actual system that has all the objective components such as data, user's interface, etc. In order to evaluate BIV, we need to first think about what the independent variables are. These variables should be common or general among all BIV, and are critical to UX. As discussed above in literature review, we have identified 4 main aspects that have influences on user's experience, and two smaller areas that have less impact as side-aspects.

3.2.1. User's Background

User's background is a widely used metric in all the surveys. It is a well-known fact that every person is a unique individual. In order to evaluate user's experience we have to put the user's background into consideration. This is a commonly used technique that many researchers have this embedded in their user study, such as Khawaja et al. (2014), Van Lammeren et.al. (2010), etc. The differences exist in both physical and psychological level. Thus, we need to consider both sides to build our framework. Thus, two kinds of background are being taken into consideration into our framework: physical background and experience background.

Physical background refers to the physical characteristics of the participants, such as age, gender, race, etc. These characteristics will provide us statistical evidence about whether a design related to user's biology traits. Previous research in information technology, for example, Liu et al. (2005) and Foudalis et al. (2011), has used this type of background investigation. Experience background refers to user's experience and history, like professions, computing device usage, familiarity to data, etc. A well-trained person will likely achieve higher efficiency and accuracy, and therefore, may require a better design to meet their expectations. This is a widely used method in research as well, such as McCarthy (1994) and Law et al. (2009) did in their research.

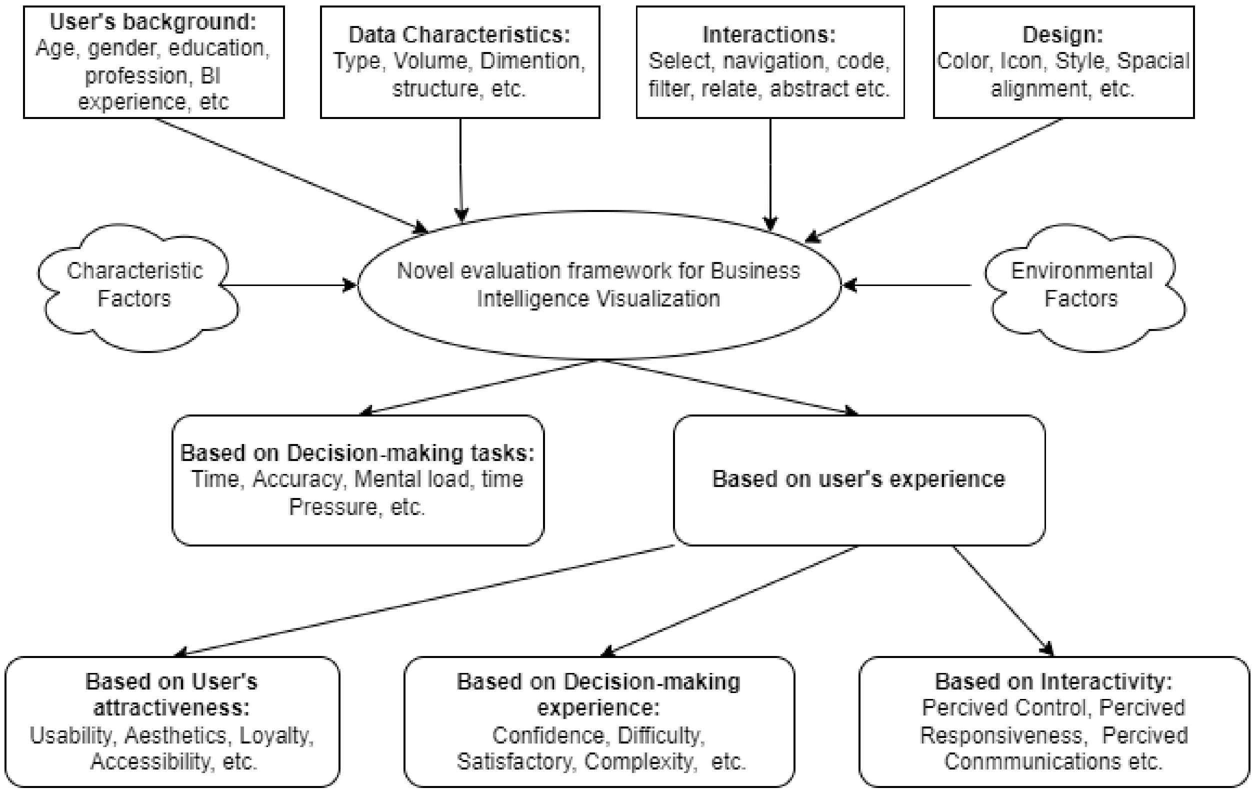

Figure 1. Novel evaluation framework

3.2.2. Data Characteristics

Even though we focus on user's experience, we still need to consider some other characteristics. Khan et al. (2014) has shown the importance of handling data correctly in the system as huge amount of new data are generated every second. Based on the survey we have conducted, each chart type has its own pros and cons. In addition, some design elements such as legend and label may help extend the usage of a chart type to cover different data types. Thus, we have to consider the mapping between data characters and design since this is directly connected with user's experience.

- Time Dependence

A data set can be either related to time or not, which can easily categorize it into time-dependent data or non-time-dependent data. Carter and Signorino (2010) have thoroughly discussed how to model time dependent data, and Heer et al. (2009) has explained the importance to choose the proper format for time-dependent series visualization. Time-dependent data usually use line chart or bar chart; in BI it is usually used in time-dependent reports such as sale report. Müller and Schumann (2003) have shown the methods to visualize time-dependent data. Non-time-dependent data such as warehouse coverage is the kind of data which are not linked to time. Usually we use map, heat-map, or tree chart to render such kind of data.

- Dimensions

Dimensionality in statistics refers to how many attributes a dataset has. (Finney, 1977) Commonly used dimensions are people, products, place and time. High Dimensional means that the number of dimensions is staggeringly high, that makes it difficult to calculate and visualize. For high dimensional data, it is necessary to determine how many dimensions are needed to be rendered in the visualization as we may not able to render them all, since the display platform is usually a 2-D display device. Spence (2004) has addressed how to effectively determine the better way of visualization dimensional data. A specialized visualization technique might be necessary in order to transfer high-dimensional data into visualizations, such as Buja et al. did in 1996 (Buja et al., 1996). Thus, we believe these needs to be evaluated for UX since the specialized visualization approach may affect usability in use.

- Volume

Volume refers to the data size or scale. The data processing and visualization with large volume of data is also known as “big data” in modern research. Some data sources have millions of data points, but the space of visualization is limited and the elements available are limited as well. In order to visualize such large scale of data within a limited displaying scope, specialized techniques are necessary. Past research, such as Gorodov and Gubarev (2013), Raghav et al. (2016) and Wang et al. (2005) have provided different solutions towards this issue. Considering that different visualization techniques may result in different visualization elements displayed and then affect usability, we need to take data volume and techniques into consideration of BIV evaluation.

3.2.3. Interactions

Interaction refers to all the tasks that the user can perform to interact with the visualization interface in order to retrieve information they want. It includes but is not limited to button, drag tool, zoom tool, color tool, etc. More interactions will provide user with more degrees of freedom, but it will also introduce more elements into one design and increase the learning curve, which might reduce the usability of the visualization. Satyanarayan et al. (2014), Yi et al. (2007), and Figueiras (2015) have discussed their understanding about the relationship between interactions and UX in visualizations.

3.2.4. Design

Design is a big term but crucial towards BIV system, the difference in design may lead to direct impact towards user's experience. As Hollands and Spence have found in 1992, choosing the right type of visualization would result in difference in user's feedback. Thus, we have to take a look into the system interface design.

- Style

Style is an abstract concept that relates to how an artefact – such as visualization – can be recognized and be potentially grouped in a specific category (Moere et al., 2012). Some empirical evidence exists that style plays an important role in the perception of users, as it is often the only ‘way’ to make a product stand out (Tractinsky, 2004). Moere et al. have categorized style into 3 types: analytical style, magazine style, and artistic style. These styles vary in many different dimensions, bring different overall visual representatives, and affect UX at a very high level of design.

- Chart Type

Chart Type refers to the visualization types such as line chart, bar chart, pie chart, etc. This is the most widely discussed term in visualization. Based on Croxton’s research in 1932, different chart types lead to different user’s experiences. Modern research, including Forsell and Cooper (2014), Merčun (2014) and Freitas et al. (2002 and 2014), has shown that this is still an important component to be discussed in visualizations. In addition, with more discussion about big data nowadays, choosing proper chart type may also have direct impact on usability.

- Aesthetics

Aesthetics refers to all other visual elements such as color, font, text size, textures, etc. A well-designed aesthetic guideline will help BI keep consistency and help improve user’s experience. Cawthon and Moere (2006) have discussed the aesthetic effect in evaluating UX in visualizations. Other researchers and designers are actively working on improving many different aspects, such as Bartram et al. (2017) for color, Heer et al. (2009) for color blending, Karoz et al. (2015) for pictographs, etc.

3.2.5. Characteristic Factors and Environmental Factors

Besides those main factors, there are some factors that may result in different user experiences, but these factors may not be related to the BI system itself. We have identified two primary groups of factors that are related to users and environments, namely, characteristic factors and environmental factors.

Characteristic factors refer to differences between participants (mostly emotional) that may affect UX result. Some elements fall into this category include holistic/ analytic thoughts, high-context/ low-context style, etc. In order to compensate user's condition during the tests, we have to pull this into consideration. Robinson et al. (2016) discussed how to identify participant characteristics. Harrison et al. (2012) have shown the impact of emotions on visual judgement. Ting et al. (2018) have discussed about emotional characteristics in design.

Environmental factors are related to environment of the test. This includes 2 aspects: the social background (cultural, technological, economical, etc.) and the experiment context of the user study taken (lab, online, office, etc.). As Imamoglu pointed out in 1985, social background has effects in user's response. Different social background may bring different think-path, and may result in difference in results. On the other hand, Cho and Sagynov (2015), Ekman and Kajastila (2009), and Hrimech et al. (2011) have discussed about experiment context may affect users in their researches. An obviously example is, the test taken in a professional lab will give the users more confidence than let them take the test online, and the data collect in the first environment will be more reliable.

These two factors may have direct impact to the results, so that we can consider these as independent variables in the research. In some occasion, while we do not use these factors as individual variables, it is necessary to set them as controlled variable, to keep result trustable and clean.

3.3. Dependent Variables and Measurement

Since we're evaluating based on a UX-based manner, we also need to think about what aspects are important for UX in BIV evaluation. Different from the independent variables, UX is measured with several subjective aspects. Based on what we have discussed in literature review, we have identified three aspects that we're going to evaluate in this framework. Each aspect has several different factors.

3.3.1. Task-Based Dependent Variables

3.3.1.1. Objective Measures

3.3.1.1.1. Reaction Time

Reaction time and accuracy are two widely used research measures for human-centered researches. Reaction time refers the time spent of a user to complete a specific task. Reaction time is used to evaluate usability and cognitive loads in user study. In 1982, Santee and Egeth have shown that these measures are related to user's recognition in evaluation. Prinzmetal et al. (2005) have revealed even more mechanisms by focusing on these two measures.

In this research the reaction time refers to the time spent by a user to complete a specific task. This can be used to evaluate aspects such as usability and cognitive loads during the study. This measure has also been applied in research conducted by Saket et al. (2016), Rind et al. (2016), and many other researchers.

3.3.1.1.2. Accuracy

Accuracy is another term that user study usually focusing on. In our research, the accuracy is the correctness of the user to complete specific tasks. This can be used to track aspects such as accessibility and cognitive loads during the test. Stasko et al. (2000), Pillat et al. (2005), Fu et al. (2017) and many other researchers have used this measure in their research.

3.3.1.1.3. Electrophysiology

Electrophysiology is another powerful support data collection method. Thanks to the development of technology, electrophysiology is becoming affordable these years. Some representative electrophysiology approaches, such as eye-tracking devices and brain computer interface devices are more common in labs, and even into our daily life (Ahn et al., 2014). This is a valuable evaluation method such that providing data that was unable to collect before. For example, an eye tracking methodology can help to uncover visual scanning strategies in a new pattern, providing rich information beyond that available from response time and accuracy-based methodologies (Goldberg & Helfman, 2011).

In the research conducted by Fu et al., graphs provide more effective mind maps to the participants, who were then more efficient at processing relevant information (Fu, Noy, & Storey, 2017). Electrophysiological device is able to identify the influence of graph design on UX, which is helpful during our evaluations. In our framework, this kind of measure is not mandatory, but it is a great addition to help us improve the evaluation.

3.3.1.2. Subjective Measures

In a controlled experiment, we can perform some measures during the task procedure. This is because UX is a term that is related to user's subjective feedback, we cannot use all objective measures to determine a whole scaled UX evaluation. As Olsson (2012) pointed out in his research: UX is associated with vague, dynamic and hard-to-quantify concepts, such as "experience", "perception", "pleasure", and "emotions". Vermeeren et al. (2010) pointed out that, to date, there are few—if any—widely accepted standard methods with which to assess UX in general. This kind of measures is directed to user's workload and satisfaction since the measure is closer to the tasks. But on the other hand, it will be influenced more by user's characteristic factors.

One common evaluation method is based on tasks and impressions. We can evaluate task-based UX by using After-Scenario Questionnaire (ASQ) (Lewis, 1991). This questionnaire is taken immediately after participants finished the user tasks during the test. A total of 3 items were incorporated into 3 different dimensions: effectiveness, efficiency, and satisfaction. All items were rated on a 7-point scale.

Another popular evaluation method is NASA Task Load Index (TLX) (Hart, 1986). It is a subjective workload assessment tool which allows users to perform subjective workload assessments on operator(s) working with various human-machine interface systems. TLX measures on 6 different dimensions: mental demand, physical demand, temporal demand, performance, effort, and frustration. All items are rated on a 10-point scale.

There are also more measures available that we can use for subjective measures. Depending on different focus of the actual evaluation taken, we could have flexibility to choose different subjective measures.

3.3.2. Overall UX as Dependent Variables

3.3.2.1. BIV Attractiveness

BIV attractiveness is a set of aspects of UX which are evaluated by user's subjective response. These aspects measure how user's feeling by using the evaluated system. During our research, we found this has overlap with SUPR-Q (Sauro, 2015). In this article, we will evaluate using SUPR-Q dimensions: usability, trust, appearances, and loyalty. In addition, we also have an extra dimension called emotional involvement.

3.3.2.1.1. Usability

Usability refers to the effectiveness, efficiency, safety, utility, and learnability of a design (A. Dix, 2009). In practice, usability is operationalized as the combination of users' actions and attitudes (Sauro, 2015). A well-designed BIV should provide sufficient information and make it easy to use. Thus, usability test is to measure how easy-to-use of a system from user's perspective. For example, if the user thinks that one design is easier to use than another, the first one should have higher rating on this metric. Standardized usability questionnaires, as opposed to homegrown questionnaires, have been shown to provide a more reliable measure of usability (Hornbæk, 2006).

3.3.2.1.2. Trust

Trust has traditionally been linked to relationships within a business environment (Dwyer, Schurr, & Oh, 1987), but nowadays it also plays a strong role in human-computer interaction (Jian et al. 2000). Trust is a “mediating factor” that determines whether consumers accept and use an automated system for self-service (Lee & See, 2004). For example, sale data A might be much higher than sale data B, but if they get visualized into a log-based chart, the difference may look much smaller and may lead to confusion. Safar and Turner (2005) developed a psychometrically validated trust scale consisting of two factors based on an online insurance quote system. A broader examination of website trust was also conducted by Angriawan and Thakur (2008).

3.3.2.1.3. Appearance

Appearance is a metric that measures influences across all visual elements. This metric evaluates user’s feedback based on visual appearance. The Web Quality (WQ) instrument by Aladwani and Palvia (2002) contains an appearance subscale, and the influential Hedonic Quality (HQ) questionnaire developed by Hassenzahl (2001) has an appeal subscale. For example, a design with well-designed color palette should have better visual feedback than a design with only black and white, and the rating should be higher.

3.3.2.1.4. Loyalty

According to Torres-Moraga et al. (2008) attitudinal loyalty includes aspects like cognitive, affective and conative inclinations of customers to continue relationship with a brand/

company. In our framework, Loyalty refers to the user's confidence about re-use evaluated system, and/or the willingness to share with others. This is an overall rating that directly demonstrates the user's satisfaction about the system. In some cases, the user does not like a specific point of design but is not willing to share, but all other three factors may still get high ratings. If this occurred, such case would indicate that something needs to be improved in the design.

3.3.2.1.5. Emotional Involvement

During the period of using the system, the person also experiences various feelings including fascination, suspense, tension, empathy, amazement, surprise, warmth, anger, fear, and other emotions (Wirth, W., Hofer, M., & Schramm, H. (2012)). Emotional involvement refers to the subjective intensity of those feelings, which is often related to the duration, the peak level, and the frequency of the feelings (Sonnemans & Frijda, 1994, 1995) This will be done with a set of subjective adverbs to let the user rate the system (e.g. boring/ interesting).

3.3.2.2. Decision-making Experience

In business field, decisions may lead to capital loss (Gessner & Volonino, 2005), so decision-making support system plays a big role in modern business. This brings decision-making a crucial component to be considered while designing BIV. Thus, it is necessary to find a way to evaluate decision-making experience for BIV. In our framework, we will evaluate from four aspects: Decision Complexity, Auxiliary Importance, Decision Quality, and Information Quality.

3.3.2.2.1. Decision Complexity

Decision complexity is a key factor in behavioral decision-making research (Shiloh et al., 2001). As Tractinsky and Meyer suggested in 1999, "capture the complexity of information usage in actual settings… should be taken into account". This involves the environmental factors, the emotional factors, the task itself and other factors. Decisions with more alternatives and attributes were evaluated by decision makers as more difficult (Timmermans & Vlek, 1992). A decision that needs to consider more elements will be rated higher on complexity. For example, predict sale-count only with historical sale data will get lower rating comparing to predict with historical sale data, popularity history, and other aspects.

3.3.2.2.2. Auxiliary Importance

Auxiliary Importance evaluates how important the evaluated system is during the decision-making process as a support system. BI is a decision support system (Sprague and Carlson, 1982), and supposes to improve decision support (Power, 2002). It provides the right information needed in decision making process and helps the organization's control, planning and operational functions be carried out effectively (Cao et al., 2008; Adeoti-Adekeye, 1997). This examines the design based on the assumption that if a decision made relies on the information system, the system should be rated higher on this metric.

3.3.2.2.3. Decision Quality

Decision quality is a function of effectiveness and efficiency in the process of decision-making (Clark Jr et al., 2007). This covers decision outcomes (DeSantis and Poole, 1994), problem-solving performance (Vessey, 1991), expectancy of success (Langer, 1975), information processing performance (Galbraith, 1974), and decision-maker risk preference (Kahneman, 1979). Others consider decision-making in terms of how decisions are made and structured (Cohen et al., 1972). Decision quality outcomes are often measured using perceived decision-maker satisfaction with the outcome as a surrogate for decision quality (Kaltoft et al.).

3.3.2.2.4. Information Quality

Information quality is key in the functioning and output of information systems (DeLone and McLean, 2003; Ge and Helfert, 2013). N. Tractinsky and J. Meyer have defined this as "relative efficacy to provide the relevant information for the viewer" in 1999. Therefore, the quality of information in the BI is critical to the quality of decisions made based on the output of the BI satisfaction (Bharati and Chaudhury, 2004). For example, a design that gives users hundreds of data points may lead to reading difficulty and the user will suspect the information retrieved may be wrong. In this case, the Information Quality rating should be lower.

3.3.2.3. Interactivity

Interactivity has been utilized in information visualization to make the data more engaging or playful, and/or in order to show data in a manageable portion (Figueiras, 2015). On behalf of user's experience we discuss such intercommunications as interactivity. This will measure the user's feedback about the bi-directional information transfer between human and computing device. We will evaluate from three aspects: Perceived Control, Perceived Responsiveness, and Perceived Communication.

3.3.2.3.1. Perceived Control

This metric evaluates the user's satisfaction based on human input. If the system provides enough control elements to let the user perform needed operations, it should be rated higher on this metric. For example, if the clients want the data of best seller in May, he can retrieve the data directly from a bar-chart or use interaction such as zoom to get the data easier from an enlarged view. The extra control provided will help the users operate as they desired.

3.3.2.3.2. Perceived Responsiveness

Perceived Responsiveness is evaluating how the system response towards a human input. The system response should follow user's expectation and provide desired information. If a user does not get what they want after performing an input to the system, the satisfaction about the system will decrease and this rating will be lower.

3.3.2.3.3. Perceived Communication

Decision quality refers to the user's satisfaction about the overall intercommunications between human and computing device. This evaluates both sides of the information transfer.

Based on all the aspects described above, we have generated a set of questionnaires (Appendix C). Combining all the objective measure, it should cover most important metrics about evaluation of BIV. However, it is just one possible approach to implement our framework; there are also other possible ways to implement. Also, in order to save time and reduce complexity of the evaluation, some metrics can be skipped during the evaluation design procedure based on the designer's judgement.

3.4. User Study Design

In order to evaluate objective components with UX, a user study is necessary. Maguire (2001) describes the controlled user test method as the chance to "gather information about the users' performance with the system, their comments as they operate it, their post-test reactions and the evaluator's observations". This user study of evaluation is twofold. First, we need to build up a series of tasks which as close as possible towards the real usage scenarios. Second, we perform measures upon the task in order to collect data.

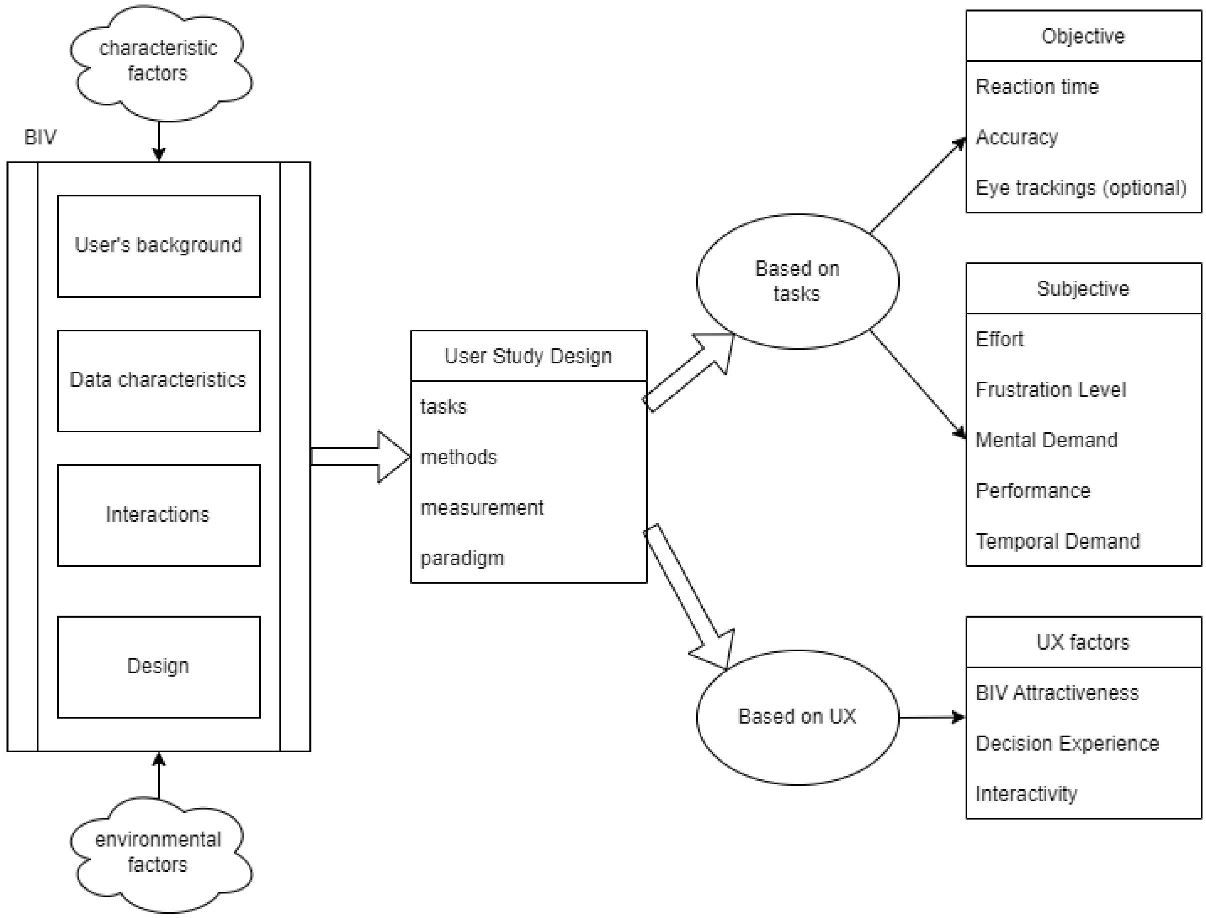

Figure 2. Evaluation Flows

3.4.1. Task

3.4.1.1. Minimal Task Category

In this section we will introduce a guideline to design evaluation tasks for the user study. Based on the research listed above and in appendix C, with the consideration of daily usage in business, we have managed to come up with a task set that would fit business visualization better:

- Precise Select/Identify: Given characteristic, find something specific (e.g. find the largest amount of sales)

- Fuzzy Select/Identify: find something not specified but can be determined by professional knowledge (e.g. find anomalies in transactions/sale data) or other characteristics (e.g. find managers who have similar performances last year)

Select/identify should be the most common task in BI since this is how the system transfers data into valuable information to help the decision-maker. This has also been mentioned by Stasko (2000) and Ji Soo Yi et al. (2007). In the consideration of business purpose, we decide to split it into precise and fuzzy based on the task purpose. In some cases, the users try to gain some information, but may not need to retrieve exact value from the visualization. As what we have discussed in the section, some designs may have advantages to show something fuzzy directly, but they may take additional steps to gain exact value. For example, a pie chart is able to show the portion of something inside an entity but needs labels or legends in order to show exact value.

- Compare: compare two or more data elements/sets or distinguish a data element/cluster from others (e.g. find a store manager who has a better performance in the past season)

Compare is also a common task in data visualizations as discussed by Stasko (2000). Whenever we have two or more data inside visualization and we need to know the relations about them we're most likely going to compare them. A well-designed visualization should have optimized this process.

- Rank/Sort: Given a set of data cases, rank them according to some ordinal metric (e.g. find top 3 best stores based on sales last year)
- Filter: Query a set of data by given conditions, may combined with other tasks (e.g. find the best store in North Dakota)

Rank/sort and filter are widely used in data analysis as well. Amar et al. (2005) and Etemadpour et al. (2015) have discussed this in their research. These tasks will benefit from user's interaction. A well-designed system should provide sufficient tools to boost these procedures.

- Cluster/segmentation: Cluster data points that have similar characteristics (e.g. find the average sales of all the stores in a specific area; find a state that has more sales last year)
- Correlate: Find the relationship between two or more elements, include trending (e.g. which store has the fastest increase in sales)

Amar et al. also propose these two tasks in their research. Both tasks above are about the relations of multiple data. There are two use cases for clustering/segmentation and correlate. First, for time-dependent visualization, cluster/segment is able to show the trend over time. On the other hand, for time-independent visualizations, cluster/segment and correlate are used to show characteristic in other field (such as geometry), and are widely used to detects anomaly in a data set.

- Estimate: Based on the information visualized, make an estimate of something that is not shown precisely, either because of hidden data (e.g. estimate how many stores available in North Dakota) or unavailable data (e.g. estimate the total sales next year across the country)

Estimate, proposed by Etemadpour et al. (2015), is a new but important task in business intelligence. Different from visualization used in other fields, the business decision-maker is focusing on prediction. Well-designed business visualization should benefit this process.

Table 2. Category of tasks used in framework

Task	Description
Precise Select/ Identify	Given characteristic, find something specific (e.g. Find the largest amount of sales)
Fuzzy Select/ Identify	Find something not specified but can be determined by professional knowledge(e.g. Find anomaly transactions/ sale data) or other characteristics (e.g. Find managers that has similar performance last year)
Compare	Compare two or more data elements/ sets or distinguish a data element/ cluster from others (e.g. Find store manager that has a better performance in the past season)
Rank/ Sort	Given a set of data cases, rank them according to some ordinal metric. (e.g. find top 3 best stores based on sales last year)
Filter	Query a set of data by given conditions, may combined with other tasks (e.g. find the best store in North Dakota)
Cluster/segmentation	Cluster data points that has similar characteristics (e.g. Find the average sales for all the stores in a specific area; Find a state have more sales last year)
Correlate	Find the relationship between two or more elements, include trending (e.g. which store has the fastest increase in sales)
Estimate	Based on the information visualized, make an estimate of something that is not shown precisely, either because hidden data (e.g. estimate how many stores available in North Dakota) or data not available (e.g. estimate the total sales next year across the country)

From the study provided above, we have discovered the past achievement for user's task on visualization and interactions. However, this research aims at general comparisons or prepared for their study in a different field. Since we focus on BIV, we need to adjust the task settings to fit the demands best.

With the novel business-related categorization of tasks, we can build high-level tasks that are closer to the real world but have more controls for analysis. For example, with a given warehouse dataset, a normal use case is to retrieve sales data based on time or destination. These tasks can be easily built by combining Precise select/ Compare/ Rank/ Cluster/ etc. depends on the interaction/visualization technique used. Controversially, we can also evaluate different designs by testing on different scenarios that built by selected low-level tasks. Our categorization, coupled with our evaluation frameworks, as well as higher-level user tasks and scenarios, would provide a holistic evaluating performance that tracks BIV performance closer to a real business context.

3.4.1.2. Combined Tasks

In the research proposed by Lee et al. (2006), they have noticed several tasks above the low-level task. Based on the low-level tasks, we can also build up some combined tasks. However, since the combinations have so many possibilities, here we will only demonstrate some examples.

Connectivity: This is a combination with precise/ fuzzy select, compare, and correlate. For example, user finds warehouses with the largest demands, and links them together for a best route to resupply.

Strategy making: This is a combination with fuzzy select, cluster, and estimate. For example, the user uses heat-map to read sales in different areas, and make estimation for next season.

3.4.2. User-Centered Methods

As stated by many studies in the literature, the "UX is dynamic, context-dependent, and subjective" (Law et al., 2009). Usability assessments in the literature have been conducted using different methods and for different purposes (Alomari et al., 2020). One possible approach is to leverage user centered design that involves speaking directly to the user at key points in the project to ensure it delivers on their needs and requirements. As Ntoa expressed in 2021, user testing is the most fundamental evaluation method and cannot be completely replaced by any other method. Some key methodologies that are commonly used are:

- Focus Groups: A focus group involves encouraging an invited group of intended or actual users of a site or digital service (i.e. participants) to share their thoughts, feelings, attitudes, and ideas on a certain subject.
- Usability Testing: Usability testing sessions evaluate a site by collecting data from people as they use it. A person is invited to attend a session in which they'll be asked to perform a series of tasks while a moderator takes note of any difficulties they encounter.
- Card Sorting: Card sorting is a method for suggesting intuitive structures/categories. A participant is presented with an unsorted pack of index cards. Each card has a statement written on it that relates to a page of the site.
- Participatory Design: Participatory design does not just ask users for their opinions on design issues, but actively involves them in the design and decision-making processes.
- Questionnaires: A questionnaire or quantitative survey is a type of user research that asks users for their responses to a pre-defined set of questions and are a good way of generating statistical data.
- Interviews: An interview usually involves one interviewer speaking to one participant at a time.

A combination of multiple methods in a single experiment may bring better results. We can combine UCD methodologies with psychological experiment design theory to perform behavioral experiments. Behavioral experiments are planned experiential activities to test the validity of a belief.

A/B testing is another user experience research methodology (Young, 2014). A/B tests consist of a randomized experiment with two variants, A and B. These values are similar except for one variation which might affect a user's behavior (Kohavi et al., 2020). A/B tests are widely considered the simplest form of controlled experiment.

3.4.2.1. Experiment Design

A typical experiment design would involve different BIV designs. Following A/B testing principle, we can either run within-group test or between-group test depends on the participant group size. The independent variable can be set to any element we have discussed above, such as design, interactions, etc. These elements should be different in the designs that are being tested. However, for those variables that are not changing between designs, we have to treat them as controlled variable and reduce side effects. The goal of such experiment is to observe expected difference between designs.

3.4.2.2. Questionnaires and Interviews

Empirical evaluation techniques are used to determine actual measures of efficiency, effectiveness and satisfaction (Faulkner, 2000). The available techniques include field tests, observations, interviews, questionnaires and formal usability testing (Wesson, 2002). In BIV evaluation, with the consideration of costs and objectives, the most efficient measures would be questionnaires and interviews. This can also be divided into several categories based on the timing of taken: pre-context, pre-test, in-test, post-test, post-context.

Pre-context questionnaire, or as known as background survey, is a common approach towards user's background. The purpose of this stage is also to gather data about each participant's expectations and frames of reference for the user experience to be tested. As we discussed above, user's background is important in this framework (Thayer and Dugan, 2009). A user with or without professional background may lead to a huge difference in feedback. Thus, beside from the common background survey which focusing on age group, gender, race, etc., the background survey in our framework should also cover user's education, profession, and experience of computing device usage or data management.

In-test questionnaire, which are taken right after a single task, would be the most direct way to measure user's feedback. The goal of this stage is to gather feedback on the specific features or areas of the product that relate to the experience goals (Thayer and Dugan, 2009). The time between task and measure are close, which would bring up clearer thoughts from the user's perspective. But this also suffers from user's characteristics factors, which may lead to reduction of reliability for data measured. In addition, if a study has a lot of tasks, this kind of questionnaire may lead to extra workload and frustration for users.

Post-test questionnaire is taken while user has finished a set of tasks. The purpose of this stage is to ask the participant to reflect on his or her experience with the product under study, and then compare the actual experience to the anticipated experience (Thayer and Dugan, 2009). The goal of this stage is to gather participant feedback about the total user experience, but to gather that feedback in a way that provides measures for our evaluations.

Interview is also a good approach to collect users' feedback. It can be tracked back to 1960 by Thomas et al. Post-context interview or questionnaire is taken after all tasks are done. The purpose of this stage is to gather general information about participants' responses to the experience they had during the study (Thayer and Dugan, 2009). Maguire (2001) states that the post-experience interview is "a prespecified list of items…allowing the user freedom to express additional views that they feel are important"

Wright et al. (2008) have managed this info and line them up as shown in table 3:

Table 3. Category of questionnaires and interviews used in framework

Study stage and usability testing goal	Data collection method(s)
Stage 1: Pre-context questionnaire	Pre-experience interview, pretest questionnaire
Study 2: Post-context questionnaire	Post-task questionnaire
Study 3: Controlled user test	Performance data, think-aloud protocol, evaluator observations
Study 4: Post-test questionnaire	Post-test questionnaire, satisfaction questionnaire
Study 5: Post-experience interview	Post-experience interview

4. USER STUDY

4.1. Purpose

We have conducted a user study in order to apply our theory and framework into an actual evaluation case. This demonstrated how to use our framework on given visualizations. In the meantime, we can use the proposed user-centralized evaluation to identify the insufficient parts of a given BI system and provide guidance to improve.

4.2. Experimental Design

This experiment is a within-group design. We selected design complexity as the independent variable. This includes interaction types and design types. Specifically, the system has three design types with increasing complexity in color and interaction. Figure 3 demonstrates a chart selected for one of the designs. Design one has the lowest complexity without toolbars. There is no interaction for this design. It contains minimum visual elements with white/black color and stripe patterns (see Figure 3 (a)). Only two charts have a legend in this design with the toolbars. Design two has the medium complexity. We applied blue colors with different brightness to the chart elements (see Figure 3 (b)). Most charts have a legend and simple interactions, such as horizontal movement and one-dimensional zooming, element selection, and reset. Design three has the highest design complexity. We utilized colors with different hue values (see Figure 3 (c)) to classify data and provide a call-out box to display additional information. Similar to design two, the legend is shown in the charts. But the interaction is more complex in design three. Users can perform move and zoom the charts in two dimensions. The toolbar enables the participants to amplify or select the chart elements and toggle call-out boxes.

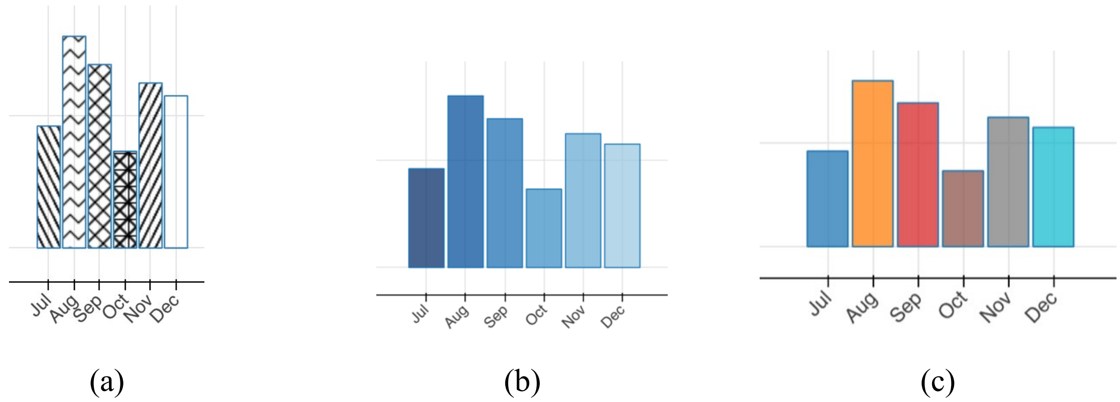

Figure 3. Color selection for different design complexity levels

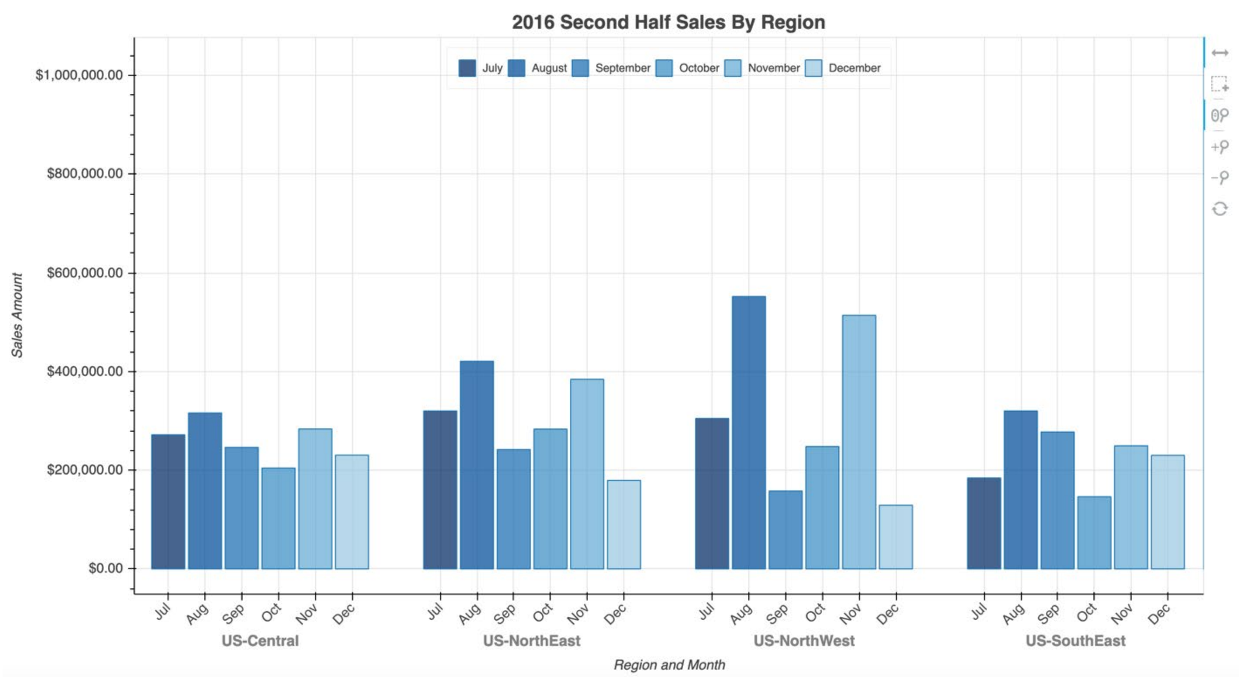

Figure 4. An example of chart for one of three designs

The dependent variables focus on the participants' efficiency decision making during the business assessment, recognition, and strategy selection. Specifically, our dependent variables will be impacted in the following aspects.

- Participants' level of mental demand, temporal demand, and efforts. We also consider their performance and frustration level during the decision making.

- Participants' experience to the user interface, which includes ease of use, degree of trust, level of design appearance and user loyalty, as well as importance of Business Intelligence and decision complexity.

4.3. Materials

We implemented a web-based business sales information visualization system written in HTML and JavaScript for this user study. The sample data are from a US shopping mall dataset, including product sales, refund rate, department turnover, product price and discount change, and the consumption of large-volume buyers, etc. The system contains different visualization types, including treemap, bar chart, bubble chart, and scatter plot, etc. Figure 3 illustrates the design of the user interface.

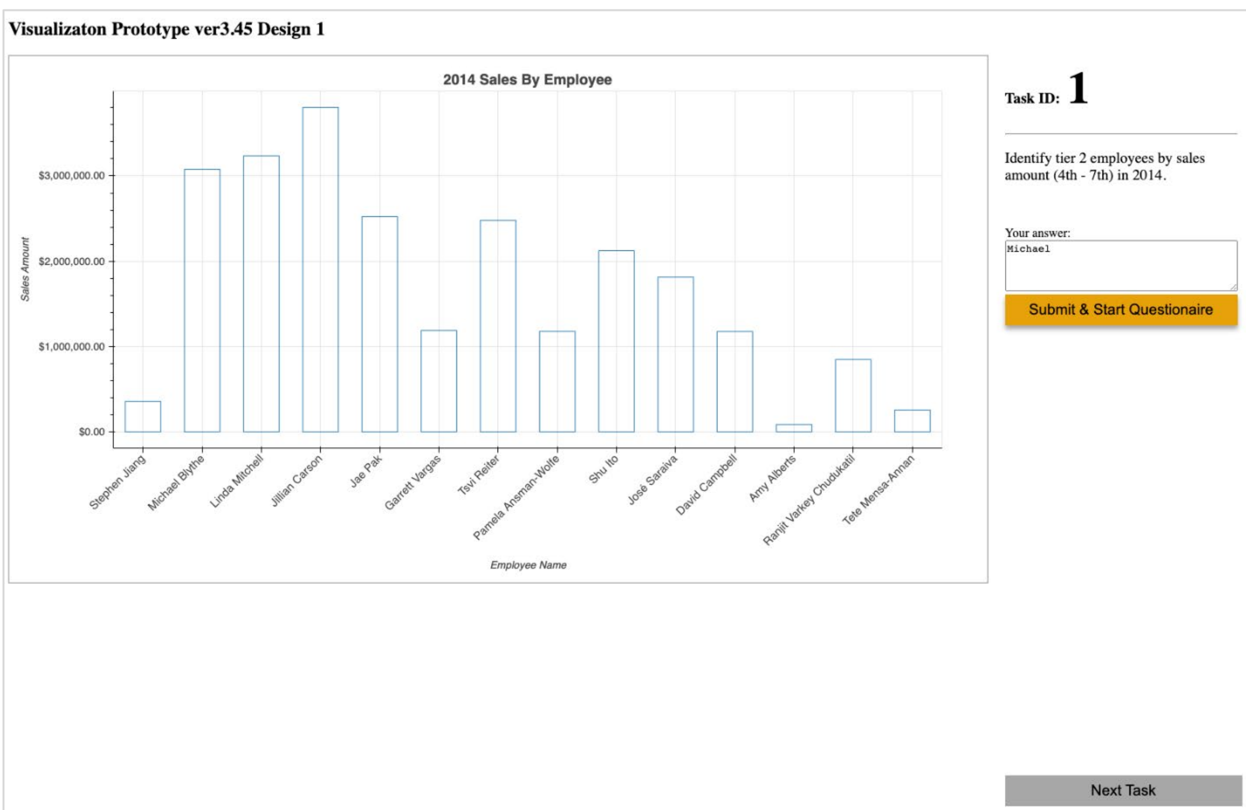

Figure 5. GUI of a single task

4.4. Participants

Fouty-seven eligible participants were recruited from a Midwest university who can speak fluent English. All the participants have normal vision or corrected vision (i.e., wear glasses). 84% of all 47 participants identified themselves as male, and 16% as female. Among all the participants, 8% of them are freshmen, 14% are sophomores, 33% are junior, 27% are Senior, 16% are graduate students. The subjects are from different majors. 51% are computer science, 17% are from management information systems, 11% are from computer engineering, 9% are in computer science and mathematics major, 2% are in statistics major, another 4% are from business analytics major, and rest 4% are from plant sciences and Electrical and Computer Engineering. In addition, 21% of the participants have ever taken or been currently taking a class related to business intelligence. None of the participants were familiar with data visualization at the time of this study.

4.5. Apparatus

The experiment was conducted on a Windows 10 desktop computer in the lab. The program was written in HTML and JavaScript and was displayed on a 24-inch LCD monitor with a resolution of 1920 x 1080 pixels.

4.6. Procedure

During the experiment, the participants sat straight in front of the desk. Their eyes were about 1.5 feet away from the screen. In addition, the participants were asked to use their dominant hands to hold the mouse and operate the program. All the tasks were randomized in ordering, and the designs were randomized in ordering as well.

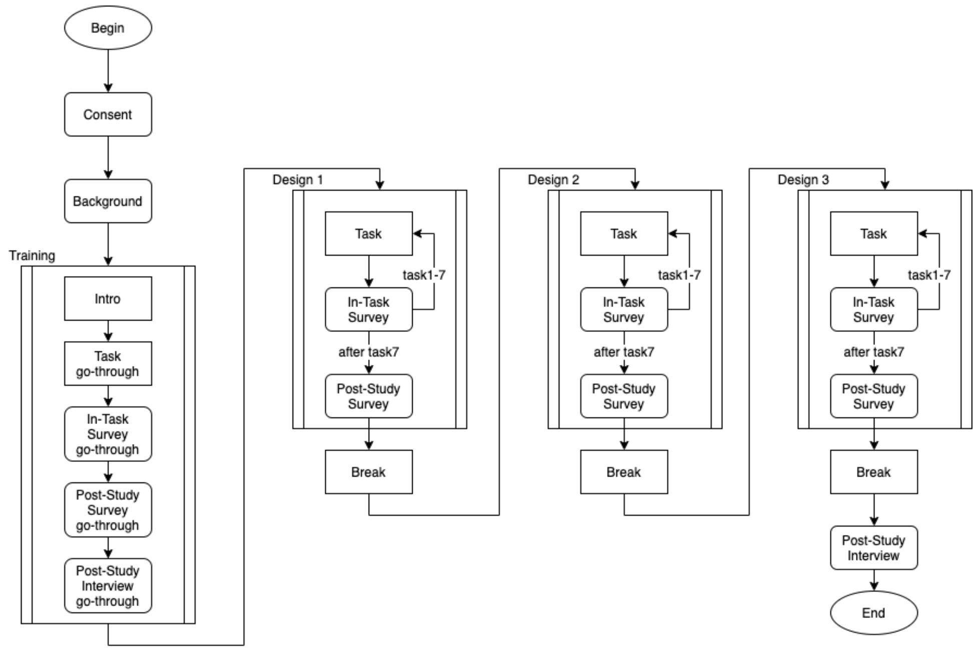

Figure 6. Procedure of the user study

Figure 6 demonstrates the process of the user study. The participants were invited into the lab to complete the user study. After reading and signing the consent form, they were asked to finish a pre-study questionnaire, followed by a short training that lets them familiarize the user study approach and tasks. After that, they completed five tasks on each of three designs. In the tasks, the participants were asked to type the answer to the question displayed next to the chart based on their observation (see Figure 5). After each task, the participants were asked to complete an in-study questionnaire to evaluate their experience to the task. Following is the list of the question in each task.

Task 1: In the second half of 2014, which region has the highest sales in September?

Task 2: For the year of 2014, in which region(s) component sales surpass bike sales?

Task 3: In which month of 2015, the sales of clothing have the highest positive growth rate?

Task 4: Identify two US regions that experienced the highest degree of sales fluctuation in the first half of 2014.

Task 5: Based on product sales in 2014 and 2015, which product category would you recommend the company to focus on in their next marketing campaign? Please briefly explain why.

Task 1 to Task 4 are about recognition. Task 5 is about strategy selection. The questions of the in-study questionnaire were categorized into five dimensions. They are mental demand, temporal demand, performance, effort, and frustration level.

During the test, for high-level tasks, we may take the measure of time, accuracy, cognitive loads, time pressure, etc. These measures are based on the task that is close to real world usage, but with the analysis shown above, we can take it down to the low-level elements and find the relations between. However, with a deep consideration of the real-world business, our evaluation framework does not include user's reaction time of time cost as a measurement. A business process is the combination of a set of activities within an enterprise with a structure describing their logical order and dependence whose objective is to produce a desired result (Ruth Sara Aguilar-Saven, 2004). The business decision-making process in real world may contain a lot of interactions between humans, sometimes across departments. This will be a time-consuming process and may lead to information loss. Comparing to the communication cost, the time advanced from user-interaction in seconds is not a major factor for decision-making performance.

In addition, as some other researchers have pointed out, time pressure causes selective and reduced information search and superficial processing (Hogarth and Makridakis 1981b). Furthermore, time pressure leads to a tendency toward ‘‘locking in on a strategy’’ (Edland and

Svenson 1993), to simplifying strategies (Wright 1974), and to conservative behavior (Hwang 1994). Summarizing these findings, Gerrit H. van Bruggen et al. have concluded in 1998 that time pressure will have a negative effect on decision quality and, consequently, on performance, since decision makers are not able to use all available information in their decision-making process.

Considering these factors, we decided not to record and count the reaction time for the decision-making process. We believe it is more important to focus on decision-making quality rather than speed. However, a better design will do a better job to deliver information, and it will be shown in the user's response as they may feel it is easier to retrieve information. Following this path, we think we have tuned our evaluation framework closer to business needs.

After they finished all five tasks for the current design, the participants evaluated their entire experience with the system on a post-session questionnaire on the dimension of usability, trust, appearance, loyalty, the importance of BI, complexity, and quality.

5. RESULT

Among the 47 participants, 3 (6%) did not complete all the tasks or answered all the questions. Thus, we collected valid results from 44 participants. All the data collected in our research were analyzed by SPSS 20.0.

5.1. Correctness of Tasks

The scoring metric for tasks are counted as follow: for tasks 1-4, each correct answer will be recorded as score 1, incorrect answer will be recorded as score 0. For task 5, each properly proposed answer worth 1 score and we count the summation.

With regard to the dimension data, chi-square analysis was conducted to do cross-tabulation comparisons. The chi-square test indicated there were no significant differences between different designs in task 1 (χ^2= 0.00, ρ=1.00). Regarding task 2, there were no significant differences between the designs (χ^2= 3.014, ρ=0.222). There were no significant differences in regard of the result from task 3 (χ^2= 0.266, ρ=0.875) and task 4 (χ^2= 2.702, ρ=0.259). Also, no significant differences have been found for task 5 (χ^2= 6.213, ρ=0.400). As it is shown in table 4, there is no difference between all three designs among all tasks.

Table 4. Correctness of tasks result

	Task 1	Task 2	Task 3	Task 4	Task 5
χ^2	0.000	3.014	0.266	2.702	6.213
ρ	1.000	0.222	0.875	0.259	0.400

5.2. Task-based Ratings

The ratings for each task will be from all 5 dimensions: Efforts, Frustration Level, Mental Demand, Performance, and Temporal Demand. However, task 5 is about strategy selection. It does not have a specific correct answer and may not suit for this analysis. All the detailed statistical analyses for task 1-4 are as follows.

5.2.1. Effort (E) Degree

Table 5. ANOVA results for different designs among tasks over effort degree

Effort	Design 1 (n=44)	Design 2 (n=44)	Design 3 (n=44)	F	p
Task 1	2.82±1.66	2.16±1.41	1.57±1.00	8.977	0.000
Task 2	3.25±1.64	2.84±1.45	2.32±1.23	4.558	0.012
Task 3	3.30±1.87	2.48±1.42	1.48±0.79	17.753	0.000
Task 4	4.09±1.72	3.55±1.53	2.25±1.24	17.215	0.000

We analyzed data by use of repeated analysis of variance (ANOVA). The design was the independent variable and the effort rating of overall function task was the dependent variable. It has shown that regard to the effort rating, there were significant differences between the designs among all the tasks ($p<0.05$).

Table 6. LSD Multiple Comparison results for different designs among tasks over effort degree

Designs		P			
I	J	task 1	task 2	task 3	task 4
1	2	0.027	0.188	0.039	0.093
1	3	0.000	0.003	0.000	0.000
2	3	0.047	0.094	0.000	0.000

We performed a further analysis using LSD Multiple Comparisons. The results show that for task 1, there are significant differences among all designs ($p < 0.05$). For task 2, there is significant difference between design 1 and 3 ($p < 0.01$), but no significant difference between design 1 and 2 ($p > 0.05$), design 2 and 3 ($p > 0.05$). For task 3, there are significant differences among all designs ($p < 0.05$). For task 4, there are significant differences between design 1 and 3

($p < 0.001$), design 2 and 3 ($p < 0.001$), but no difference between design 1 and 2 ($p > 0.05$). Therefore, there were significant differences in general tasks' effort between design 1, 2 and 3.

5.2.2. Frustration Level (FL) Degree

Table 7. ANOVA results for different designs among tasks over frustration level degree

Effort	Design 1 (n=44)	Design 2 (n=44)	Design 3 (n=44)	F	p
Task 1	2.89±1.79	1.86±1.27	1.34±0.68	15.417	0.000
Task 2	2.95±1.78	2.61±1.59	1.66±1.03	8.819	0.000
Task 3	3.73±1.65	3.09±1.57	1.82±0.99	20.246	0.000
Task 4	3.52±2.03	3.14±1.82	1.61±0.97	16.036	0.000

We analyzed data by use of repeated analysis of variance (ANOVA). The design was the independent variable and the frustration level of overall function task was the dependent variable. It has shown that regard to the effort rating, there were significant differences between the designs among all the tasks ($p < 0.001$).

Table 8. LSD Multiple Comparison results for different designs among tasks over frustration level degree

Designs		P			
I	J	task 1	task 2	task 3	task 4
1	2	0.000	0.288	0.008	0.280
1	3	0.000	0.000	0.000	0.000
2	3	0.067	0.003	0.001	0.000

We performed a further analysis using LSD Multiple Comparisons and the results show that for task 1, there are significant differences between design 1 and 2 ($p < 0.001$), design 1 and 3 ($p < 0.001$) but no difference between 2 and 3 ($p > 0.05$). For task 2, there are significant differences between design 1 and 3 ($p < 0.001$), design 2 and 3 ($p < 0.01$), but no significant difference between design 1 and 2 ($p > 0.05$). For task 3, there are significant differences among all designs ($p < 0.01$). For task 4, there are significant differences between design 1 and 3 ($p < 0.001$), design 2 and 3 ($p < 0.001$), but no difference between design 1 and 2 ($p > 0.05$). Therefore, there were significant differences in general tasks' effort between design 1, 2 and 3.

5.2.3. Mental Demand (MD) Degree

Table 9. ANOVA results for different designs among tasks over mental demand degree

Effort	Design 1 (n=44)	Design 2 (n=44)	Design 3 (n=44)	F	p
Task 1	3.23±1.88	2.48±1.52	1.77±1.18	9.674	0.000
Task 2	3.52±1.50	3.32±1.47	2.39±1.38	7.630	0.001
Task 3	4.05±1.74	3.23±1.48	2.07±1.07	20.566	0.000
Task 4	4.39±1.69	3.84±1.45	2.34±1.33	22.095	0.000

We analyzed data by use of repeated analysis of variance (ANOVA). The design was the independent variable and the mental demand of overall function task was the dependent variable. It has shown that regard to the effort rating, there were significant differences between the designs among all the tasks ($p < 0.001$).

Table 10. LSD Multiple Comparison results for different designs among tasks over mental demand degree

Designs		p			
I	J	task 1	task 2	task 3	task 4
1	2	0.000	0.288	0.008	0.280
1	3	0.000	0.000	0.000	0.000
2	3	0.067	0.003	0.001	0.000

We performed a further analysis using LSD Multiple Comparisons. The results show that for task 1, there are significant differences among all designs ($p < 0.05$). For task 2, there are significant differences between design 1 and 3 ($p < 0.001$), design 2 and 3 ($p < 0.01$), but no significant difference between design 1 and 2 ($p > 0.05$). For task 3, there are significant differences among all designs ($p < 0.01$). For task 4, there are significant differences between design 1 and 3 ($p < 0.001$), design 2 and 3 ($p < 0.001$), but no difference between design 1 and 2 ($p > 0.05$). Therefore, there were significant differences in general tasks' effort between design 1, 2 and 3.

5.2.4. Performance (P) Degree

Table 11. ANOVA results for different designs among tasks over performance degree

Effort	Design 1 (n=44)	Design 2 (n=44)	Design 3 (n=44)	F	p
Task 1	6.09±1.14	6.68±0.74	6.84±0.57	9.524	0.000
Task 2	5.66±1.24	5.89±1.15	6.61±0.69	9.886	0.000
Task 3	5.52±1.23	5.98±1.09	6.73±0.54	16.321	0.000
Task 4	5.23±1.60	5.43±1.53	6.32±0.98	7.572	0.001

We analyzed data by use of repeated analysis of variance (ANOVA). The design was the independent variable and the performance of overall function task was the dependent variable. It has shown that regard to the effort rating, there were significant differences between the designs among all the tasks ($p < 0.001$).

Table 12. LSD Multiple Comparison results for different designs among tasks over performance degree

Designs		p			
I	J	task 1	task 2	task 3	task 4
1	2	0.001	0.313	0.035	0.494
1	3	0.000	0.000	0.000	0.000
2	3	0.381	0.002	0.001	0.004

We performed a further analysis using LSD Multiple Comparisons. The results show that for task 1, there are significant differences between design 1 and 2 ($p < 0.001$), design 1 and 3 ($p < 0.001$) but no difference between 2 and 3 ($p > 0.05$). For task 2, there are significant differences between design 1 and 3 ($p < 0.001$), design 2 and 3 ($p < 0.01$), but no significant difference between design 1 and 2 ($p > 0.05$). For task 3, there are significant differences among all designs ($p < 0.05$). For task 4, there are significant differences between design 1 and 3 ($p < 0.001$), design 2 and 3 ($p < 0.01$), but no difference between design 1 and 2 ($p > 0.05$). Therefore, there were significant differences in general tasks' effort between design 1, 2 and 3.

5.2.5. Temporal Demand (TD) Degree

Table 13. ANOVA results for different designs among tasks over temporal demand degree

Effort	Design 1 (n=44)	Design 2 (n=44)	Design 3 (n=44)	F	p
Task 1	2.14±1.46	1.64±0.99	1.52±0.98	3.470	0.034
Task 2	2.30±1.36	2.18±1.30	1.75±1.04	2.375	0.097
Task 3	2.55±1.68	2.07±1.25	1.52±0.88	6.736	0.002
Task 4	2.75±1.73	2.30±1.27	1.64±0.99	7.428	0.001

We analyzed data by use of repeated analysis of variance (ANOVA). The design was the independent variable and the effort of overall function task was the dependent variable. It has shown that regard to the temporal demand rating, there were significant differences ($p < 0.05$) between the designs among all the tasks except task 2 ($p > 0.05$).

Table 14. LSD Multiple Comparison results for different designs among tasks over temporal demand degree

Designs		p			
I	J	task 1	task 2	task 3	task 4
1	2	0.046	0.668	0.089	0.120
1	3	0.015	0.041	0.000	0.000
2	3	0.647	0.104	0.053	0.025

We performed a further analysis using LSD Multiple Comparisons. The results show that for task 1, there are significant differences between design 1 and 2 ($p < 0.05$), design 1 and 3 ($p <$

0.05) but no difference between 2 and 3 ($p > 0.05$). For task 2, there is significant difference between design 1 and 3 ($p < 0.05$), but no significant difference between design 1 and 2 ($p > 0.05$), design 2 and 3 ($p > 0.05$). For task 3, there is significant difference between design 1 and 3 ($p < 0.001$), but no difference between design 1 and 2 ($p >0.05$), design 2 and 3 ($p > 0.05$). For task 4, there are significant differences between design 1 and 3 ($p < 0.001$), design 2 and 3 ($p < 0.05$), but no difference between design 1 and 2 ($p > 0.05$). Therefore, there were significant differences in general tasks' effort between design 1, 2 and 3.

5.3. Overall Factor Analysis

5.3.1. Item Analysis

Item-total correlation analysis was applied to calculate the correlation between the total score and each dimension. Those that have a low correlation mean that they don't measure the same qualities as the whole scale. The criteria for item reduction were as follows. First, the item-total correlations were significant ($p < 0.05$). Second, the items with the item-total correlations coefficients below 0.4 were eliminated. The two criteria above guarantee the items measure the same qualities as the whole scale. Results showed that all the correlations were significant ($r = 0.410 \sim 0.924$, ps< .01), which indicated on all dimensions measured, the 3 designs have significant differences.

5.3.2. Exploratory Factor Analysis

The remaining 12 items were subjected to the exploratory factor analysis (i.e., principle components with varimax rotation); the results show KMO = 0.942 and $\chi^2 = 1495.301$， $p < 0.001$. The level is significant, indicating that the data are suitable for factor analysis.

Table 15. Result of item analysis

	Overall	P
Usability(A)	0.894	0.000
Trust (A)	0.924	0.000
Appearance(A)	0.832	0.000
Loyalty(A)	0.906	0.000
Information Quality(A)	0.917	0.000
Decision Complexity(B)	0.410	0.000
Auxiliary Importance(B)	0.625	0.000
Decision Quality(B)	0.791	0.000
Perceived Control(C)	0.806	0.000
Perceived Responsiveness(C)	0.749	0.000
Perceived Communication(C)	0.793	0.000
Emotional Involvement(A)	0.877	0.000

Table 16. Result of factor analysis

	Factor 1	Factor 2	Factor 3
Usability(A)	0.86		
Trust(A)	0.857		
Appearance(A)	0.825		
Loyalty(A)	0.841		
Information Quality(A)	0.799		
Decision Complexity(B)			0.911
Auxiliary Importance(B)			0.555
Decision Quality(B)			0.704
Perceived Control(C)		0.751	
Perceived Responsiveness(C)		0.729	
Perceived Communication(C)		0.796	
Emotional Involvement(A)	0.657		

As illustrated in table above, three main principal components or factors were identified after the exploratory factor analysis. Factor 1 includes usability, trust, appearance, loyalty, information quality, and emotional involvement; conclude as users' attractiveness dimension.

Factor 2 includes decision complexity, auxiliary importance and decision quality; conclude as users' decision experience dimension. Factor 3 consisted of perceived control, perceived responsiveness, perceived communication, which can be concluded as interactivity dimension. Therefore, the resulting 12 items constituted three dimensions: Attractiveness, Decision Experience and Interactivity. Three factors can account for 79.758% total variance.

5.3.3. Reliability

Based on the data in current study, we also conducted the internal consistency reliability analysis respectively. The Cronbach's α we calculated from the samples revealed that the items of the BIV evaluation scale had high inner reliability (Cronbach's $\alpha = 0.721$). Since α is higher than 0.70, it is showing good internal consistency for the whole questionnaire as well as its three factors.

5.4. Dimension-based UX Difference Analysis

The results of evaluation rating for different designs on various dimensions are illustrated in Figure 7. The detailed statistical analyses are as follows.

Table 17. Factor based ratings and total ratings

	Factor 1	Factor 2	Factor 3	Total
Design 1	87.64	49.45	38.2	175.3
Design 2	108.52	56.66	40.95	206.14
Design 3	144.52	69.32	45.8	259.64

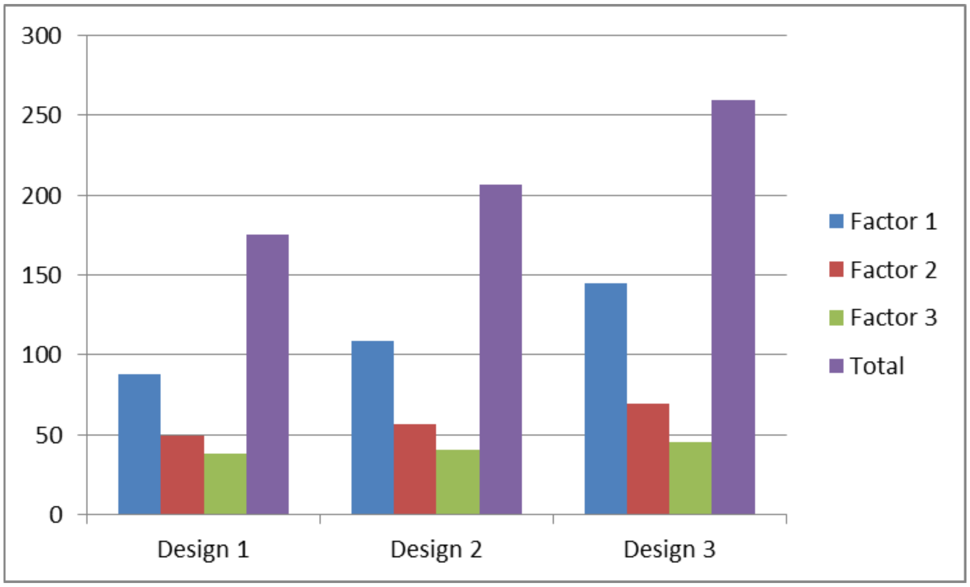

Figure 7. Ratings for three designs

Table 18. Factor-based/ Overall LSD comparison results

	factor 1			factor 2			factor 3			Total		
I	1	1	2	1	1	2	1	1	2	1	1	2
J	2	3	3	2	3	3	2	3	3	2	3	3
p	0.015	0.000	0.000	0.103	0.000	0.000	0.359	0.000	0.005	0.024	0.000	0.000

5.4.1. The General Evaluation Rating Differences

We analyzed data by applying the repeated analysis of variance (ANOVA). Design was the independent variable and the overall evaluation rating score was the dependent variable. The main effect of design was significant, $F(2, 80.236) = 40.082$, $p < 0.001$. The result of LSD Multiple Comparisons among different designs showed that the general evaluation rating for design 3 was significantly higher than design 1 ($p < 0.001$) and design 2 ($p < 0.001$), and the appraisals of design 2 were significantly higher than design 1, $p > 0.05$. Therefore, there were significantly differences in evaluation ratings among these three designs; design 3 performs significantly better than other 2 designs.

5.4.2. The Attractiveness Rating Differences

A repeated analysis of variance (ANOVA), with design as the independent variable and the attractiveness rating as the dependent variable revealed that the main effect of design was significant, $F(2, 80.746) = 47.889$, $p < 0.001$. The result of LSD Multiple Comparisons among different designs showed the attractiveness appraisals of design 1 was significantly lower than design 2 ($p < 0.05$) and design 3 ($p < 0.001$), and the attractiveness appraisals of design 3 was significantly higher than design 2. Therefore, there were significant differences in attractiveness appraisals among the three designs; design 3 performs significantly better than other 2 designs.

5.4.3. The Decision Experience Rating Differences

A repeated analysis of variance (ANOVA), with design as the independent variable and the decision quality rating as the dependent variable revealed that the main design was significant, $F(2, 84.136) = 21.432$, $p < 0.001$. The result of LSD Multiple Comparisons among different designs showed the decision quality appraisals of design 1 was significantly lower than design 3 ($p < 0.001$), but not significantly lower than design 2 ($p > 0.05$). The decision quality appraisal of design 3 was significantly higher than design 2 ($p < 0.001$). Therefore, there were significant differences in decision quality appraisals among the three designs; design 3 performs significantly better than other 2 designs.

5.4.4. The Interactivity Rating Differences

A repeated analysis of variance (ANOVA), with design as the independent variable and the interactivity rating as the dependent variable revealed that the main design was significant, $F(2, 84.149) = 10.643$, $p < 0.001$. The result of LSD Multiple Comparisons among different designs showed the interactivity appraisals of design1 was significantly lower than design 3 ($p < 0.001$), but not significantly lower than design 2 ($p > 0.05$). And the interactivity appraisals of design 3 was significantly higher than design 2 ($p < 0.001$). Therefore, there were significant differences in interactivity appraisals among the three designs; design 3 performs significantly better than other 2 designs.

6. DISCUSSION

We have demonstrated a novel evaluation framework that can be used in business intelligence visualization (BIV). First, we did an extensive survey to obtain a good understanding of research progress on BIV evaluation and related fields, and then established a conceptual framework. Second, with a user study approach, we have implemented this framework with a set of questionnaires to demonstrate how our framework can be used in real business.

6.1. Rationality of Framework

This framework is obtained through systematic literature investigation and analysis. Our research team conducted a survey across past research related to UX and business needs. We have investigated several fields, such as BI, Visualization, UX, evaluation and Decision-making. Based on literature analysis and professional understanding of this area, the research team constructed an evaluation framework for UX of BIV. In this framework, the definition of each element and the relationship of each potential element are based on selected literature. All these have provided a solid foundation for the rationality of this framework.

Especially, compared with Bačić and Fadlalla (2016), the set of independent variables we summarized have more advantages in UX research. Although according to visual mental abilities, Bačić and Fadlalla (Bačić & Fadlalla, 2016) proposed BIV elements as independent variables such as perception, cognition, memory etc., these elements are too abstract and indirect for BIV designers. For example, if the perception of BIV affects the users' decision-making performance, how can we through perception quickly identify the corresponding problems of visual design? It is difficult for designers to manipulate. Therefore, in our framework, the independent variables are related to attributes of the system itself or users, including users' background, data characteristics, interaction, design, etc. These independent variables are more practical and easier to manipulate for designers of BIV. Therefore, for both users and designers, our framework is a reasonable framework, because it embodies the human centric design philosophy.

Overall user experience, a crucial sub-framework of our framework, has good validity and reliability. First, correlation analysis showed that all 12 sub-elements of overall UX certainly measure BIV's user experience. Secondly, discrimination analysis proved that the assumed 12 sub-elements of overall UX can well distinguish BIV designs with different design quality. Third, exploratory factor analysis confirmed three main factors of overall UX within the sub-frame we proposed: attraction, decision evaluation and interaction. The statistical results of Cronbach's α show that the measurement of the overall UX has high stability and reliability.

Information quality was initially considered to be a sub-element of decision experience, but exploratory factor analysis found that information quality was classified into the attractiveness. According to the literature analysis, information quality refers to "relative efficiency to provide the relevant information for the viewer" (Tractinsky & Meyer, 09 1999), focusing on whether information is easily to extract, interpret and use etc. Although information quality has a significant impact on decision quality (Visinescu et al., 2017), it does not directly reflect the decision quality, but is closer to visual design of interfaces, so it is more reasonable to belong to the category of attractive subframe. Figure W shows the structure of overall UX based on exploratory factor analysis.

6.2. Practical Application of UXBIV Framework

Our research fulfills a pressing need in the field of BIV research. First, the current research and applications of BIV requires an evaluation for UX, but research in this field is still in its infancy. Theoretical and methodological development in this field lags behind the overall level of current user experience research. Secondly, BIV visualization designers are more focused on research and development new visualization technology. UX evaluation involving theories and methods in psychology, decision science and other fields, but lack of a systematic evaluation guide, which also greatly affects the development of user experience research in the field of BIV. Third, "user-centered" is an important principle that has emerged in interaction design in recent years. In order to promote users' perception, analysis and application of business information, BIV visualization should also emphasize “user-centered” principle. Therefore, it is very important and urgent to carry out a series of research on user experience in the field of BIV. The ultimate goal of this framework constructed in this research is to gain insight into the user experience of BIV systems, optimize the design of BIV, and promote good understanding, communication and interaction among BIV designers, BIV systems, and BIV users.

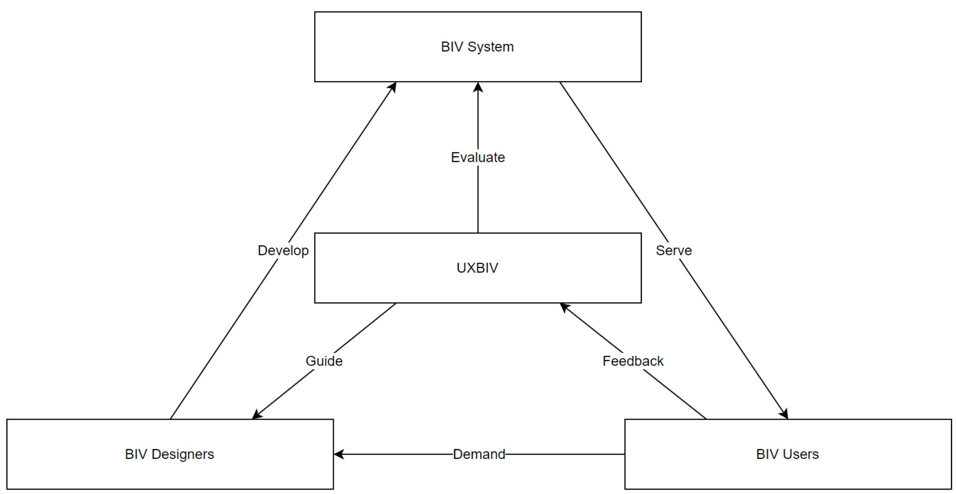

Figure 8. A typical lifecycle of BIV system

As the Figure 8 shown above, a typical lifecycle of BIV system includes three elements: BIV users, BIV designers, and BIV system itself. Users make demands to the designers in order to resolve real world issues and obtain BIV systems. The designers (and developers) work on to provide technical solutions and deliver a BIV system based on user's demand. The built BIV system serves the user and resolves the issues they were facing. By introducing this framework, we can benefit all the elements: This framework is able to evaluate existing BIV system, collect and evaluate user's feedback, and provide a series of design principles based on UX study in order to guide the designers to improve the BIV system. Obviously, this framework will improve the flow of BIV system lifecycle.

Although BIV is considered to be the core component of business intelligence (Mohan, 2016), there are only several published papers on BIV user experience. At present, none of them are UX framework specially designed for BIV. It is the first time we put forward a framework, which provides valuable insights for this research areas. It is suitable for systematically collecting user experience of visualization in business fields. The framework provides a powerful tool for collecting various user experiences in detail and refining design principles. The analysis results of this framework can observably highlight the advantages of BIV and improve the competitiveness of BIV development enterprises.

Our framework starts from four main factors: user's background, data characteristics, interactions and design. Plus, we also take characteristic factors and environmental factors into the consideration. These factors helped us to cover as many independent variables as possible. As a dependent variable, UX analysis includes task-based UX and overall impression UX analysis. With regard to the task-based analysis, we will evaluate BIV in decision-making tasks with objective and subjective indicators. With respect to the overall impression UX analysis, we will assess three main aspects: BIV Attractiveness, Decision-Making Experience and Interactivity. User study design serves as a bridge connecting independent variables and dependent variables. User study design provides task design, method design and research paradigms. Differ from existing research on UX of BIV, this framework evaluates user's experience far more than usability. In this framework, the most outstanding contribution lies in the category of independent variables, task design, combination of methods and the paradigm, and new elements of dependent variables such as decision experience and interactivity. If you intend to evaluate the UX quality of a BIV design, you should use this framework. If you try to compare the UX quality of a set of BIV, you should use this. If you plan to evaluate the same the BIV design many times, for example, to find out whether the continuous optimization of BIV design has promoted a better user experience, then you should use this.

The case study is an empirical study that combines behavioral experiment with questionnaire survey. The purpose of this study is to demonstrate how to apply our framework into actual evaluation of a set of BIV. According to the framework, we compare the user experiences of three BIV designs with different complexity. The whole study contains pre-task, in-task, post-task stages. Result analysis consists of three aspects: first, we have analyzed the correctness of tasks, this makes sure all the designs in the tests are functional and can finish the objective given. Then we did a task-based analysis with five subjective elements. Then we analyzed the overall UX from three elements: BIV attractiveness, decision-making experience, and interactivity. According to the results, design 3 with the highest design complexity is significantly rated better than the other two designs on almost all cases on all task-based ratings (mental demand, temporal demand, performance, effort, and frustration) and overall UX (BIV attractiveness, decision-making experience, interactivity). Therefore, appropriately increasing the complexity of visual design, such as color and interaction, can reduce users' workload and pressure, and provide more positive user experience. It shows the sensitivity of our proposed framework to detecting the quality of different designs and proves this framework can be used to guide BIV design in the future.

6.3. Future Directions

With the development of BIV design, this framework should be constantly developed and gradually updated. This section points out the future research directions in this field.

First, we only provided research on traditional platform such as personal computer with mouse, keyboard and monitor. Nowadays there are more and more new technologies that applies to visualizations, such as virtual realities (VR), augmented realities (AR), holographs, multi-device visualizations, etc. Our framework may also be adjusted to better detect user experiences of systems with these new technologies.

Second, the evaluation of BIV should adopt a combination of methods. Due to the limitation of our lab situation, collection methods in case study are mostly subjective ratings in questionnaire. Electrophysiology or brain-computer interface (BCI), interview and think-aloud can play an important auxiliary role in discovering various details in system design and understand and analyze user experience of BIV.

Third, in our user study, most of the participants are students, although many of them are studying in business field. Considering user's background, we need more real business professionals to help us improve this framework. In the future, we plan to extend the test group to business professionals. We believe they will provide us with valuable feedbacks to improve this framework.

Finally, in view of environmental factors, such as social backgrounds (culture, economy, etc.) and experiment contexts (online, office, etc.), in order to enhance its applicability in different environments, this framework may also be modified in accordance with changes in environmental factors. This topic is also a meaningful direction in the future.

7. CONCLUSION

This research is the first to propose a UX framework to investigate the user experience of BIV. This framework is based on rigorous literature survey and analysis. It includes independent variables, dependent variables, research design in UX evaluation. In this framework, the main contributions are the classification of independent variables, task design, the combination of methods and paradigms, and new elements of dependent variables. Moreover, we also undertook a case study to validate this framework and evaluated three BIV designs with different complexity. On the basis of analysis of case study combined with literature survey, we believe that this framework is quite a reasonable framework for assessing user experience of BIV. Besides, user experience of three BIV designs is significantly different. Design 3 with the highest design complexity is significantly rated better than the other two designs on all task-based rating and overall UX. Therefore, the framework provides a powerful tool for designers to evaluate user experiences of BIV designs. It is expected that this framework can promote decision-making performance and customer satisfaction, and enhance the competitiveness and influence of BI development companies.

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APPENDIX A. RESEARCH ABOUT VISUALIZATIONS

Tag	Title	Year	Journal/ Conference
Design Techniques	Combining Design and Performance in a Data Visualization Management System	2017	8th Biennial Conference on Innovative Data Systems Research (CIDR '17)
Evaluation UX	A Conceptual Model for Evaluating Aesthetic Effect within the User Experience of Information Visualization	2006	Proceedings of the Information Visualization (IV'06)
Design Technique	A human cognition framework for information visualization	2014	Computers &Graphics 42(2014) 42–58
Design Theory Evaluation	A Knowledge Task-Based Framework for Design and Evaluation of Information Visualizations	2004	IEEE Symposium on Information Visualization 2004
Technique	A Nested Model for Visualization Design and Validation	2009	IEEE Transactions On Visualization And Computer Graphics, Vol. 15, No. 6, November/December 2009
Business Intelligence Survey	A Survey on Business Intelligence tools for University Dashboard development	2016	2016 3rd MEC International Conference on Big Data and Smart City
Design Survey	A survey on information visualization: recent advances and challenges	2014	Vis Comput (2014) 30:1373–1393
Design Survey	A Survey on Multivariate Data Visualization	2006	Department of Computer Science and Engineering Hong Kong University of Science and Technology
Evaluation Review	A Systematic Review on the Practice of Evaluating Visualization	2013	IEEE Transactions On Visualization And Computer Graphics, Vol. 19, No. 12, December 2013
Design Survey	A Unified Taxonomic Framework for Information Visualization	2000	2nd Australian Institute of Computer Ethics Conference (AICE2000), Canberra. Conferences in Research and Practice in Information Technology, Vol. 1. J. Weckert, Ed.
Design Technique	A User Study to Compare Four Uncertainty Visualization Methods for 1D and 2D Datasets	2009	IEEE Transactions On Visualization And Computer Graphics, vol. 15, no. 6, November/December 2009
Technique	A Visualization Framework for Real Time Decision Making in a Multi-Input Multi-Output System	2008	IEEE Systems Journal, Vol. 2, No. 1, march 2008
Design	Action Design Research and Visualization Design	2016	BELIV '16, October 24 2016, Baltimore, MD, USA
Technique Survey	An Empirical Comparison of Visualization Tools to Assist Information Retrieval on the Web	2001	Journal Of The American Society For Information Science And Technology, 52(8):666–675, 2001

Tag	Title	Year	Journal/ Conference
Evaluation Usability UX	An Heuristic Set for Evaluation in Information Visualization	2010	AVI'10, May 25–29, 2010, Rome, Italy.
Design Technique Evaluation	An Introduction and Guide to Evaluation of Visualization Techniques Through User Studies	2014	Handbook of Human Centric Visualization
Evaluation Review	Analysis and visualisation of movement: an interdisciplinary review	2015	Movement Ecology (2015) 3:5
Technique Survey	Approaches to visualising Linked Data: A survey	2011	Semantic Web 2 (2011) 89–124
Business Intelligence Design	Architecture and Evaluation Design of a Prototypical Serious Game for Business Information Visualization	2017	Proceedings der 13. Internationalen Tagung Wirtschaftsinformatik (WI 2017), St. Gallen, S. 1271-1274
Technique Usability UX	Assessing User Engagement in Information Visualization	2017	CHI'17 Extended Abstracts, May 06-11, 2017, Denver, CO, USA
Usability Survey	Attacking Information Visualization System Usability Overloading and Deceiving the Human	2005	(SOUPS) 2005, July 6-8, 2005, Pittsburgh, PA, USA
Evaluation Survey Usability UX	Beyond Usability and Performance: A Review of User Experience-focused Evaluations in Visualization	2016	BELIV '16 Baltimore, Maryland USA
Business Intelligence Design	Big Data Analytics as a Service for Business Intelligence	2015	14th Conference on e-Business, e-Services and e-Society (I3E), Oct 2015, Delft, Netherlands. Lecture Notes in Computer Science, LNCS-9373, pp.200-211, 2015, Open and Big Data Management and Innovation
Business Intelligence Design	Business Analytics-Based Enterprise Information Systems	2016	Journal of Computer Information Systems, 57:2, 169-178
Business, Design	Business Information Visualization	1999	Communications of AIS Volume 1, Article 4
Business Design Technique	Business process impact visualization and anomaly detection	2006	Information Visualization (2006) 5, 15–27
Business, Guideline	Business visualization: a new way to communicate financial information	2007	Business Strategy Series vol. 8 No. 4 2007, pp. 283-292
Technique	CAEVA: Cognitive Architecture to Evaluate Visualization Applications	2003	Proceedings of the Seventh International Conference on Information Visualization (IV'03)

Tag	Title	Year	Journal/ Conference
Design Theory	Choosing Effective Colours for Data Visualization	1996	Proceedings of Seventh Annual IEEE Visualization'96
Design Techniques	Combining Design and Performance in a Data Visualization Management System	2017	8th Biennial Conference on Innovative Data Systems Research (CIDR '17)
Design Technique Usability	Computers, Environment and Urban Systems	2010	Computers, Environment and Urban Systems 34 (2010) 465–475
Evaluation Design Survey UX	Controlled User Evaluations of Information Visualization Interfaces for Text Retrieval: Literature Review and Meta-Analysis	2007	Journal Of The American Society For Information Science And Technology, 59(6):1012–1024, 2008
Design	Creative User-Centered Visualization Designfor Energy Analysts and Modelers	2013	IEEE Transactions On Visualization And Computer Graphics, Vol. 19, No. 12, December 2013
Technique Survey	Data and Information Visualization Methods, and Interactive Mechanisms: A Survey	2011	International Journal of Computer Applications (0975 – 8887) Volume 34– No.1, November 2011
Design	Data Visualization and Infographicsin Visual Communication Design Education at the Age of Information	2014	Uyan Dur, Banu İnanç. (2014). Data Visualization and Infographics In Visual Communication Design Education at The Age of Information. Journal of Arts and Humanities. 3. 39-50.
Design Guideline	Data Visualization as a communication tool	2015	Library Hi Tech News Number 2 2015, pp. 1-9
Business Intelligence	Data Visualization in Business Intelligence	2017	Munoz, J. (Ed.). (2018). Global Business Intelligence. New York: Routledge, Chapter 6
Design Theory	Data Visualization Optimization via Computational Modeling of Perception	2012	IEEE Transactions On Visualization And Computer Graphics, Vol. 16, No. 2, February 2012
Business, Technique	Data visualization process through storytelling technique in Business Intelligence	2016	Avances En Interacción Humano-Computadora, 2016, Vol. 1, Núm. 1, pp. 49-52
Design	Data Visualization versus Data Perception	2017	VRST 17
Design	DataTone: Managing Ambiguity in Natural Language Interfaces for Data Visualization	2015	UIST' 15
Design	Declarative Interaction Design for Data Visualization	2014	UIST' 14
Design	Design of a Haptic Data Visualization System for People with Visual Impairments	1999	IEEE Transactions On Rehabilitation Engineering, Vol. 7, No. 3, September 1999

Tag	Title	Year	Journal/ Conference
Design Survey	Designing the Visualization of Information	2015	International Journal of Image and Graphics Vol. 15, No. 2 (2015)
Design	Development, implementation and evaluation of an information model for archetype based user responsive medical data visualization	2015	Journal of Biomedical Informatics 55 (2015) 196–205
Evaluation	Empirical evaluation of information visualizations: an introduction	2000	Int. J. Human-Computer Studies (2000) 53, 631}635
Evaluation Survey	Empirical Studies in Information Visualization: Seven Scenarios	2011	Manuscript received 8 Sept. 2010; revised 6 Nov. 2011; accepted 9 Nov. 2011
Business	Enabling Personalized Visualization of Large Business Processes through Parameterizable Views	2012	SAC EE'12 March 25-29, 2012, Riva del Garda, Italy.
Design Usability UX	Enhancing Contract Usability and User Experience Through Visualization	2012	2012 16th International Conference on Information Visualisation
Technique Evaluation	Evaluating exploratory visualization systems: A user study on how clustering-based visualization systems support information seeking from large document collections	2012	Information Visualization 12(1) 25–43
Design Evaluation UX	Evaluating the Effect of Style in Information Visualization	2012	IEEE Transactions On Visualization And Computer Graphics, Vol. 18, No. 12, December 2012
Evaluation	Evaluating Visualizations: Do Expert Reviews Work?	2005	IEEE Computer Graphics and Applications September/October 2005
Design Evaluation UX	Evaluation of information visualization techniques: analysing user experience with reaction cards	2014	BELIV '14, November 10 2014, Paris , France
Technique Usability	Experimental Study on Evaluation of Multidimensional Information Visualization Techniques	2005	CLIHC'05, October 23–26, 2005, Cuernavaca, Mexico.
Business, Case Study	Exploring contract visualization: clarification and framing strategies to shape collaborative business relationships	2016	Journal of Strategic Contracting and Negotiation 2016, Vol. 2(1-2) 69–100
Usebility Mobile Application	Exploring the impact of trust information visualization on mobile application usage	2013	Pers Ubiquit Comput (2013) 17:1295–1313

Tag	Title	Year	Journal/ Conference
Eye Tracking Evaluation	Eye Tracking to Understand User Differences in Visualization Processing with Highlighting Interventions	2014	UMAP 2014, LNCS 8538, pp. 219–230, 2014.
Usability Technique	FacetMap: A Scalable Search and Browse Visualization	2006	IEEE Transactions On Visualization And Computer Graphics, Vol. 12, No. 5, september/october 2006
Design	Fluid interaction for information visualization	2011	Information Visualization 10(4) 327–340
Design Technique	GGobi: evolving from XGobi into an extensible framework for interactive data visualization	2003	Computational Statistics & Data Analysis 43 (2003) 423 – 444
Technique Survey	Graph Visualization and Navigation in Information Visualization: A Survey	2000	IEEE Transactions On Visualization And Computer Graphics, Vol. 6, No. 1, January-March 2000
Technique	Graphical Histories for Visualization: Supporting Analysis, Communication, and Evaluation	2008	IEEE Transactions On Visualization And Computer Graphics, Vol. 14, No. 6, November/December 2008
Evaluation	Heuristics for Information Visualization Evaluation	2006	BELIV 2006 Venice, Italy
Technique Usability	Indented Tree or Graph? A Usability Study of Ontology Visualization Techniques in the Context of Class Mapping Evaluation	2013	H. Alani et al. (Eds.): ISWC 2013, Part I, LNCS 8218, pp. 117–134, 2013.
Design Evaluation UX Eye Tracking	Individual User Characteristics and Information Visualization: Connecting the Dots through Eye Tracking	2013	CHI 2013: Changing Perspectives, Paris, France
Design Survey	Infographics And Public Policy: Using Data Visualization ToConvey Complex Information	2015	Health Affairs Vol. 34, No. 11: Food & Health
Business, Survey	Information Visualization Applications in the Real World	1997	Information Visualization Business Notes July/August 1997 pp. 66-70
Technique Usability	Informative or Misleading? Heatmaps Deconstructed	2009	J.A. Jacko (Ed.): Human-Computer Interaction, Part I, HCII 2009, LNCS 5610, pp. 30–39, 2009.
Technique	InSense: Interest-Based Life Logging	2006	IEEE MultiMedia 13.4 (2006): 40-48
Survey	Introduction:design and evaluation of notification user interfaces	2003	Int. J. Human-Computer Studies 58 (2003) 509–514
Technique Theory	Knowledge Precepts for Design and Evaluation of Information Visualizations	2005	IEEE Transactions On Visualization And Computer Graphics, Vol. 11, No. 4, July/August 2005

Tag	Title	Year	Journal/ Conference
Technique	Many Eyes: A Site for Visualization at Internet Scale	2007	IEEE Transactions On Visualization And Computer Graphics, Vol. 13, No. 6, November/December 2007
Evaluation Theory UX	Measuring Aesthetics for Information Visualization	2009	2009 13th International Conference Information Visualisation
Evaluation	On Evaluating Information Visualization Techniques	2002	AVI 2002, Trento, Italy.
Design Technique	On the role of design in information visualization	2011	Information Visualization 10(4) 356–371
Evaluation Survey	Patterns for visualization evaluation	2013	Information Visualization 2015, Vol. 14(3) 250–269
UX Eye Tracking	Predicting Confusion in Information Visualization from Eye Tracking and Interaction Data	2016	Proceedings of the Twenty-Fifth International Joint Conference on Artificial Intelligence (IJCAI-16)
Design Techniques	Reducing the Analytical Bottleneck for Domain Scientists: Lessons from a Climate Data Visualization Case Study	2016	Computing in Science & Engineering
Design Usability UX	Seeking information with an information visualization system: a study of cognitive styles	2011	Information Research Vol. 16 No. 4, December 2011
Evaluation Case Study	Seven Guiding Scenarios for Information Visualization Evaluation	2011	University Of Calgary Techreport #2011-992-04
Technique	Show Me: Automatic Presentation for Visual Analysis	2007	Ieee Transactions On Visualization And Computer Graphics, Vol. 13, No. 6, November/December 2007
Evaluation	Space, time and visual analytics	2010	International Journal of Geographical Information Science Vol. 24, No. 10, October 2010, 1577–1600
Design Theory Evaluation	Task Cube: A three-dimensional conceptual space of user tasks in visualization design and evaluation	2016	Information Visualization 2016, Vol. 15(4) 288–300
Technique Design Evaluation	Task Taxonomy for Graph Visualization	2006	BELIV 2006 Venice, Italy.
Design Guideline Survey	Ten guidelines for effective data visualization in scientific publications	2011	Environmental Modelling & Software Volume 26, Issue 6, June 2011, Pages 822-827
Technique	Testing User Interaction With a Prototype Visualization-Based Information Retrieval System	2005	Journal Of The American Society For Information Science And Technology, 56(8):824–833, 2005
Evaluation Survey	The Challenge of Information Visualization Evaluation	2004	AVI '04, May 25-28, 2004, Gallipoli (LE), Italy

Tag	Title	Year	Journal/ Conference
Case Study	The Dynamics of Infographics:Transforming Tabular Data into an Interactive Story	2018	
Design Usability Technique UX Survey	The Effect of Aesthetic on the Usability of Data Visualization	2007	11th International Conference Information Visualization (IV'07)
Design	The Role of Visual Perception in Data Visualization	2002	Journal of Visual Languages and Computing(2002)13,601^622
Business	The Use of Visualization in the Communication of Business Strategies: An Experimental Evaluation	2015	International Journal of Business Communication 2015, Vol. 52(2) 164–187
Theory Technique	Toward a Deeper Understanding of the Role of Interaction in Information Visualization	2007	IEEE Transactions On Visualization And Computer Graphics, Vol. 13, No. 6, November/December 2007
Evaluation	Toward Measuring Visualization Insight	2006	IEEE computer graphics and applications 26.3 (2006): 6-9.
Design Guideline	Toward User Interfaces and Data Visualization Criteria for Learning Design of Digital Textbooks	2014	Informatics in Education, 2014, Vol. 13, No. 2, 255–264
Usability Evaluation	Towards Adaptive Information Visualization: On the Influence of User Characteristics	2012	UMAP 2012, LNCS 7379, pp. 274–285, 2012.
Evaluation Survey Eye Tracking	Towards User-Adaptive Information Visualization	2015	Proceedings of the Twenty-Ninth AAAI Conference on Artificial Intelligence
Technique UX	Understanding and Characterizing Insights: How Do People Gain Insights Using Information Visualization?	2008	BELIV ’08, April 5, 2008, Florence, Italy.
Business, Evaluation	Usability of Business Information Semantic Network Search Visualization	2015	MIDI '15, June 29-30, 2015, Warsaw, Poland
Design Evaluation	User Evaluation of Polymetric Views Using a Large Visualization Wall	2010	SOFTVIS’10, October 25–26, 2010
Design	User Studies in Visualization: A Reflection on Methods	2014	Handbook of Human Centric Visualization
Design Technique	User-adaptive explanatory program visualization: evaluation and insights from eye movements	2010	User Model User-Adap Inter (2010) 20:191–226

Tag	Title	Year	Journal/ Conference
Design Evaluation Technique	User-Centered Evaluation of Information Visualization Techniques: Making the HCI-InfoVis Connection Explicit	2014	Handbook of Human Centric Visualization
Design Survey	Using color in visualization: A survey	2011	Computers & Graphics 35 (2011) 320–333
Case Study Technique	Using Multi-dimensional In-depth Long-term Case Studies for information visualization evaluation	2008	BELIV'08, April 5, 2008, Florence, Italy
Design	Using Word Clouds For Fast,Formative Assessment Of Students' Short Written Responses	2014	Chemical Engineering Education
Design Survey	Visual Analysis of Large Graphs: State-of-the-Art and Future Research Challenges	2011	Computer Graphics Forum Volume 30 (2011), number 6 pp. 1719–1749
Technique Survey	Visualization and Visual Analysis of Multifaceted Scientific Data: A Survey	2013	IEEE Transactions On Visualization And Computer Graphics, Vol. 19, No. 3, March 2013
Technique	Visualization techniques supporting performance measurement system development	2016	Measuring Business Excellence, 20(2), 13-25
Design Technique UX	VOWL 2: User-Oriented Visualization of Ontologies	2014	EKAW 2014, LNAI 8876, pp. 266–281, 2014
Design Technique Case Study	Voyagers and Voyeurs: Supporting Asynchronous Collaborative Information Visualization	2017	CHI 2007 Proceedings • Distributed Interaction
Design Technique	WebQuilt: A Framework for Capturing and Visualizing the Web Experience	2001	

APPENDIX B. RESEARCH IN DESIGN ELEMENTS AND AESTHETICS

- Line Chart

M Gattis et al. (1996) described it as the independent variable is usually plotted on the x-axis and the dependent variable on the y-axis. They tend to see slope as representative of quickness, height, amount or rate above anything else. When line graphs showed trend reversals, people studied them longer. This is not the case when vary the number of data points, symmetry or linearity. (CM Carswell et al, 1993) When researchers presented participants with a graph showing a third variable of data, the line chart descriptions remained focused on x-y relationships, whereas the bars branched out a bit more to include this new variable. (P Shah & EG Freedman, 2009)

- Bar Chart

Zacks and Tversky found that when participants were shown bar graphs and asked to describe the data, they continually referenced contrasts between the variables in the bars (e.g., “A is greater in X quantity than B”). Whereas with line charts, participants described trends (e.g., “As X increases, Y increases”). They found that participants described contrasts between the x-axis variables more when presented with bar charts, and relationships between the x-axis variables more with line charts.

Hollands and Spence found that as the number of components in bar charts increase, their effectiveness at communicating proportions decreases. In fact, for each new component in bar charts, a reader needs an additional 1.7 seconds for processing.

- Scatter Chart

Cleveland and coauthors found people come to conclusions about the correlation in scatterplots partly based on the size of the point cloud. When the same correlation is represented in two graphs, but in one graph the scale is blown out so the point cloud becomes very small, people perceive it as having a higher correlation.

In 1989, Experimenting with symbol type in scatterplots, Lewandowsky and Spence find that altering color is most discernible to the eye. When varying color is not an option, varying fill or shape (or even non-confusable lettering) has “no great loss in accuracy.”

- Pie Chart

Eells was among the rest to publish a paper on this topic in 1926. In his time, pie charts were ridiculed much as they are today for their assumed perceptual inadequacies. For example, he was told that the human eye cannot judge arcs, angles or chords very efficiently. As the number of components in the chart increased, bars become less efficient encoding the data. The opposite was true for pie charts

Spence and Lewandowsky found that comparisons among multiple segments take longer and have lower accuracy. Pie charts fared the worst except when multiple segments had to be compared. Tables were found to be inferior to everything except for communicating absolute values

- Tree-map

Ziemkiewicz and Kosara found that directing participants to navigate treemaps with metaphors to complete certain tasks made them more accurate. For example, directing participants to find a data point “inside” a container-like treemap and telling them to look “below” in a cascading treemap worked best.

Kong, Heer and Argawala found that people discern values in treemaps best when the components are rectangles with diverse aspect ratios. Somewhat counterintuitively, squares are not easy to compared to each other. Extreme ratios in rectangles are also ineffective for comparisons. They additionally found that small multiples of bar charts were better than treemaps at representing datasets with fewer than about 1,000 data points for leaf-to-leaf comparisons

- Dimensional Chart (2D/3D)

Siegrist finds that among bar charts, 2d is not superior to 3d, but 3d charts take slightly longer to process. With pies, 2d is better, and the perspective angle makes a big difference in how accurately the slices are evaluated, most likely because some of the slices are more obscured than others.

Levy and coauthors acknowledge that 3d graphics, while "glitzy" and "sexy," do not convey any additional information and force the reader to "deal with redundant and extraneous cues." Their participants were given the option to select among 2d and 3d charts. When they were told to select a chart to present to other people, they tended to choose 3d charts. They also selected 3d charts when they were told the data had to be remembered. They selected 2d bar graphs more when they were told they needed to convey specific details, and selected line charts when the message had to be communicated quickly. The authors conclude that 3d charts can be useful in some cases

Two experiments by Spence deal with Steven's law, which again (very simplistically) says that an object's size appears larger when presented with larger objects, or smaller when presented with smaller objects. Spence found that contrary to popular physics, this distortion does not happen when comparing two shapes of the same dimensionality. Only when you vary the dimensionality among shapes does this distortion occur.

For **low-level** design elements we're talking about some fragmental aspects such as color, hue, chroma, brightness, transparency, font and text sizes, arrangements, etc. These elements can hardly to be divided further and should be considered as the minimal pieces of a design. Table B1 has shown different research on this level.

Table B1. Research on low level design elements

title	Author	year	elements
Affective Color in Visualization	L. Bartram et al.	2017	Color Chroma
Rainbow Color Map (Still) Considered Harmful	David Borland and Russell M. Taylor II	2007	Color
Color Design for Illustrative Visualization	L. Wang et al.	2008	Color Hue Chroma Brightness
Using color in visualization: A survey	S. Silva et al.	2011	Color Grayscale
Sizing the horizon: the effects of chart size and layering on the graphical perception of time series visualizations	J. Heer et al.	2009	Color blends
Serial processing and the parallel-lines illusion: Length contrast through relative spatial separation of contours	K. Jordan et al.	1986	Arrangement
Perceptual and conceptual factors in distortion in memory for graphs and maps	B. Tversky et al.	1989	Arrangement
Structure and strategy in encoding simplified graphs	DJ Schiano et al.	1992	Arrangement
Judgments of Change and Proportion in Graphical Perception	JG Hollands and I. Spence	1992	Arrangement
ISOTYPE Visualization—Working Memory, Performance, and Engagement with Pictographs	S. Haroz et al.	2015	Shape

APPENDIX C. DETAILED TASK RESEARCH

Author	Year	Tasks
John Stasko	2000	Identify: looking for some data with characteristics (e.g. find the largest or second largest) Locate: Find something and deliver its relatives (e.g. find a file and return its path) Filter: Find directory containing files of particular type Compare: Compare size of two files and identify the larger Find duplicate: Find identical elements Compare cluster: Compare two directories
Amar et al.	2005	Retrieve Value: Given a set of cases, find attributes of those cases. Filter: Given some conditions on attributes values, find data cases satisfying those conditions. Compute Derived Value: Given a set of data cases, compute an aggregate numeric representation of those data cases. (e.g. average, median, and count) Find Extremum: Find data cases possessing an extreme value of an attribute over its range within the data set. Sort: Given a set of data cases, rank them according to some ordinal metric. Determine Range: Given a set of data cases and an attribute of interest, find the span of values within the set. Characterize Distribution: Given a set of data cases and a quantitative attribute of interest, characterize the distribution of that attribute's values over the set. Find Anomalies: Identify any anomalies within a given set of data cases with respect to a given relationship or expectation, e.g. statistical outliers. Cluster: Given a set of data cases, find clusters of similar attribute values. Correlate: Given a set of data cases and two attributes, determine useful relationships between the values of those attributes.
Bongshin et al.	2006	Scan: Quickly review the list of items, requires users to review many items at once but not necessarily to retrieve exact values Set Operation: Given multiple sets of nodes, perform set operations on them. For example, find the intersection of the set of nodes.
Ji Soo Yi et al.	2007	Select: Select provide users with the ability to mark a data item(s) of interest to keep track of interest. Explore: Explore enable users to examine a different subset of data case Reconfigure: Reconfigure provide users with different perspectives onto the data set by changing the spatial arrangement of representations Encode: Encode enable users to alter the fundamental visual representation of the data including visual appearance (e.g., color, size, and shape) of each data element Abstract/Elaborate: Abstract/Elaborate provide users with the ability to adjust the level of abstraction of a data representation Filter: Filter enable users to change the set of data items being presented based on some specific conditions Connect: Connect refers to that are used to (1) highlight associations and relationships between data items that are already represented and (2) show hidden data items that are relevant to a specified item
Mark A. Livingston et al.	2012	Find Extremum of change: Localizing the greatest increase or greatest decrease subjective evaluation of user experience in interactive 3D-visualization in a medical context Counting: How many strings are in the scene Find Extremum: Which string is the closest to you Find relevance: Find the place where the two marked strings are closest to each other Estimate: Estimate the distance between two markers

Author	Year	Tasks
Ronak Etemadpour et al.	2015	Estimate: Estimate the number of observed cluster/subcluster/outliners Identify: Identify the closest cluster to a given cluster/object Rank: Rank the objects based on the distance to a given cluster/ Rank cluster based on density
Yujie Liu et al.	2012	Browsing: A serendipitous task in which you may visit the data with no specific goal in mind e.g. Find as many distinct topics from the dataset as possible; Describe each topic using a few sentences Fact finding: A task in which you are looking for specific facts or pieces of information e.g. Find as many articles as possible about humanitarian aid during the Haiti earthquake. Information gathering: A task that involves the collection of information, often from multiple sources. Unlike fact finding, you do not always know when you have completed the task and there is no specific answer e.g. Summarize the activity of President Obama in Human Health Insurance Revisit: A task that happens when you need to revisit some source that you previously used e.g. List as many keywords as possible that can be used to retrieve articles in the previous task

APPENDIX D. QUESTIONNAIRE EXAMPLE

Pre-Study Questionnaire

The following statements/questions ask about participants' information related to our research. Your answers are confidential and are for research purposes only.

1. Please tell us your age _____________.

2. Gender: (Circle one)

Male   Female   Other   No Response

3. What is your profession?

□Employed with ______________ years of experience

□Student

□Other, please indicate ______________

4. If you are a student, please answer the following questions:

Please select: □Freshman □Sophomore □Junior □Senior □Master's student □Ph.D student

5. What is your major of study? __________________________

6. How would you rate your English language skills?

1	2	3	4	5	6	7
Completely Not Proficient	Moderately Not Proficient	Slightly Not Proficient	Neutral	Slightly Proficient	Moderately Proficient	Completely Proficient

Scale for questions 7-9:

1	2	3	4	5	6	7
Extremely Unfamiliar	Moderately Unfamiliar	Somewhat Unfamiliar	Neutral	Somewhat Familiar	Moderately Familiar	Extremely Familiar

7. Please indicate how well you know about business:

8. Please indicate how well you know about visualization

9. Please indicate how well you know about business intelligence (BI)

10. Which of the following best describes your frequency of using business intelligence (BI)?

1	2	3	4	5	6	7
Never	Rarely	Occasionally	Moderately	Frequently	Usually	Always

11. Please indicate how well you know about marketing data (sales, inventory, etc.)

1	2	3	4	5	6	7
Extremely Unfamiliar	Moderately Unfamiliar	Somewhat Unfamiliar	Neutral	Somewhat Familiar	Moderately Familiar	Extremely Familiar

12. Have you ever taken or are currently taking a class related to Business Intelligence (BI)? (Circle One)

Yes ---- No

In-Study Questionnaire

The following statements/questions ask about your experience while doing task on this BI system. Please respond by checking your choice using the scale ranging from 1 point to 7 point. Your answers are confidential and are for research purposes only.

Scale for questions 1-4:

1	2	3	4	5	6	7
Very Low	Moderately Low	Slightly Low	Neutral	Slightly High	Moderately High	Very High

1. How mentally demanding was required (e.g., thinking, deciding, calculating, remembering, looking, searching, etc.) for the task?

2. How much time pressure did you feel during the task?

3 How hard did you have to work (mentally and physically) to accomplish your level of performance during the task?

4. How discouraged or frustrated did you feel during the task?

5. How successful do you think you were in accomplishing the goals of this task?

1	2	3	4	5	6	7
Very unsuccessful	Moderately unsuccessful	Somewhat Unsuccessful	Neutral	Somewhat Successful	Moderately Successful	Very Successful

Post-Study Questionnaire

The following statements/questions ask about your experience while using this BI system. Please respond by checking your choice using the scale ranging from 1 point to 7 point. Your answers are confidential and are for research purposes only.

section 1:

1	2	3	4	5	6	7
Strongly Disagree	Moderately Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Moderately Agree	Strongly Agree

1. This system is easy to use.
2. It is easy to navigate within the system.
3. I enjoy using the system.
4. I feel comfortable fulfill tasks by using this system.
5. I can count on the information I get on this system.
6. I found the system to be attractive.
7. I feel confident making decisions by using this system.
8. The system keeps the promises it makes to me.
9. I will likely return to this system in the future.
10. I will recommend this system to peers or colleagues.

section 2:

1	2	3	4	5	6	7
Strongly Disagree	Moderately Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Moderately Agree	Strongly Agree

1. The outcome of the decision depends on the interaction of different factors (variables or elements in the business data such as year, region, sales amount, etc.)

2. The decision involves a large number of factors (variables or elements in the business data such as year, region, sales amount, etc.).

3. I believe I made a good decision.

4. The information my BI system provides is:

   1) Not overwhelming

   2) Available when I need it

   3) Easy to extract

5. I relied highly on BI visualization functionality while making the decision.

6. When making the decision I have to consider many different alternatives.

7. How satisfied were you with the decision-making process?

1	2	3	4	5	6	7
Very Unsatisfied	Moderately Unsatisfied	Somewhat Unsatisfied	Neutral	Somewhat Satisfied	Moderately Satisfied	Very Satisfied

section 3:

1	2	3	4	5	6	7
Strongly Disagree	Moderately Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Moderately Agree	Strongly Agree

1. This system facilitates two-way communication between the users and the system.

(Two-way communication refers to the ability for reciprocal interaction between the system and the user. In such a communication, the system and the user can interact with each other.)

2. The system gives users the opportunity to talk back. (talk back = react, respond)

3. I felt that I had a lot of control over my interactive experiences on this system.

4. While using the system, I could choose freely what I wanted to see.

5. The system processed my input very quickly.

6. Getting information from the system is very fast.

7. I was able to obtain the information I want without any delay.

section 4:

1	2	3	4	5	6	7
Extremely	Moderately	Slightly	Neutral	Slightly	Moderately	Extremely

1. Boring/Interesting
2. Unexciting/Exciting
3. Unappealing/Appealing
4. Mundane/ fascinating
5. Uninvolving /Involving