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RESEARCH ARTICLE

UXBIV: An Evaluation Framework for Business Intelligence Visualization

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ABSTRACT Nowadays, 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, research on BIV evaluation is severely lacking; most evaluation studies for BIV focus on usability, which have limited aspects covered for customers' needs. The purpose of this research is to develop a UX framework that evaluates BIV (UXBIV), including decision-making experience and interactivity. First, we did a literature survey for good understanding of research progress in related fields, and established a conceptual framework. Second, we performed a case study that implemented this framework to demonstrate how our framework can be used in real business. Our analysis shows that this UXBIV framework is quite reasonable, and it can capture the differences among various BIV designs from the users' standpoints. This UXBIV framework can help design BIV and promote better decision-making on business affairs.

INDEX TERMS Business intelligence, visualization, evaluation, user experience, framework.

I. INTRODUCTION

Business processes are one of the most important assets of organizations, because they determine the success or failure of the organization in global markets [76]. Business Intelligence (BI) system is becoming more needed by organizations to analyze data and make strategic decisions [36]. As a vital part of the modern BI systems emphasizing self-service, visualization has been rising rapidly in the BI and analytics industry for the past few years. Business intelligence visualization (BIV) can assist business decision makers to extract information from data, facilitate business judgement and decision making, thereby improving organizational performance and fostering modern business processes to be faster and smoother than ever before [89].

With the wide application of BIV in the business process, the demand for better visualization effects is stronger and stronger. A good UX can enhance the decision-making performance and strengthen the competitiveness of corporate. Thus, a human-centric evaluation of UX is obviously vital to BIV. However, according to our investigation, there exist some limitations in the research and application of BIV evaluation. First of all, systematic research on UX evaluation is still scarce in this field. A framework towards UX of BIV is much needed. Second, research on BIV evaluation mostly focuses on usability, lacking other valuable factors of user experience for the successful design of BIV. Third, the current research on evaluation of BIV rarely covers the

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decision-making experience; nevertheless, BIV values more on the role of visualization in promoting decisions. In a word, considering business needs, it is necessary to establish a new UX evaluation framework for BIV.

This research aims to develop a framework for assessing the user experience of BIV, named UXBIV [106]. First, we conduct an in-depth literature survey to investigate necessary aspects in BIV evaluations. Then, we propose an evaluation framework of BIV, which contains independent variables, dependent variables and corresponding measurements, and the user study design for UXBIV. Furthermore, we carry out an empirical case study to test this framework, and compare three visualization designs with the guidance of UXBIV. In the future, designers can systematically study user experience by referring to UXBIV and develop BIV design strategies.

The remainder of this paper is organized as follows. Section II presents the background and motivation for user experience of BIV. Section III describes in detail the evaluation framework of BIV. Section IV provides a case study using the proposed framework to evaluate three kinds of BIV designs. Section V discusses rationality of UXBIV, practical application of UXBIV and future directions of this research, whereas section VI concludes this paper.

II. BACKGROUND AND MOTIVATION

This section includes concepts related to BIV, user experience of BIV, and motivations.

A. 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 [24]. 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'' [52]. 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 [74]. 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 [74]. Currently, information visualization technology has been widely applied in Internet, medicine, biology, industry, agriculture, military affairs, political relations, entertainment information and business information [10], [21].

Business intelligence (BI) is the process of collecting, managing and analyzing business information, and its purpose is to promote the decision-making of enterprises [20], [25]. 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 [9], [72]. 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 understanding of data, business, and behavior and enhance the insight of decision making on business processes [9]. 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.

B. USER 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 [75]. UX involves all aspects of users' interaction with a product or service [4]. ISO 9241–210 defines UX as the users' perceptions and responses when interacting with a product, system or service [44]. Users' demands, subjective evaluation and emotional feelings during this process are considered as the core of positive experience [55]. Providing excellent user experience can at least prevent the loss of existing users [45]. As people's demands continue to escalate, 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 [77]. Existing research indicates that it is necessary to define the corresponding elements or dimensions of UX according to the objects to be investigated [45].

In visualization field, there are several 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 [58]. Stefania Passera has concluded visualization helped 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 [22]. Khawaja et al. have researched how to measure cognitive load in behave for usability evaluation [51]. In 2006, De Angeli et al. proposed that not only usability is important to UX, but also interaction and aesthetics [19]. Wright et al. proposed a guideline about the aesthetics and UX-centered design [100]. And in 2009, Filonik and Baur have discussed how to measure aesthetics in information visualization [29]. Some other research has been conducted in interaction and interactivity, such as the survey proposed in 2011 by Khan and Khan [49]. 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 [54]. Buja et al. have discussed about interactions on high-dimensional data visualization [13]. 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 [6]. Lee et al have performed taxonomy about tasks in graph visualization which concluded from various research [58]. Yi et al. also performed research to analyze interactions in information visualization [101]. Even there are such fields being researched, while we focus on the UX, we find that most of the research only cover usability. Saket et al. also noticed this in 2016 and proposed several other important aspects for UX in visualization [83]. Thus, we believe it is necessary to expand UX evaluation in BIV to somewhere beyond usability.

Another emerging field related to BIV is dashboard evaluation. Dashboard is only a subset of BIV that includes the broader scope of displaying and analyzing various data visually to support decision-making. Some of the dashboard research focus on usability: Magdalena et al. have presented a strategy to increase the utilization of BI dashboards by conducting user testing and heuristic evaluation, their evaluation includes learnability, memorability, efficiency, error detections, and user's satisfaction [107]. Almasi et al. emphasized that a framework based on usability principles is necessary, proposes specific dashboard usability criteria (such as usefulness, operability, learnability, etc.) and identifies commonly used evaluation questionnaires (such as System Usability Scale (SUS), Technology Acceptance Model (TAM), Situation Awareness Rating Technique (SART), etc.) [109]. Orlando and Sunindyo proposed a flow to development and modification of a BI dashboard and evaluate the usability with SUS and Usability Metric for User Experience (UMUX) [110]. From a starting point of usability, some researchers have shifted their focus towards a broader concept of UX: Muppidi et al. stated that user experience is critical to the development of successful business intelligence solutions, proposes a new UX model for decision-making in the design and development of BI dashboards. They use 16 UX factors to evaluate dashboard design such as operability, memorability, satisfaction, etc. [108]. Burnay et al. proposed a review of existing BI modeling notations and a framework of dashboard, their UX evaluation focus on efficiency and expressiveness [112]. However, there are several limitations in existing dashboard evaluation studies. Firstly, dashboards are a subset or specific application of visualization, so dashboard evaluation cannot substitute for the evaluation of the entire visualization in BI. Secondly, few studies have examined decision-making experience, which is a crucial aspect of user experience in BIV. Thirdly, current research on evaluation has not summarized independent variables and decision-making tasks, which have overlooked the perspectives of designers and developers, and has not provided convenience for manipulating design features. Furthermore, previous research has not yet conducted empirical analysis to examine the validity and reliability of the evaluation framework of BIV.

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 [8]. However, current UX studies about BIV mainly focus on usability evaluation. Specifically, Chung and Leung [16] 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. [102] 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. [66] 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. [12] 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 [9] 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.

C. 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 [103]. The business success of products depends more and more on a pleasant user experience [55]. Most users of BIV do not have enough technical background and do not know the technical details of the system, so the quality of user experience about 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 development companies.

Second, research on BIV evaluation mostly focuses on usability. For example, Amyrotos noticed the importance of UX in BIV and proposed a user-centered framework, but his research focuses on usability such as effectiveness and accuracy [111]. 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 [38], that is, from traditional usability to aesthetics, appeal, and pleasure, etc. [1], [55]. Users' needs and their subjective and emotional evaluation of interaction are considered as the core of positive experience [55]. UX should also customize elements according to the characteristics of products or services [45]. 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 [42], [97]; In addition, decision-making style of users will also affect the decision-making performance in BIV [2]. All these factors can help BIV design is 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 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 should 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 decision performance and customer loyalty, and enhance the competitiveness and influence of BI development companies.

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

III. FRAMEWORK OF UX EVALUATION FOR BIV

This section includes the evaluation methodology for BIV, the independent and dependent variables of the evaluation for BIV, and the user study design of the evaluation for BIV.

A. METHODOLOGY

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

- *Search phase:* we have obtained various of 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.). We have found 287 articles at the end of this phase, including 177 from Google Scholar, and 110 from Web of Science.
- *Screen phase:* when an article has been found, we conducted a screening on the article, and categorize it into several different interested areas based on their research goals. In this phase we have removed 146 articles that not very related to our topic, and pushed 141 articles into Identifying phase.
- *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:

Findings from this literature study are used to create UXBIV evaluation framework. This framework compiled from all the interested areas based on existing research. The structure of UXBIV is shown in Figure.3, and we will introduce our findings in the following sections.

B. INDEPENDENT VARIABLE OF BIV EVALUATION

According to literature analysis, we have identified 4 main aspects that have influences to user's experience, and two smaller areas that have fewer impacts as side-aspects. Figure 1 shows the independent variables (IV) in UXBIV.

1) USER'S BACKGROUNDS

User's background is a widely used metric in surveys. In order to evaluate user experience, background information must be considered, and we can use related questionnaires to measure this information [51], [56]. Two kinds of backgrounds are being taken into consideration into our framework: Physical background and experience background. Physical background is referring to the demographic features of users,

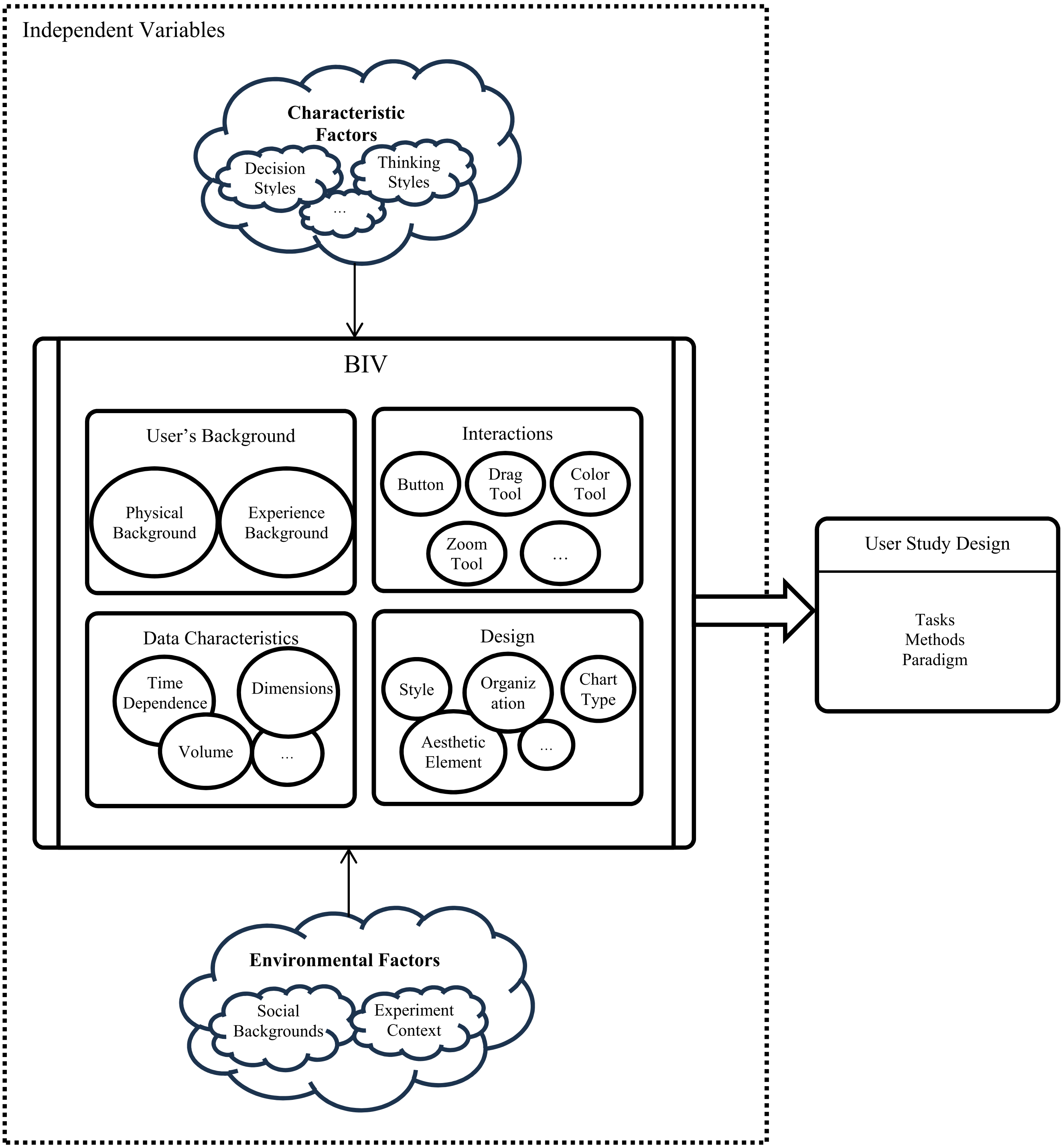

FIGURE 1. Independent variables (IV) in UXBIV.

such as age, gender, race, etc. These features will provide us statistical evidence about whether a design related to user's biology traits [32], [61]. Experience background refers to user's experience and history, like professions, computing device usage, familiarity to data, etc. A well-trained person will have higher efficiency and accuracy, and may require a better design to meet their expectations [57], [68].

2) DATA CHARACTERISTICS

Accurate handling of data is essential to ensure the performance and reliability of the system, and any errors can have significant impacts [50]. 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 experience. These are objective measures that can be computed from a dataset.

- *Time Dependence:* A data set can be either related to time or not, which can be easily categorized into time-dependent data or non-time-dependent data. It is important 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 [39]. Non-time-dependent data such as warehouse coverage is the kind of data which are not linked to time, and usually we use map, heat-map, or tree chart to render such kind of data [73].
- *Dimensions:* Dimension refers to how many attributes a dataset has [30]. Commonly used dimensions are people, products, place and time. High Dimensional data are difficult to calculate and visualize. Specialized visualization techniques might be necessary to transfer high-dimensional data into visualizations [13], [87]. Thus, we believe these techniques needs to be evaluated because different visualization approach may affect UX.
- *Volume:* Volume refers to the data size or scale [98]. The data processing and visualization with large volume of data is also known as "big data" in modern research. In order to visualize large volume of data within a limited displaying scope, specialized techniques are necessary [35], [81], [98]. Considering different visualization techniques may result in different visualization elements displayed, the UX might be affected, we need to take the data volume and techniques into consideration of BIV evaluation.

3) INTERACTIONS

Interaction refers to all the tasks that the user can perform to interact with the visualization interface to retrieve information they want [101]. It includes but not limited to button, drag tool, zoom tool, color tool, etc. We can compare different interactions used in designs: the more interactions provided will grant user more degrees of freedom, but more interaction elements might reduce the usability of the visualization [28], [84]. Therefore, the relationship between interactions and UX should be explored in visualizations.

4) DESIGNS

The difference in design may lead to direct impact towards user's experience. Choosing the diverse type of visualization would result in difference in users' feedback [40]. Thus, we have to think about interface design. We can count different design types based on the following aspects:

- *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 [71]. 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 [93]. Moere et al. [71] have categorized style into 3: analytical style, magazine style, and artistic style. These styling have difference in many distinct dimensions, bringing diverse overall visual representatives and affecting UX in an upper level of design.
- *Organization*: Organization refers to the layout and arrangement of design elements in visualization [2]. Different approaches of information organization can affect users' cognitive load, interpretation, performance and user satisfaction [2]
- *Chart Type:* Chart Type refers to the visualization types such as line chart, bar chart, pie chart, etc. Various chart type leads to different user's experience [18]. UX of Chart Type is still a key component to be discussed in visualizations [31], [33], [70].
- *Aesthetic Element:* Aesthetic elements refer to visual elements such as color, color blending, font, text size, textures, layout, etc. Well-designed aesthetics will help BIV to improve user experience [11], [14], [39].

5) CHARACTERISTIC FACTORS AND ENVIRONMENTAL FACTORS

Characteristic factors and environmental factors may have direct impact on user experience, so we can consider these factors as independent variables in UXBIV. In some cases, although we do not take these factors as independent variables, it is necessary to set them as controlled variables, to ensure the reliability of the research.

In our framework, characteristic factors refer to distinguishing features of individuals' personality that may affect user experience; we can use related questionnaires to measure this information. Some dimensions which might fall into this category is: decision styles (directive, analytical, conceptual, and behavioral), time perception (monochronic/polychronic), high-context/low-context, long-term/short-term orientations, thinking styles (holistic/analytic thoughts) and uncertainty avoidance [2], [95].

Environmental factors are related to the surroundings of users, including two aspects: the social backgrounds (cultural, technological, economical, etc.) and the experiment contexts (lab, online, office, etc.). Social background, which brings different thinking path, affects user's response [43]. Besides, experiment context may influence users' performance: users felt more confident in testing in a professional lab than online, and the data collect in the first environment was more reliable [15], [41]. We can count different types of environment factors that user may involves.

C. DEPENDENT VARIABLES AND MEASUREMENT

Based on the literature analysis, we summarized the dependent variables (DV) in UXBIV. Dependent variables of UX can be based on tasks or overall impressions. The task-based UX can be rated by users at the end of each decision-making task. Meanwhile, the overall UX is usually evaluated immediately after participants complete all the interactions with BIV. Figure 2 shows the dependent variables (DV) in UXBIV.

1) TASK-BASED DEPENDENT VARIABLES

a: OBJECTIVE MEASURES

- *Reaction Time and Accuracy*: Reaction time and accuracy are two widely used research measures for human-centered research. Reaction time (RT) refers the time spent of a user to complete a specific task. RT be used to evaluate usability and cognitive loads in user study [82], [83]. In our research, the accuracy is the correctness of the user to complete specific tasks. This can be used to track accessibility and cognitive loads [34], [80].
- *Electrophysiology*: Electrophysiology is another powerful method of collecting objective data. Some representative electrophysiology includes eye-tracking, electroencephalography (EEG), electrocardiography (ECG) and electrodermal activity (EDA), etc. Electrophysiological techniques can measure user experience in real time, such as attention, cognitive load and emotional state in the process of human-computer interaction, and facilitate identifying the influence of graph design towards UX [3], [34]. The combination of subjective and objective evaluation can make a more comprehensive and convincing evaluation of user experience. In our framework, this kind of measure is not mandatory, but it is a great addition to help us improving the evaluation.

b: SUBJECTIVE MEASURES

UX is a term that related to user's subjective feedback, so we should also use subjective measures to analyze UX [78]. The task-based UX can be rated by users immediately after each decision-making task. This kind of measures is direct to user's workload and satisfaction of tasks [96].

One common measure is After-Scenario Questionnaire (ASQ) [60]. A total of 3 items are incorporated into 3 different dimensions: effectiveness, efficiency, and satisfaction. All items can be rated on a 7-point scale. Another popular measure is NASA Task Load Index (TLX) [37]. It allows users to perform subjective workload assessments on various human-machine interface systems. TLX measure on 6 different dimensions: mental demand, physical demand, temporal demand, performance, effort, and frustration. All items can be rated on a 7 -point scale.

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

2) OVERALL UX AS DEPENDENT VARIABLES

According to literature analysis, Overall UX of BIV should contain three major aspects: attractiveness, decision-making experience and interactivity. The overall UX is usually evaluated immediately after participants complete all the interactions with BIV.

- *Attractiveness*: Based on the concept of user experience, BIV attractiveness comprises a set of UX aspects which measure the traditional comprehensive impression of the evaluated BIV system. BIV attractiveness consist of usability, trust, appearances, emotional involvement and loyalty. These ingredients can be measured with Standardized User Experience Percentile Rank Questionnaire (SUPR-Q) [85] and Personal Involvement Inventory [104].
- *Usability*: Usability refers to the effectiveness, efficiency, safety, utility, and learnability of a BIV design [12]. A well-designed BIV should provide sufficient information and make it easy to use. Thus, usability test is about to measure how easy-to-use of a system from user's perspective. For example, if the user think one design is easier to use than another, the first one should have higher rating on this metric.
- *Trust*: In UXBIV, trust is defined as attitudes held by a user derived from his or her perceptions about certain the brand, products or services. Trust is not only linked to relationships within a business environment [23], but also plays a strong role in human-computer interaction [47]. Trust is a "mediating factor" that determines whether consumers accept and use an automated system for self-service [59].
- *Appearance*: Appearance is a metric that measures aesthetic appeal of BIV design. This metric evaluates user's feedback based on design appearance. Cawthon [14] thinks that visualization attractiveness is an important part of user experience. 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.
- *Loyalty*: Loyalty refers to users' strong commitments and attachments toward products or services [27]. Loyal users have more confidence about re-using BIV system, and/or the willingness to share with others. Furthermore, loyal users are not easily distracted to slightly more attractive alternatives. According to Torres-Moraga et al. [92], loyalty combines high attitude orientation and repeated purchase behavior. Ratings of loyalty directly demonstrates the user's satisfaction about the system.
- *Emotional Involvement*: During the interaction with the system, users also experience various feelings including positive and negative emotions [99]. Emotional involvement measures the emotions, moods and feelings evoked by interacting with systems [46]. Emotional Involvement Scale (EIS) is Seven-point Semantic Differential Scale with a set of adjectives to let the user rate the system (e.g., boring/ interesting).

3) DECISION-MAKING EXPERIENCE

Decision-making is a crucial component to be considered while designing BIV. Thus, in our framework, we will evaluate it from four aspects: decision complexity, auxiliary

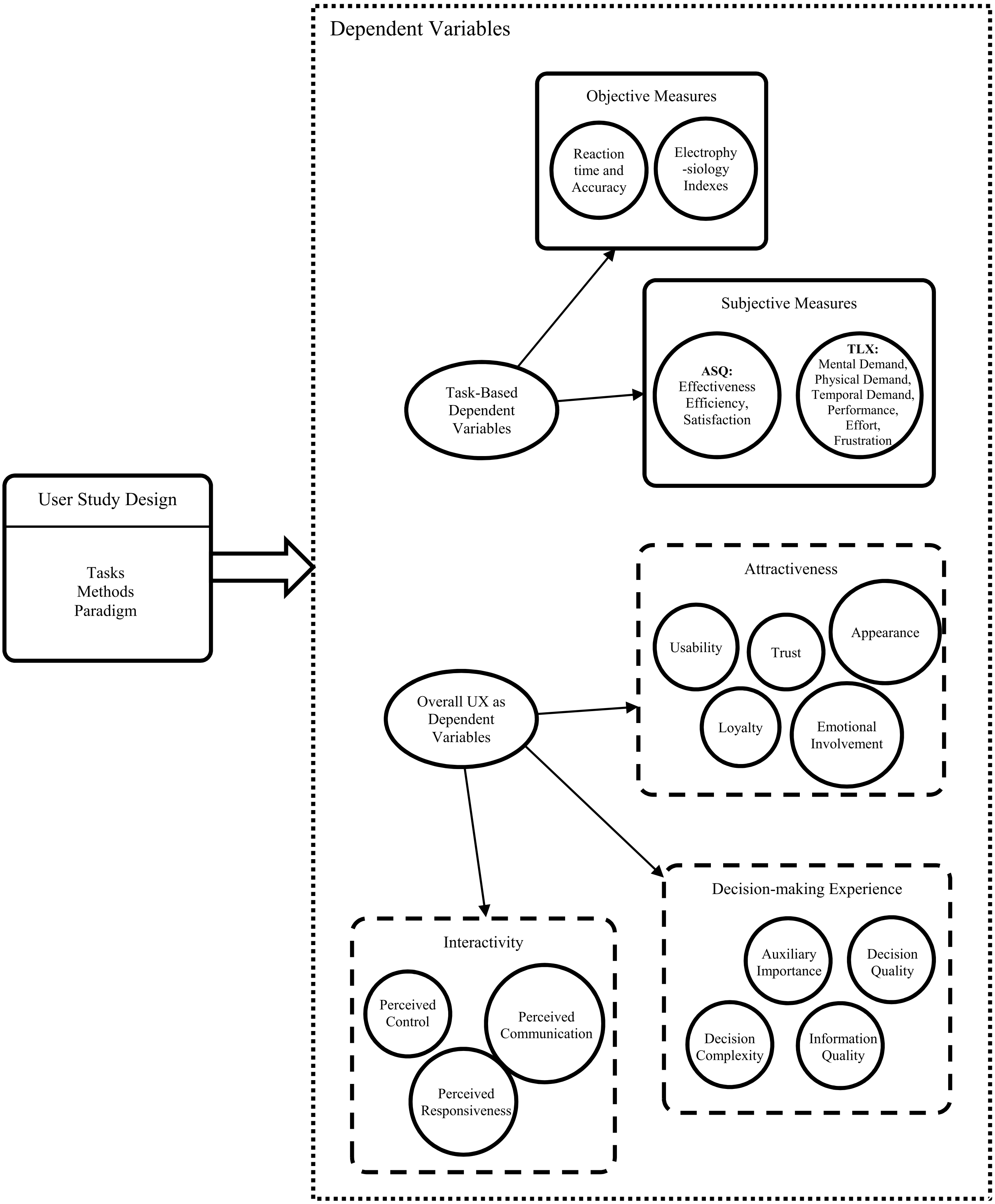

FIGURE 2. **Dependent variables (DV) in UXBIV.**

importance, decision quality, and information quality. The measurements of these four aspects come from the Decision-making Quality Questionnaire (DQQ) published by Visinescu, Jones and Sidorova in 2016 [97].

- *Decision Complexity*: Decision complexity is defined according to the number and kinds of variables or elements involved in decision-making and their interactions [53], [97]. Decisions with more alternatives and attributes were evaluated by decision makers as more difficult [91]. A decision that needs to consider more elements and their relationships will be rated higher on complexity [97].

- *Auxiliary Importance*: In UXBIV, Auxiliary Importance evaluates how important the visualization is during the decision-making process. This dimension depends on the usage level of BIV, which refers to the extent to which users use and rely on BIV to make decisions [17], [97]. If decision-making relies more on the BIV system, the rating of this system should be higher.
- *Information Quality*: Tractinsky and Meyer [94] have defined this as ''relative efficacy to provide the relevant information for the viewer''. In UXBIV, information quality is measured by two dimensions: representational (e.g., understandability) and accessibility (e.g., ease of use) [97]. For example, a design that gives users hundreds of data points may lead to difficult to understand and the user will suspect the information retrieved may be wrong. In this case, the Information Quality rating should be lower.
- *Decision Quality*: Decision quality is often reflected by decision performance, such as decision-making accuracy and speed. However, Subjective measurement is also indispensable and significant. The perceived decision quality can be considered as the perception of the decision results, which can be measured by perceived satisfaction, confidence and trust of the outcomes in decision-making process [97].

4) INTERACTIVITY

In UXBIV, we propose to use interactivity as an indicator of interaction. Interactivity refers to the degree to which two or more communication parties can act on each other on the interaction system, the information and synchronization [64]. Interactivity can be evaluated from three aspects: perceived control, perceived responsiveness, and perceived communication.

- *Perceived Control:* Perceived control refers to the ability to manipulate the information flow [7]. This metric evaluates the satisfaction of human operation. If the system provides enough control elements to let the user can choose the timing, content, and sequence of a communication, it should be rated higher on perceived control. This metric can be measured by Interactivity Perceptions Scale (IPS) [63], [69].
- *Perceived Responsiveness:* Perceived responsiveness refers to the degree to which the responses in a communication are perceived to be appropriate and relevant, and resolving the information need of the interaction episode or event [48]. The system response should follow user's expectation and provide desired information. If the user does not get what they want after performing an input to the system, the satisfaction about the system will be decreased, and this rating will be lower. This metric can also be measured by IPS [63], [69].
- *Perceived Communication:* Perceived Communication is defined as the extent to which users believe that the system facilitates two-way communication [86]. This metric evaluates the satisfaction of communication reciprocity between human and systems. A good perceived communication offers individuals active control and allows them to communicate both reciprocally and synchronously. This metric can also be measured by IPS [63], [69].

D. USER STUDY DESIGN

User study based on behavioral science is 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'' [67]. The section of user study design in UXBIV include decision-making tasks, methods and paradigm (Figure 3).

1) TASK

In this section we will introduce a guideline to design evaluation tasks for the user study. Based on literature analysis, with the consideration of daily usage in business, we come up with a task set that would fits business visualization better.

a: MINIMAL TASK CATEGORY

In Table 2, we list the tasks of visual evaluation in the core literature. In Table 3 we summarize the minimal task unit commonly used in BIV evaluation and provide examples of each task.

Since we're focusing on BIV, with this novel business-related categorization of tasks, we can create propriate tasks for BIV design 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.

b: COMBINED TASKS

Lee et al. [58] noticed several tasks above low-level tasks. Similarly, we can also develop some combined tasks. However, as there are so many possibilities for the combinations have so many possibilities, here we will only provide 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.

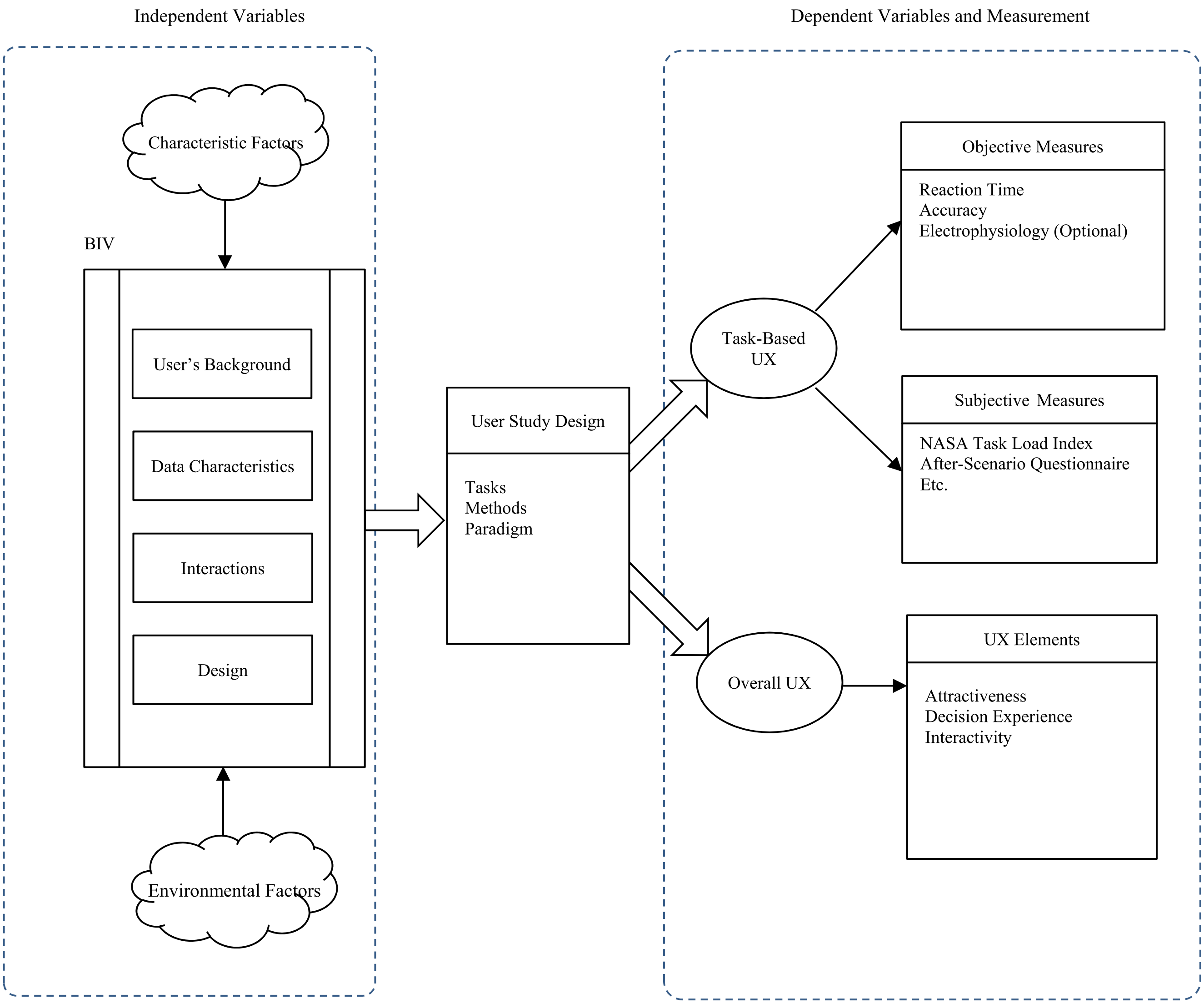

FIGURE 3. **UXBIV framework.**

2) USER-BASED METHODS AND PARADIGM

As viewed from application, how to evaluate user experience is a very important issue. Similar to the traditional UX research, there are various user-based methods for UXBIV. Qualitative methods include interview, focus group, and thinking-aloud; quantitative methods include questionnaire, behavioral experiment and electrophysiology [55], [105]. These methods can be combined in an evaluation of user experience. The quantitative data collection can be obtained by automated tools; meanwhile, the combination of qualitative research methods such as interviews and focus groups is expected to enable evaluators to have a deeper understanding of user experience and optimize BIV design through user feedback [55], [79], [105].

In addition, enlightened by Thayer and Dugan [90], we also provide a paradigm of user test for BIV, which includes all important phases: (i) Participants enter the research site, and researchers introduce the research content; (ii) Participants read the informed consent form and sign it; (iii) Participants receive background survey; (iv) Participants complete the experiment training with the aid of researchers; (v) In the formal experiment, every time the subjects complete a task, they immediately evaluate this task; (vi) After all the in-task surveys on each design, participants complete the post-study survey on each design; (vii) Researcher conducts the interview study; (viii) Participants have a short break; (ix) The sequence of steps from (v) to (vii) can be repeated several times; (x) After interview, participants are acknowledged and given compensation. Figure 4 shows the stages of whole user test and corresponding methods.

IV. CASE STUDY

The main purpose of the user study was to apply our evaluation framework to an actual evaluation case. This demonstrated how to use our framework in the BI visualizations that we developed. Besides, we also assess the diverse designs

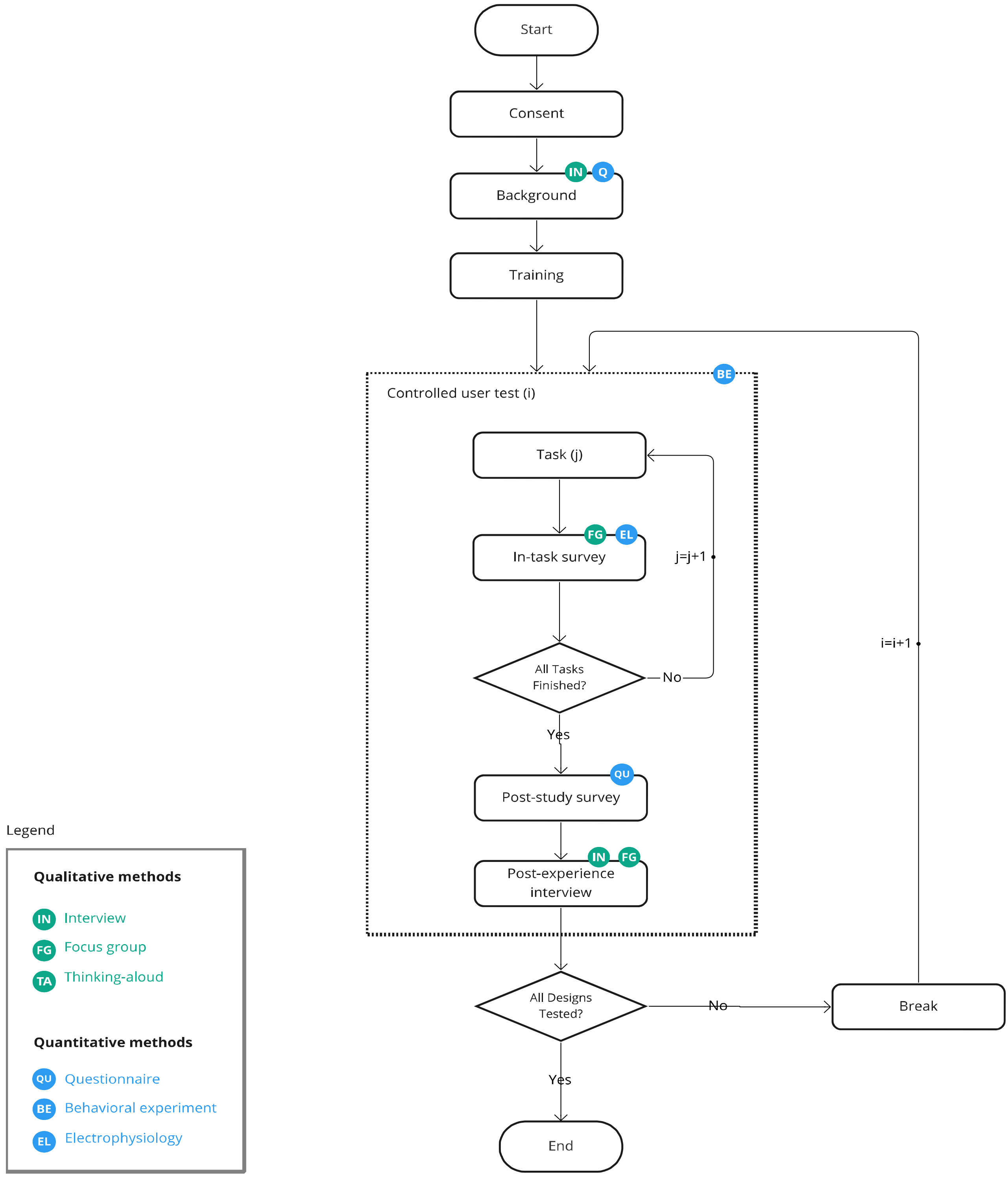

FIGURE 4. **Combination of the Paradigm and corresponding methods.**

of the given BIV system by user-centralized evaluation and make design decisions.

A. PARTICIPANTS

We used on-campus online advertisements to recruit users that are familiar with business visualization systems. 47 eligible participants who can speak fluent English were recruited from a university in the United States. All the participants have normal vision or corrected vision. 84% of all 47 participants are male, and 16% are female. The subjects are from different majors (62% of computer science, 17% of management information systems, 9% of mathematics major,

TABLE 2. Task categories in previous research.

Author	Year	Tasks
Stasko et al. [88]	2000	Identify: looking for some data with characteristics. Locate: Find something and deliver its relatives. 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 and Stasko [5]	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. 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.
Lee et al. [58]	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.
Yi et al. [101]	2007	Select: Mark a data item(s) of interest to keep track of interest. Explore: Examine a different subset of data case. Reconfigure: Provide users with different perspectives onto the data set by changing the spatial arrangement of representations. Encode: Alter the fundamental visual representation of the data including visual appearance (e.g., color, size, and shape) of each data element. Abstract/Elaborate: Adjust the level of abstraction of a data representation. Filter: Change the set of data items being presented based on some specific conditions. Connect: (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.
Livingston and Decker [65]	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.

TABLE 2. *(Continued.)* Task categories in previous research.

Etemadpour et al. [26]	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.
Liu et al. [62]	2013	Browsing: Visit the data with no specific goal in mind. Fact finding: Look for specific facts or pieces of information. Information gathering: Collect information often from multiple sources. Users do not always need to know when you have completed the task and there is no specific answer. Revisit: Revisit some source that you previously used.

TABLE 3. Category of tasks used in framework.

Task	Description and Examples
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/ segmentat-ion	Cluster data points that have 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).

2% of statistics major, 4% of business analytics, and rest 4% of plant sciences).

B. EXPERIMENTAL DESIGN

This experiment is a within-group design. The independent variable is design complexity, the combination of interaction types and visual element types. The system has three levels of appropriate design complexity, including increasing complexity in color and interaction. Figure 5 shows 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 minimal visual elements with white/black color and stripe patterns (see Figure 5 (a)). In this design, only two charts have a legend with the toolbars. Design two is of medium complexity. We applied blue colors with different brightness to the chart elements (see Figure 5 (b)).

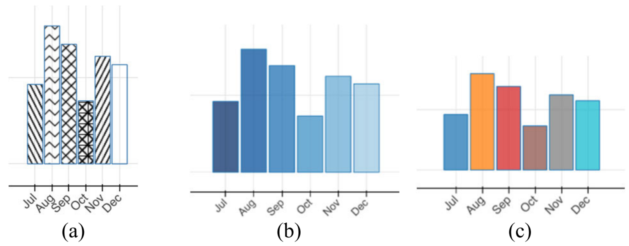

FIGURE 5. Color selection for different design complexity levels.

TABLE 4. Results of effort degree.

E	Design 1	Design 2	Design 3	F	p
Task 1	2.82±0.250	2.16±0.213	1.57±0.151	8.977	0.000
Task 2	3.25±0.247	2.84±0.219	2.32±0.185	4.558	0.012
Task 3	3.30±0.282	2.48±0.214	1.48±0.119	17.753	0.000

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 5 (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. These actions tie into our dependent variables, which involve measuring decision task-based user experience. The dependent variables include decision task-based user experience (mental demand, temporal demand, efforts, performance and frustration level) and the overall user experience (usability, aesthetics, trust, loyalty, emotion involvement, decision-making experience and interactivity). These dimensions were measured by SUPR-Q, EIS, DQQ and IPS mentioned above.

C. MATERIALS AND APPARATUS

We implemented a web-based business sale 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 7 illustrates the design of the user interface. The experiment was conducted on a Windows 10 desktop computer in the human-computer interaction lab. The program was written in HTML and JavaScript and was displayed on a 24-inch LCD monitor with a resolution of 1920×1080 pixels.

D. PROCEDURE

During the experiment, the participants sat straight at the front of the desk. Their eyes were about 1.5 feet away from the screen. In addition, the participants were asked to hold the mouse and operate the program with their dominant hands. Figure 8 shows the process of the user study. The participants were invited into the human-computer interaction lab. After reading and signing the consent form, they were asked to fill in a pre-study questionnaire, followed by a short training familiarizing themselves with the approach and tasks. Then, they completed three tasks on each of three designs. In these tasks, participants typed the answers to the question displayed next to the chart according to their observation (see Figure 6). After each task, the participants were asked to complete an in-study questionnaire to evaluate their experience of that task. Following are the examples of questions for Task1, Task2 and Task3. Task1: In the second half of 2014, which region had the highest sales in September? Task2: In 2014, in which region(s) did component sales surpass bike sales? Task3: In which month of 2015, did the sales of clothing have the highest positive growth rate? After they finished all three tasks for the current design, the participants evaluated their overall impressions of the system with a post-session questionnaire.

E. RESULT

Among the 47 participants, 3 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.

1) CORRECTNESS OF TASKS

The scoring metric for tasks are counted as follow: for task 1-3, each correct answer will be recorded as a score 1, incorrect answer will be recorded as score 0. 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 ($\chi^2 = 0.00$, ρ =1.00), task 2 ($\chi^2 = 3.014$, ρ =0.222) and task 3 ($\chi^2 = 0.266$, $\rho = 0.875$).

2) TASK-BASED RATINGS

The results of task rating for three designs on three tasks are analyzed by use of repeated Analysis of Variance (ANOVA). All the detailed statistical analyses for task 1-3 are as follows.

a: EFFORT (E) DEGREE

The design was the independent variable, and the rating of effort was the dependent variable. Regard to the effort rating, there were significant differences between the designs among all the tasks ($p< 0.05$). The result of Least Significant Difference (LSD) Multiple Comparisons showed that: there was significant differences among all designs for task 1 ($p < 0.05$). there is significant difference between design 1 and 3 for task 2 ($p < 0.01$), but no significant difference between design 1 and 2 ($p > 0.05$), design 2 and 3 ($p > 0.05$). For task 3, there was significant differences among all designs

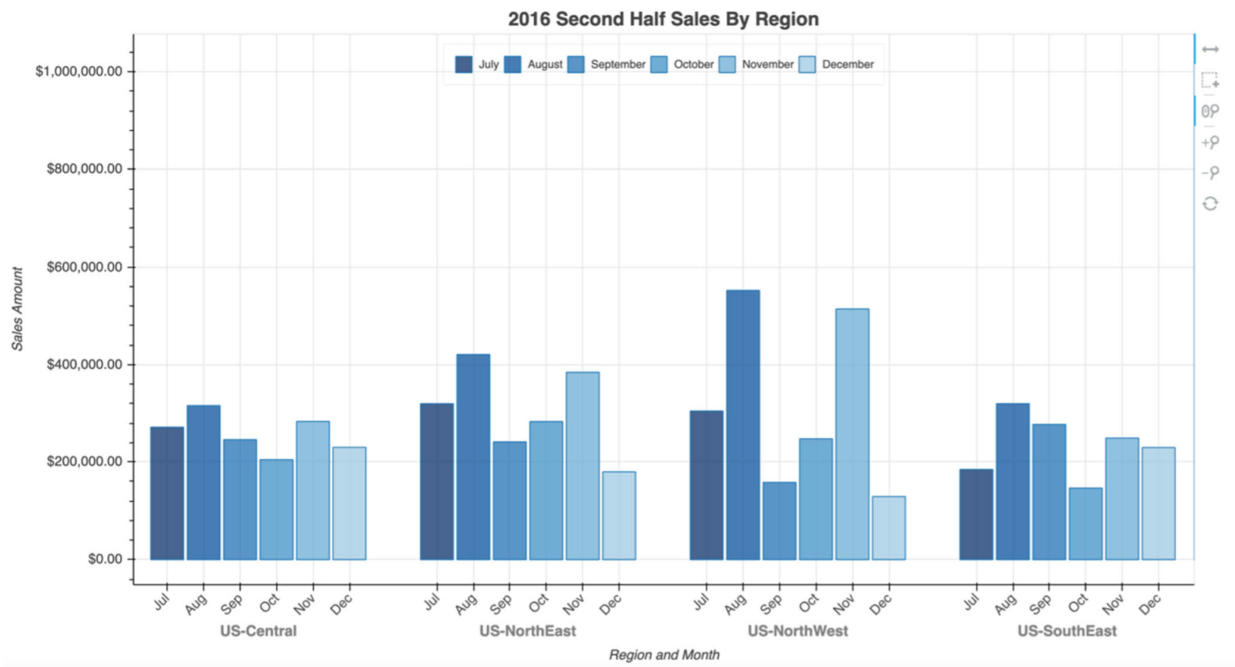

FIGURE 6. An example of chart for one of three designs.

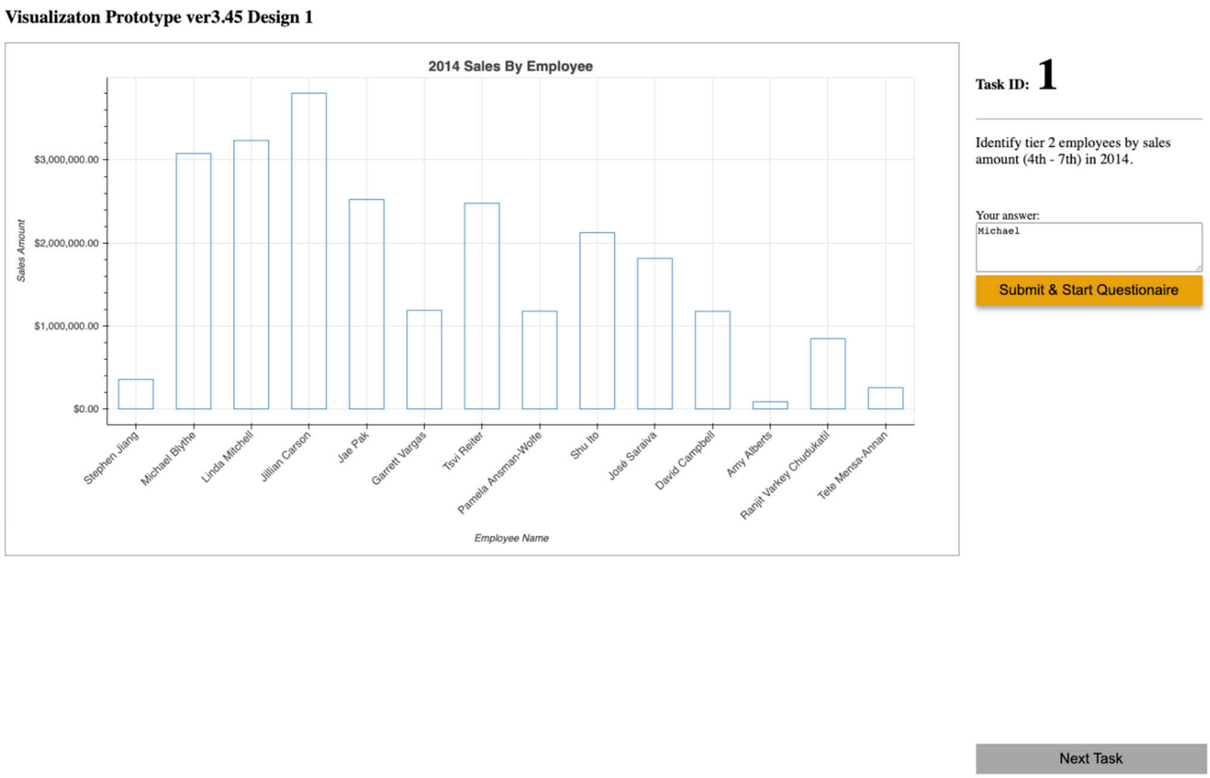

FIGURE 7. GUI of a single task.

($p < 0.05$). Therefore, there was significant differences in general tasks' effort between design 1, 2 and 3.

b: FRUSTRATION LEVEL (FL) DEGREE

The design was the independent variable, and the frustration level was the dependent variable. Regard to the effort rating, there were significant differences between the designs among all the tasks ($p < 0.001$). The result of LSD Multiple Comparisons showed that: For task 1, there was significant differences between design 1 and 2 ($p < 0.001$), design 1 and 3 ($p < 0.001$) but no difference between 2 and 3 ($p > 0.05$).

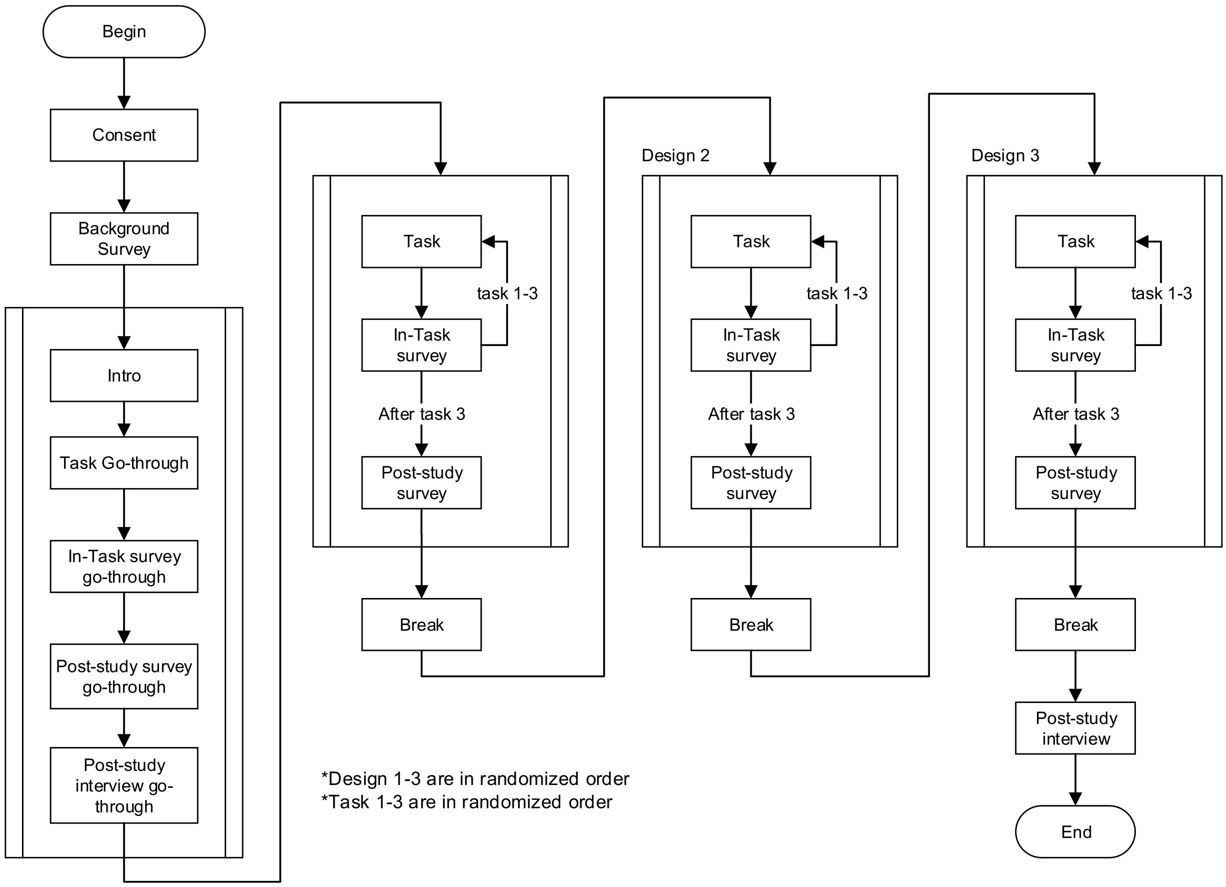

FIGURE 8. Procedure of the user study.

For task 2, there was 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 was significant differences among all designs ($p < 0.01$).

TABLE 5. Results of frustration level.

FL	Design 1	Design 2	Design 3	F	p
Task 1	2.89±0.270	1.86±0.191	1.34±0.103	15.417	0.000
Task 2	2.95±0.268	2.61±0.240	1.66±0.155	8.819	0.000
Task 3	3.73±0.249	3.09±0.237	1.82±0.149	20.246	0.000

c: MENTAL DEMAND (MD) DEGREE

The design was the independent variable, and the mental demand was the dependent variable. Regard to the mental demand, there were significant differences between the designs among all the tasks ($p < 0.001$). The result of LSD Multiple Comparisons showed that: For task 1, there was significant differences among all designs ($p < 0.05$). For task 2, there was 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 was significant differences among all designs ($p < 0.01$).

TABLE 6. Results of mental demand degree.

MD	Design 1	Design 2	Design 3	F	p
Task 1	3.23±0.283	2.48±0.229	1.77±0.178	9.674	0.000
Task 2	3.52±0.226	3.32±0.222	2.39±0.208	7.630	0.001
Task 3	4.05±0.262	3.23±0.223	2.07±0.161	20.566	0.000

d: PERFORMANCE (P) DEGREE

The design was the independent variable, and the performance was the dependent variable. Regard to the effort rating, there were significant differences between the designs among all the tasks ($p < 0.001$). The result of LSD Multiple Comparisons showed that: For task 1, there was 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 was 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 was significant differences among all designs ($p < 0.05$).

TABLE 7. Results of performance degree.

P	Design 1	Design 2	Design 3	F	p
Task 1	6.09±0.172	6.68±0.112	6.84±0.086	9.524	0.000
Task 2	5.66±0.187	5.89±0.173	6.61±0.104	9.886	0.000
Task 3	5.52±0.185	5.98±0.164	6.73±0.081	16.321	0.000

e: TEMPORAL DEMAND (TD) DEGREE

The design was the independent variable, and the temporal demand was the dependent variable. Regard to the temporal demand, there were significant differences ($p < 0.05$) between the designs among all the tasks except task 2 ($p > 0.05$). The result of LSD Multiple Comparisons showed that: For task 1, there was 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 was 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 was 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 ($p > 0.05$).

TABLE 8. Results of temporal demand degree.

TD	Design 1	Design 2	Design 3	F	p
Task 1	2.14±0.22	1.64±0.149	1.52±0.148	3.470	0.034
Task 2	2.30±0.205	2.18±0.196	1.75±0.157	2.375	0.097
Task 3	2.55±0.253	2.07±0.188	1.52±0.133	6.736	0.002

3) OVERALL FACTOR ANALYSIS

a: ITEM ANALYSIS

The purpose of this analysis was to determine whether the elements were valid and appropriate. First, the distinguishability analysis (T-test) was used to examine whether there was significant difference between high score group (27%) and low score group (73%) on each element. Results showed that all the T-test values were significant ($p< 0.001$ or $p= .001$), which meant that a total of 12 elements had a great discrimination and quite reasonable. Second, correlation analysis was applied to calculate the correlation between the total score and each element. Results showed that all the correlations were significant ($r = 0.410\sim .924, p < 0.01$), which indicated all the elements measured the user experience of BI.

b: EXPLORATORY FACTOR ANALYSIS

The Kaiser-Meyer-Olkin (KMO) analysis and Bartlett's Test of Sphericity showed that the 12 elements were ideal for factor analysis ($KMO = 0.942$, $\chi 2 = 1495.301$, $p < 0.001$). Table 9 shows the result of exploratory factor analysis.

As illustrated in Table 9, three factors were identified after the exploratory factor analysis. Factor 1 included usability, trust, appearance, loyalty, information quality, and emotional involvement, so Factor 1 was named as Attractiveness. Factor 2 involved decision complexity, auxiliary importance and decision quality, so this factor was called Decision Experience. Factor 3 was similar to the original Interactivity elements, consisting of perceived control, perceived responsiveness, perceived communication, so this factor can be still named as Interactivity. Therefore, the resulting 12 elements constituted three factors: Attractiveness, Decision Experience and Interactivity. Three factors can account for 79.758% total variance.

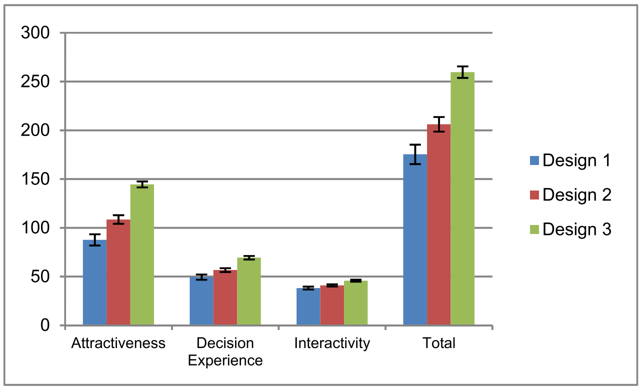

FIGURE 9. UX Ratings of three visualization designs.

c: RELIABILITY

We also evaluated the internal consistency using Cronbach's α. The Cronbach's α we calculated from the samples revealed that three factors had high inner reliability (Cronbach's $\alpha =$ 0.712, 0.849, 0.940), and the Cronbach's α of the total scale of BIV User Experience was 0.721. Since all of them are higher than 0.70, it is showing good internal consistency for the whole questionnaire as well as its three factors.

4) ELEMENT-BASED UX DIFFERENCE ANALYSIS

The results of evaluation rating for different designs on various elements are illustrated in Figure 9. The detailed statistical analyses are as follows.

a: THE OVERALL EVALUATION DIFFERENCES

Design was the independent variable, and the overall evaluation 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 for design 3 was significantly higher than design 1 ($p < 0.001$) and design 2 ($p < 0.001$), and the overall evaluation of design 2 were significantly higher than design 1, $p > 0.05$. Therefore, there were significantly differences in overall evaluation among

TABLE 9. Result of exploratory factor analysis.

	Factor 1	Factor 2	Factor 3
Usability(A)	0.860		
Trustiness(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		

TABLE 10. Factor based ratings and total ratings.

	Attractiveness	Decision Experience	Interactivity	Total
Design 1	87.64±5.756	49.45±2.720	38.2±1.476	175.3
Design 2	108.52±4.400	56.66±1.985	40.95±1.096	206.14
Design 3	144.52±3.069	69.32±1.839	45.8±0.996	259.64

these three designs; design 3 performs significantly better than other 2 designs.

b: THE ATTRACTIVENESS DIFFERENCES

Design was the independent variable, and the attractiveness was the dependent variable. 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 of design 1 was significantly lower than design 2 ($p < 0.05$) and design 3 ($p < 0.001$), and the attractiveness 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.

c: THE DECISION EXPERIENCE DIFFERENCES

The design was the independent variable, and the decision experience was the dependent variable. 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 experience of design 1 was significantly lower than design 3 ($p < 0.001$), but not significantly lower than design 2 ($p > 0.05$). The decision experience of design 3 was significantly higher than design 2 ($p < 0.001$). Therefore, there were significant differences in decision experience among the three designs; design 3 performs significantly better than other 2 designs.

d: THE INTERACTIVITY DIFFERENCES

The design as the independent variable and the interactivity was the dependent variable. 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 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 among the three designs; design 3 performs significantly better than other 2 designs.

V. DISCUSSION

We have proposed and proved UXBIV framework, a novel evaluation framework that can be used in Business Intelligence Visualization. The aim of this section is to explain rationality, practical application, and future directions of UXBIV framework.

A. RATIONALITY OF UXBIV FRAMEWORK

The UXBIV 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 business intelligence, visualization, user experience, 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 potential relationships between elements are based on selected literature. All of these have provided a solid foundation for the rationality of this framework.

Especially, compared with Bačić and Fadlalla [9], the set of independent variables we summarized has more advantages in UX research. Although according to visual mental abilities, Bačić and Fadlalla [9] 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 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 UXBIV, the independent variables should be related to attributes of the system itself or users, including data characteristics, interaction, design, users' background, etc. These independent variables are more practical and easier to manipulate for designers of BIV. Therefore, both for users and designers, UXBIV is a reasonable framework, because it embodies the human centric design philosophy.

Overall user experience, a crucial sub-framework of UXBIV, has good validity and reliability. Firstly, correlation analysis showed that all 12 sub-elements of overall UX certainly measure the user experience of BIV. Secondly, discrimination analysis proved that the 12 sub-elements assumed in the overall UX can well distinguish BIV designs with different design quality. Thirdly, factor analysis confirmed three main factors of overall UX within the sub-frame we proposed: attractiveness, decision-making experience and interactivity. 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 as a sub-element of decision-making experience, but exploratory factor analysis found that information quality was classified into attractiveness. According to the literature analysis, information quality refers to ''relative efficiency to provide the relevant information for the viewer'' [94], focusing on whether information is easy to extract, interpret and use etc. Although information quality has a significant impact on decision quality [97], 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 attractiveness subframe. Figure 10 shows the structure of overall UX based on exploratory factor analysis.

B. PRACTICAL APPLICATION OF UXBIV FRAMEWORK

Our research fulfills a pressing need in the field of BIV research. First of all, the current research and application of BIV require evaluating UX, but research in this field is still in its infancy. The development of theories and methods in this field lags behind the overall level of current user experience research. Secondly, BI visualization designers are more focusing on research and advancing new visualization technology. BIV evaluation involves theories and methods in psychology, decision science and other fields, but it lacks a systematic evaluation guideline, which has greatly affected the advancement of user experience research in the field of BIV. Thirdly, ''user-centered'' is an important principle emerged in interaction design in recent years. In order to promote users' perception, analysis and application of business information, BI visualization should also emphasize the ''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 UXBIV 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.

As shown in Figure 11, a typical lifecycle of a BIV system includes three elements: BIV users, BIV designers, and the 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 users and resolves the issues they were facing. By introducing the UXBIV framework, we can benefit all the elements in this lifecycle: This framework is able to evaluate the existing BIV system, collect and evaluate users' 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 the lifecycle of BIV system lifecycle.

Although BIV is regarded as the core component of business intelligence [72], only a few papers on BIV user experience have been published. At present, there is no UX framework specially designed for BIV. It is the first time we have put forward a UXBIV framework, which provides valuable insights for the visualization in business fields. The framework provides a powerful tool for systematically collecting various user experiences in detail and refining BIV design principles. The analysis results of this framework can significantly facilitate highlighting the advantages of BIV and improve the competitiveness of BIV development enterprises.

Our framework starts from four main factors: user's backgrounds, data characteristics, interactions and designs. Plus, we also take into consideration characteristic factors and environmental factors. These factors helped us to cover as many independent variables as possible. As a dependent variable, UX analysis includes task-based UX analysis and overall impression UX analysis. With regard to the task-based analysis, we will utilize objective and subjective indicators to evaluate BIV in decision-making tasks. 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 UXBIV 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 UXBIV. If you try to compare the UX quality of a set of BIV, you should use UXBIV. 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 UXBIV.

The case study was an empirical study that combines behavioral experiment with questionnaire survey. The purpose of this study is to demonstrate how to apply our framework to the practical evaluation of a set of BIV. According to the UXBIV framework, we compare the user experience of three BIV designs with different complexity, following the paradigm in UXBIV. The whole study contained pre-task, in-task, post-task stages. Result analysis consists of three aspects: first, we analyzed the correctness of tasks, which ensured that 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. Subsequently, 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 in almost

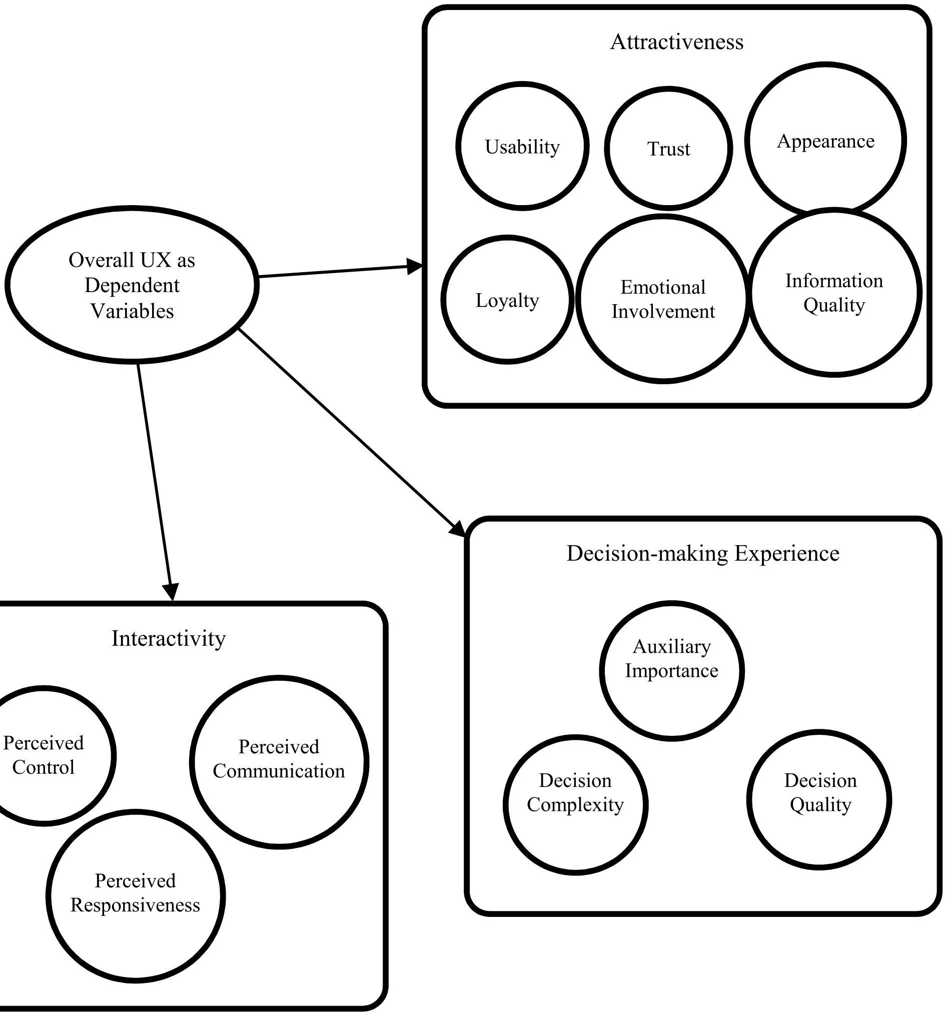

FIGURE 10. **The structure of overall UX based on EFA.**

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 that this framework can be used to guide BIV design in the future.

C. FUTURE DIRECTIONS

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

First of all, we only provided research on traditional platforms, 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), the metaverse, artificial intelligence (AI), holographs, multi-device visualizations, etc. Our framework may also be adjusted to better detect user experiences of systems with these new technologies.

Secondly, the evaluation of BIV should adopt a combination of various methods. Due to the limitation of our laboratory situation, collection methods in the 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 understanding, as well as analyzing user experience of BIV.

Thirdly, in our study, most of the participants were students, although many of them were studying in the business field. Considering users' backgrounds, we need to expand the test group to include business professionals who are more familiar and experienced with BI systems. The feedbacks they provide as users can help us further optimize the UXBIV framework.

Finally, in view of environmental factors, such as social backgrounds (culture, economy, etc.) and experimental contexts (online, office, etc.), in order to promote its applicability in diverse environments, UXBIV may also be modified in

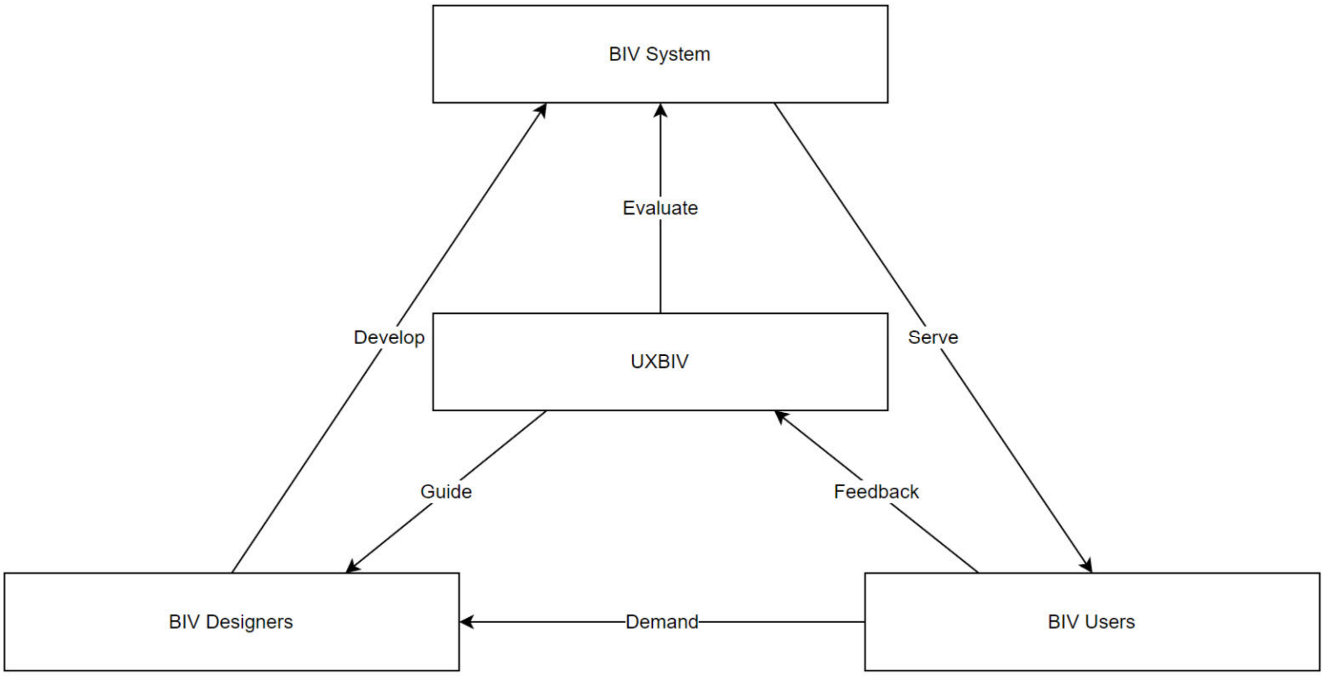

FIGURE 11. A typical lifecycle of BIV system.

accordance with changes in environmental factors. This topic is also a meaningful direction in the future.

VI. CONCLUSION

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

VII. APPENDIX

A. PRE-STUDY QUESTIONNAIRE EXAMPLE

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 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

B. IN-STUDY QUESTIONNAIRE EXAMPLE

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

C. POST-STUDY QUESTIONNAIRE EXAMPLE

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.

1) 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.

2) 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

3) 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.

4) 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

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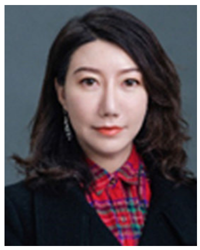

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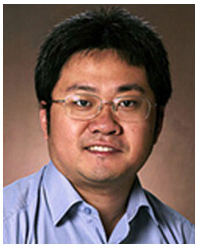

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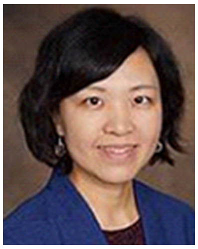

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