Usability Guidelines for Designing Information Visualisation Tools for Novice Users

Martin Smuts
Nelson Mandela Metropolitan University
South Africa

Brenda Scholtz
Nelson Mandela Metropolitan University
South Africa

Andre P. Calitz
Nelson Mandela Metropolitan University
South Africa

Abstract
Despite the benefits of effective Enterprise Resource Planning (ERP) and Business Intelligence and Analytics (BI&A) systems, the adoption of such systems remains fairly low in developing countries due to a number of factors. Research has indicated that severe skills shortages are predicted in the field of BI&A, as university graduates are not properly prepared to conduct data analysis. Several studies have proposed curricula to increase the skills of Information Systems (IS) graduates studying towards BI&A fields. Additionally, BI vendors are realising that a wider audience of users are participating in the process of data analysis and are not limited to the stereotypical statisticians or technical experts. The field of Information Visualisation (IV) is addressing the need to produce software products that eliminate the technical skills required to operate such software tools. This study aims to investigate some of the usability factors hindering BI&A knowledge transfer and skills in developing countries by conducting a field study at a South African university. A number of problem categories was identified during the field study and a set of guidelines for designing IV tools for novice users is proposed to eliminate these problems.

Keywords
Visualisation guidelines, Business Intelligence (BI), information visualisation tools.

Introduction
Business Intelligence and Business Analytics (BI&A) have become increasingly important fields in both academic and business communities over the past two decades (Chen & Storey 2012). Developing countries are generating very large amounts of data through the use of mobile technologies, which can be mined to improve human well-being, track

Steyn, J., Van Belle, J.P. (Eds.). 2015. Beyond development. Time for a new ICT4D paradigm?
Proceedings of the 9th IDIA conference, IDIA2015, Nungwi, Zanzibar: 148-162
ISBN: 978-0-620-68395-1

emerging markets, or identify the needs of customers. Many organisations have implemented Enterprise Resource Planning (ERP) systems to integrate their various processes and departments, which gives employees a holistic view of all information that has a financial impact on the organisation. BI, together with ERP systems, is seen as a priority in an increasing number of organisations, with benefits to different levels of the organisation ranging from front-end workers to executives in strategic management. According to Gartner, the BI market grew by 9% and is projected to grow at a compound annual growth rate of 8.7% until 2018 (Sallam et al. 2015). Sallam et al. (2015) further motivate that capabilities such as smart data-discovery and self-service BI are extending data discovery to a wider range of non-traditional users of BI to enhance insights and data interpretation. These capabilities allow users to identify hidden patterns in large, complex and increasingly multi-structured datasets, without having the foundational skills to build models or write algorithms and queries (Sallam et al. 2015). Moreover, the increase in interactive information visualisation (IV) tools is enabling non-traditional users of BI to explore, understand and analyse data through progressive and iterative visual exploration (Schröter 2015). These tools are often desktop software that have the capabilities to connect to underlying data architectures that are set up for BI and are often marketed as "*Visualisation*", "Data Discovery", "*Business Analytics*" or "*Data Exploration*" tools.

A number of studies has shown that the adoption of BI remains low, particularly amongst smaller institutions and organisations with resource constraints (Muriithi & Kotzé 2013; Pitula & Radhakrishnan 2011). Many of these constraints relate to high failure rates, problems with data irregularities and lack of compatibility with existing systems (Nofal & Yusof 2013). Additionally, current research has predicted severe shortages in the number of graduates prepared to work in the field of BI and ERP (Calitz, Cullen & Greyling, 2015; Chiang, Goes, & Stohr, 2012; Gupta et al., 2015; Wang & Harbert, 2015; Wixom & Goul, 2014). Research produced by the McKinsey Global Institute (MGI) reported that by 2018, the United States alone may experience a shortage of 140,000 to 190,000 data analysts professionals as well as 1.5 million data-savvy managers (Manyika et al. 2011). A need exists to increase the knowledge and skills of students intending to work in the field of data analysis and BI. Skills in data analysis are especially necessary to improve the socio-economic status in developing countries and to provide real-time feedback on socio-economic programs and policies that might require rapid alternations (Letouzé 2012). A number of projects have addressed curriculum design for BI&A in order to lessen the shortage of BI skills and knowledge (Wixom & Goul 2014; Gupta et al. 2015; Chiang et al. 2012; Wang & Harbert 2015). The Developing and Strengthening Industry-driven Knowledge-transfer between developing Countries (DASIK) project (DASIK, 2014) and Global Pulse (Global Pulse, 2015) are initiatives that aim to increase the data analysis skills of people in developing countries.

The low usability of BI tools makes it difficult for novices to gain the required skills (Jooste et al. 2014). BI platforms are developed using a range of software tools from different vendors that require users to have strong technical skills and domain knowledge. Novice users do not have such skills as they are in the process of learning and struggle to develop and interpret moderately complex visualisations of data. The low usability of tools worsen the situation (Bostock & Heer 2009; Elias 2012; Yigitbasioglu & Velcu 2012). Fan and Bifet (2013) motivate that the main task of data analysis is how to visualise data, but is often difficult to find user-friendly visualisations that are interpretable by less experienced users.

The poor usability of BI systems makes it difficult for users to interact with these systems, which often creates an environment where users are expected to either apply strong programming skills or domain knowledge (or both) to develop visualisations, synchronise these into different views and connect to different data sources and applications (Elias 2012; Pantazos et al. 2013). These problems often affect the learnability of the system as students need time to master the complex interface. Moreover, users follow a common development process to create visualisations of their data, which provides users with logical mental models (Liu et al. 2014). If the development process is moderately complex, users often struggle to map their data to visualisation techniques (Grammel et al. 2010; Huron et al. 2014). As a result, users with less technical knowledge must seek the assistance from experts to extract the required data from various applications, apply statistical techniques and present the reviewed data accordingly (Elias 2012). These problems are worsened in developing countries where individuals lack ICT skills.

The research problem investigated in this study is prompted by the realisation that Information Systems' (IS) graduates may not be fully prepared (knowledgeable and skilled) to satisfy the BI and data analysis requirements of industry. Moreover, novices often struggle with the usability of BI tools and mapping data to visual presentations. The primary aim of this paper is to investigate how novice users experience the usability of IV tools and the difficulties they experience when learning these tools with a particular focus on dashboards. The secondary aim proposes a set of guidelines for designing or evaluating IV tools that can aid novices in learning data analysis.

The structure of this paper is as follows. A literature review analyses the problems encountered in the field of ERP and BI. This is followed by a discussion of the research methodology adopted and the participants involved in this study. The results of a field study are then presented and guidelines are proposed based on the findings from literature and the field study results. The final section deals with conclusions and future recommendations.

Information Visualisation

Organisations have realised that the implementation of ERP and BI systems is a key strategic tool. The most current information is collected from ERP systems and then loaded into data warehouses, which can then be linked to BI tools for analysis. The term BI can be understood as a set of tools, techniques and processes that aids organisations in retrieving, analysing and distributing information retained, in large data sets, to make effective decisions (Sabherwal & Becerra-Fernandez 2013). The overall objective of BI is to increase organisational performance through decision support. A BI system should provide both a technical and organisational platform that presents its users with historical, current and predicative information for analyses to enable effective decision making and predictive management support. Some of the benefits that can be derived from BI are faster and easier access to information, improved profitability, reduced costs and improved efficiency and customer service.

Despite the benefits of BI, many organisations and development countries have low adoption rates for these types of enterprise systems (Pitula & Radhakrishnan 2011). A recent study (Calitz, Cullen & Greyling, 2015) was conducted in South Africa and reported that BI, Business Process Management (BPM) and Knowledge Management are skills that are highly in demand, while Infrastructure Management and Information Security were skills that would be in high demand in future. These demands are aggravated in developing countries since they lack the technological infrastructures and experience high volumes of economic and human resource scarcity (Hilbert 2013). Pitula and Radhakrishnan (2011) further argue that some of the issues related to large ICT4D projects are the existence of inadequate requirements gathering from end-users. In many ICT4D projects existing technologies are introduced without sufficiently adapting or reinventing the requirements with regard to the users' needs, infrastructure or socio-cultural context (Pitula & Radhakrishnan 2011).

Chiang et al. (2012) explains that the analytics software industry produces products that are difficult and cumbersome to use when individuals do not having a deep understanding of the underlying systems and technologies. Considering that a wider audience are starting to utilise analytics tools, there is a need to develop tools that assist users throughout the whole process of learning (Ritsos & Roberts 2014). BI tools need to support users from the beginning, when they are novices, and help them advance to expert levels where they progress from shallow thinkers to deep thinkers in order to identify and solve more complex problems (Ritsos & Roberts 2014). In this study, the definition of "novice" users, or just novices, is adapted from Heer et al. (2008) and Grammel et al. (2010). Novice users refer to those who are not familiar with IV and data analysis beyond the charts and graphics encountered in everyday life, but may be domain experts in their area of expertise (Grammel et al. 2010). Additionally, novice users may be constrained by their lack of programming skills in general, let alone programming for IV (Heer et al. 2008).

IV has been widely used in a variety of data analysis applications (Liu et al. 2014). IV refers to the interdisciplinary field concerned with the visual displays of complex information to assist humans in understanding information, resolving logical problems and to think with reason (Patterson et al. 2014). The diverse nature of data requires the formulation of a various IV techniques that can communicate important patterns and trends from abstract data sources. A popular visualisation technique that is often used in the BI domain are dashboards (Elias & Bezerianos 2011; Yigitbasioglu & Velcu 2012). Dashboards are visual displays of the most important information that is consolidated and organised on a single screen to achieve one or more objectives (Yigitbasioglu & Velcu 2012). The most popular visualisation process was presented by Card, Mackinlay and Shneiderman (1999) and was also refined by others (Chi 2000; Tobiasz et al. 2009; Jansen & Dragicevic 2013). The process describes three activities of how visualisations are essentially developed, interpreted and interacted with. The first activity relates to the transformation of raw data into data tables (*Data Transformations*). These data tables can be further refined by applying filters, calculations and merging with other tables (Grammel et al. 2010). The data tables are then mapped to visual constructs (*Visual Mappings*), typically taking the form of generic visualisations such as bar, pie, or line graphs with their corresponding properties. Visual mappings have been identified as the most difficult activity for novices to perform, since they lack understanding of which visualisation types are best suited for the selected data. Views are created from visual structures (*View Transformations*) that display data at varying levels of abstraction, allowing users to view data from various perspectives by using operators such as zoom, filter, aggregate, drill-down and brushing (Heer et al. 2012). View transformations do not change the overall layout of the visual structure, but only allow for a data set to be viewed from a different perspective. Finally, users interpret the views with predefined objectives in mind, for example when examining the top 10 products sold.

Research Design

The main research question of this study is: *What design guidelines can be proposed to alleviate the usability problems of IV tools for novice users?* In order to answer the main research question, two secondary questions were formulated, namely:

RQ1: What specific problems do novice users experience when conducting IV and data analysis?
RQ2: What guidelines can be proposed to guide the design of visualisation tools for novice users?

The research strategies used to answer the research questions include a literature review and a field study to investigate the research problems of data analysis in more detail. The results of these were used to identify and propose guidelines for designing and developing BI tools that may aid novices. The field study was conducted by administering a dashboard workshop with third year IS students at a South African HEI, and was therefore facilitated in a controlled environment in a traditional computer laboratory with desktop PCs. Prior to the field study the students were given a small theoretical introduction to performance dashboards. The learning outcome for the workshop was to develop a dashboard of inventory data with information about quantities on hand, selling values on hand, and estimated gross profits for a number of warehouses on the SYSPRO ERP database. Students are expected to follow a number of steps to use four different software tools that constitute the dashboard system (Figure 1). These software tools are Microsoft SQL Server, SYSPRO ERP, Crystal Xcelsius and Microsoft Excel. The dashboard workshop has been often criticised by students for being complex and requiring too many steps. Students were given three hours to complete the tasks, were allowed to seek the assistance of the facilitators if a problem was encountered and were encouraged to record the problem and how the problem was solved on the task-list.

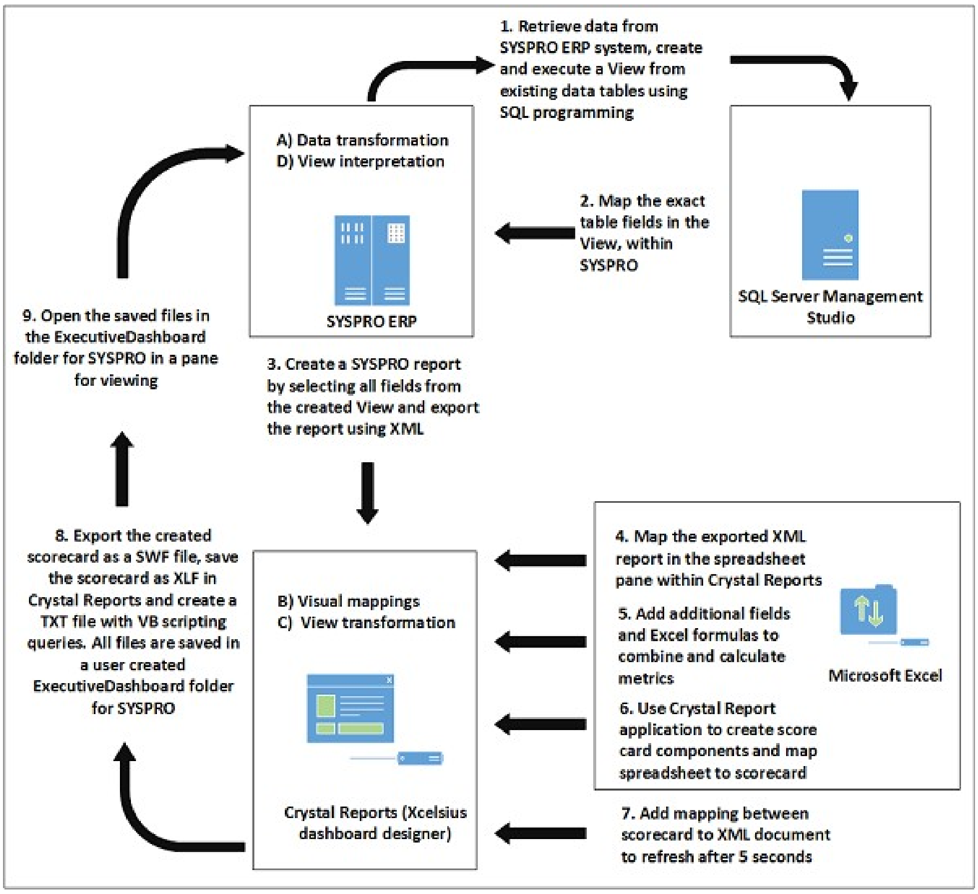

Figure 1, Software tools used to create a dashboard for SYSPRO.

The first section of the questionnaire handled biographical information, whilst the second section of the questionnaire, Cognitive Load, was adapted from the National Aeronautics and Space Administration Task Load Index (NASA-TLX). The NASA-TLX measures the cognitive workload with three sub-scales: task-related, behaviour related, and subject related scales (Hart 2006). Measuring cognitive load during a usability study is important, since difficult tasks are likely to increase cognitive load and may cause users to forget some of the steps required to create visualisations (Toker et al. 2013). The task-related subscale measures were factors surrounding the participant's mental demand), physical demand and temporal demand. Behaviour related aspects refer to subscales measuring perceived level of effort (EF) and personal performance (PP). The subject-related subscale measures the perceived level of frustration (FR) during the evaluation (Hart 2006). The participants were required to rate each of these factors based on a 5-point Likert scale (1= Strongly Disagree and 5 = Strongly Agree). The overall workload score is calculated based on a weighted average of each subscale and presented as an overall score out of 100.

The third section of the questionnaire related to user satisfaction. Satisfaction is an important measurement of usability, as users will not utilise a tool if they are not satisfied with the way it operates. The questions relating to the overall satisfaction were adapted from the Computer System Usability Scale questionnaire (CSUQ), which was firstly introduced by Lewis (1995). The questions used in the CSUQ are developed to evaluate the psychometric properties for use in scenario-based computer system usability evaluations. Although the CSUQ offers 19 different questions in total, only five questions

Steyn, J., Van Belle, J.P. (Eds.). 2015. Beyond development. Time for a new ICT4D paradigm?
Proceedings of the 9th IDIA conference, IDIA2015, Nungwi, Zanzibar: 148-162
ISBN: 978-0-620-68395-1

were used and reported on due to time constraints and for the purposes of this evaluation. The questions that were used from the CSUQ are worded positively and measured four broad factors namely: ease-of-use, learnability, overall satisfaction and information quality. The participants were required to rate each of these factors based on a 5-point Likert scale (1 = *Strongly Disagree* and 5 = *Strongly Agree)*. The third section of the questionnaire included an open-ended question, which enabled students to give feedback on the perceived negative features of the system. The participant profile consisted of 14 students who formed part of a third year ERP course. None of the participants had any industry experience and were all fulltime students enrolled for IS degrees. None of the participants had received training on ERP or BI systems before the DASIK course. The sample size was split equally between males (n=7) and females (n=7). The participants were all in the age group of 18-29.

Field Study Results

All participants successfully completed the task-list. The mean time to complete the task-list was 121 minutes, with the quickest time being 82 minutes and the slowest time being 143 minutes which was acceptable when compared to the expert's task time. However, the analysis of the NASA-TLX questions (Figure 2) revealed that the development process required a high cognitive load. The mean for each closed-ended Likert scale item in the NAXA-TLX was classified according to the following ranges:

- Strongly disagree [$1.0 \geq \mu < 1.8$)
- Disagree [$1.8 \geq \mu < 2.6$)
- Neutral [$2.6 \geq \mu \leq 3.4$)
- Agree [$3.4 > \mu \leq 4.2$)
- Strongly agree [$4.2 > \mu \leq 5.0$)

Participants agreed that the development process was mentally challenging (μ=4.07) and required a great deal of effort (μ=4.00) to complete the complete the tasks. Participants were, however, neutral regarding the physical (μ=2.79) and temporal (μ =2.86) demand required to complete the tasks. Although all participants completed the tasks successfully, they perceived their performance with the system to be low (μ=2.43) and agreed that they experienced high levels of frustration (μ=3.50).

Steyn, J., Van Belle, J.P. (Eds.). 2015. Beyond development. Time for a new ICT4D paradigm?
Proceedings of the 9th IDIA conference, IDIA2015, Nungwi, Zanzibar: 148-162
ISBN: 978-0-620-68395-1

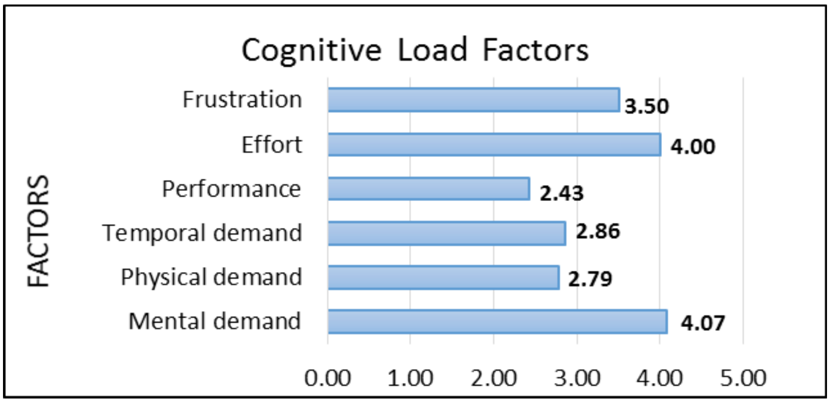

Figure 2, Cognitive load factors using a 5-point Likert Scale (n=14).

The ranges for the Likert-scale items could be further categorised into negative (1.0 ≥ μ < 2.4), neutral (2.4 ≥ μ < 3.6), and positive (3.6 ≥ μ ≤ 5) ranges. The analysis of the CSUQ questions (Figure 3) revealed that the highest mean related to the overall satisfaction and was rated *neutral* (μ=2.86). Some of the metrics had mean ratings in the *negative* range. It can therefore be deduced that usability problems were encountered and this is supported by the high ratings of frustration, effort and mental demands required from the tasks. The metric with the lowest mean was information quality (μ=1.43). It can be deduced that participants did not receive sufficient assistance from the system when they encountered a problem. Participants disagreed that the system is easy to use (μ=2.43) and thought that it was difficult to learn the various development steps (μ=2.50) and software components (μ=2.57) respectively. This result indicates that students struggled to understand how software components communicate to one another. Moreover, the result may be because the students are not knowledgeable about software tools that support IV and have never worked with such tools before. Participants also disagreed that the amount of time to complete the task-list was insufficient (μ=2.36) and stated that the process takes too long to develop a single visualisation.

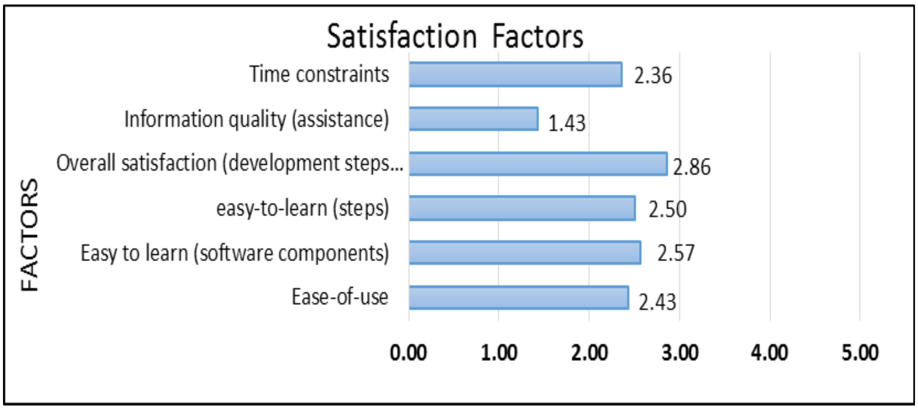

Figure 3, Satisfaction measures adapted from CSUQ.

Participants were asked to describe the features of the system that they disliked (open-ended question) as well as to make notes of any problems that were experienced during the tasks (Table 1). The responses were analysed qualitatively by using content analysis whereby the text is categorised or coded into themes. Although there were some problems

Steyn, J., Van Belle, J.P. (Eds.). 2015. Beyond development. Time for a new ICT4D paradigm?
Proceedings of the 9th IDIA conference, IDIA2015, Nungwi, Zanzibar: 148-162
ISBN: 978-0-620-68395-1

relating to the UI of the SYSPRO ERP system and Xcelsius Crystal Reports tool, the focus was to identify problems relating to the overall development environment and process.

			Open-ended questions	Task-list notes
Problem number	**Problem Theme**	**Description**	**Frequency (f)**	**Frequency (f)**
P1	Complexity of software	• Too many software tools. • Difficult to understand and learn. • Lack of knowledge of software tools.	6	3
P2	Development steps	• Too many steps required for each tool • Steps are difficult to learn and to remember. • Steps are time-consuming	6	2
P3	Flexibility	• Lack of undo functions • Cannot change the data attributes easily • Cannot change visualisations	5	4
P4	Information quality	• Minimum feedback on successes or errors • Navigation and menus are not well structured • No guide for to assist in the development steps	8	7
P5	Assistance/ help	• Required assistance from a human mediator • Insufficient help functions	5	2
P6	Data selection	• Querying and mapping of the data is a difficult task since it requires a series of steps involving various tools.	4	9
P7	Dashboard customisation and visual output	• Mapping data to a visualisation is difficult • Needs immediate display of data in selected visualisation • Exporting dashboards into other software is difficult and tedious	3	9
P8	Lack of pre-knowledge	• Lack of pre-knowledge of software tools. • Also a lack of SQL and VB languages. • Lack of visualisation types and measures	4	2

Table 1, Problems identified for IV tools.

The highest frequency (f) of responses for the open-ended question related to the *information quality* theme. Participants struggled to identify menu items in SYSPRO and Xcelsius, and criticised the minimal feedback that the software provided to guide users in the development steps or any issues that were incurred. Moreover, participants indicated that the tasks were complex and difficult to learn. While others stated that the *system* was not designed with the user in mind, many complained that the development environment was inflexible and resulted in many participants re-doing tasks. The main reason for this was that students were not sure where exactly they made a mistake. Some of the negative comments cited by participants were: “too many steps are involved here”, “the development environment is too complex”, and “menus aren’t easy to find”. The two themes with the highest frequency of responses from the task-list related to *data selection* and *dashboard customisation and visual output.* Since the data attributes needed to be selected using a query in SQL server and then needed to be mapped manually in SYSPRO, many mistakes were made regarding the syntax and spelling of attribute names. Another issue was that only one dashboard was created and did not allow students to explore the data set.

Steyn, J., Van Belle, J.P. (Eds.). 2015. Beyond development. Time for a new ICT4D paradigm?
Proceedings of the 9th IDIA conference, IDIA2015, Nungwi, Zanzibar: 148-162
ISBN: 978-0-620-68395-1

Discussion of Design Guidelines for Visualisation Tools

The results revealed that students experienced the development of dashboard as a challenging activity. While some experienced usability issues relating to the design of the software tools' User Interface (UI), others found it hard to remember all the steps to develop a dashboard using the various software tools. A number of guidelines are therefore proposed to guide the design of IV tools for novices (Table 2). The qualitative negative responses revealed that many of the problems related to the lack of *information quality* and *assistance* provided by the tools. These findings are consistent with a similar study on BI tools in South Africa by Jooste et al. (2014), who proposed that BI tools need to be designed with a high degree of *visibility* and *error control and help* functions. Students struggled to understand instructions, find menu and navigation options, and often asked assistance from human mediators. Sufficient navigation mechanisms (menu items, navigation, system status, hide/show etc.) and interactions are necessary to ensure easy navigation. Features such as tree structures, bread crumb trails, minimise and maximise icons, double click actions, and back buttons are highly important for novices when exploring the interface and moving through different levels of data granularity using drill-down/up features (Elias 2012; Heer et al. 2012).

Guideline number	Description	Related Problem
G1	Easy navigation, onscreen help, hide/show	P4 & P5
G2	Promote learning through explanations	P5 & P8
G3	Guided development process	P2
G4	Flexible customisation process	P3
G5	History tools, storytelling, undo/ redo	P2 & P3
G6	Single, integrated environment with immediate and interactive visual feedback	P1 & P7
G7	Easily connect to a variety of data sources and select/ deselect attributes interactively	P6
G8	Search, filter and drill-down/up	P6 & P7
G9	Multiple coordinated views	P6 & P7
G10	Automatic visualisation creation and suggestion with useful defaults.	P2, 3 & P8

Table 2, Design guidelines for IV tools.

Learning the development steps and features of the software tools was also described as a problem by the students. IV tools need to support and promote learning through explanations (Elias & Bezerianos 2011; Grammel et al. 2010; Jooste et al. 2014). These explanations should be provided with terminology that is familiar to the users and can relate to additional information about the tool's features and operations, or the visualisation types supported by the tool (reason for use, when to use, or advantages/disadvantages of each chart type). Often these explanations are provided by means of tooltips (Heer et al. 2008; Pantazos et al. 2013). Students stated that there was no guide and the process was difficult to follow. This result emphasises the need for an easy, guided development process (Grammel et al. 2010; Heer et al. 2012; Huron et al. 2014). Guided development may be useful by providing a systematic set of common steps that are followed in a workflow type manner, that also allows users to keep track of where they are in the process and can alleviate the mental demand of users (Heer et al. 2012). Users do however need a rich, systematic approach to data analysis that allows them to experiment with different data types, IV techniques, and other features in a flexible manner (Heer et al. 2012). Using a systematic approach to data analyses supports users to keep track of their analyses findings (Heer et al. 2012) and is also motivated as an approach to supporting a user's mental model (Schröter 2015; Patterson et al. 2014). The use of history tools, storytelling and textual annotations are popular techniques that have been identified as affective approaches to keep track of analysis findings (Elias et al. 2013; Heer et al. 2008; Huron et al. 2014). Since users refine their visualisations in a series of iterations, novices may often want to revise their notes on the data analysis activities performed and may wish to collaborate with others to share their analyses findings (Elias et al. 2013; Huron et al. 2014).

The lack of *undo* functions and flexibility was another negative feature that was commonly cited. However, this poses a greater issue when users are working with different tools as they are often not aware in which tool the mistake was made and need re-do an entire step. Sufficient undo and navigation principles are important to revert to a previous state easily and quickly (Elias 2012). Flexibility is especially important for novices as they need to explore different datasets and features of the UI, as well as refine their visualisations (labels, colours, size etc.) through a series of iterations (Huron et al. 2014; Elias & Bezerianos 2011). There is a need to design a single, interactive IV tool that facilitates the entire IV process, from connecting to data sources (querying or importing data), support data manipulations (merging data or adding calculations), selecting alternative data attributes, and viewing those attributes in a variety of visualisation techniques (Pantazos et al. 2013; Elias & Bezerianos 2011). Moreover, the IV tool needs to be able to easily connect to a number of data sources and allow for selecting/ deselecting attributes. Further, users need to merge data from ERP, BI or any data source that is of interest to the user for analysis. The easy connectivity should also be complemented by strong search, filter and drill-down facilities when exploring a data set (Pantazos et al. 2013; Elias 2012; Kienle & Muller 2007; Heer et al. 2008). The search facilities are important for novices since they often know what data attribute they want to view, for example "Sales", but it can be difficult to find that particular data attribute when sieving through hundreds of fields in the data set. Additionally, search facilities may render any text that may be of interest, whether the user is searching for specific data sources, tables, attributes or any descriptive text in the visualisation dashboard (Elias 2012; Grammel et al. 2010). Search features are typically supported by dynamic queries to efficiently and by interactive explore and change the parameters in the visualisations (Elias 2012).

The use of dynamic queries are especially relevant to multiple coordinated views, where more than one chart is displayed on a single screen, each representing the same data set from a different perspective (Few 2012). Coordinated views can also be linked together, allowing a change in the one chart to affect the other. Dynamic queries are also implemented through the use of filters and aggregation that can be applied by using radio buttons, check boxes, dropdown menu's and sliders (Heer et al. 2012). Filtering allows removing unwanted data items from the entire display (Heer et al. 2012). Moreover, sufficient hide/show tabs should be supported when multiple views are used to avoid visualisations from being cluttered.

One of the negative statements made by a participant was that "*it only started making sense when I saw the visualisation".* This result indicates that students struggled to map the data to a visual construct and this is consistent with the findings of Elias (2012) and Grammel et al. (2010). Automatic visualisation creation and useful suggestions are strongly emphasised for this reason as this may prevent the partial or incomplete selection of data attributes (Elias & Bezerianos 2011; Heer et al. 2008; Kienle & Muller 2007). This is an important requirement for novices as they need to see the immediate effect of their actions (Bostock & Heer 2009; Pantazos et al. 2013). Viewing the immediate outcome on the selected data also reduces the need for integrating visualisations in external tools, which also reduces the time to develop visualisations. By providing automatic charts or reasonable defaults, users are only presented with the most appropriate visualisations based their selected data (Heer et al. 2008). Moreover, interaction types need to be considered when selecting data attributes and visualisations, applying filters, or moving from different aggregations and granularity levels. Some tools incorporate the use of auto-completion, hovering, buttons, drag-and-drop, sliders, checkboxes and scrolling techniques to query, select or arrange the data for visualisations (Heer et al. 2012; Pantazos et al. 2013).

Conclusion

The results revealed that the participants could effectively create a dashboard. However, a number of problems were identified. Several problems related to the usability of the UI and the results confirmed other studies reporting that novices struggle to map data to visual constructs. The main findings of this paper revealed that novices need a guided approach to developing visualisations without help from a human mediator and several design guidelines for IV tools are proposed. The most important guideline is to provide guidance for novices through an interactive environment where they can keep track of where they are in the IV process. The guidelines proposed in this paper may be considered as criteria for designing or evaluating IV tools. The insights provided by this paper provide important contributions to Human Computer Interaction (HCI) and BI researchers and can assist with a deeper understanding of similar problems that novices face when working with enterprise systems. The use of quantitative and qualitative data analysis techniques provided insight into understanding how novices think while learning to use tools that aid in data analysis activities. This paper is part of a larger study whereby the design guidelines will form part of a framework for designing and evaluating IV tools. One limitation of this study is the small sample size and the fact that only one case study was used. Future research should include additional IV contexts and platforms and other case studies.

References

Bostock, M., & Heer, J. (2009). Protovis: A Graphical Toolkit for Visualization. IEEE Transactions on Visualization and Computer Graphics, 15(6), 1121–1128.

Calitz, A.P., Cullen, M. D.M., & Greyling, J. H. (2015). South African Alumni Perceptions of the Industry ICT Skills Requirements. In *Proceedings of the SACLA 2015 Conference, Johannesburg, South Africa, June 2-3, 2015*.

Card, S., Mackinlay, J. D., & Shneiderman, B. (1999). Information Visualization: Using Vision to Think. San Francisco: Morgan Kaufmann.

Chen, H., & Storey, V. C. (2012). Business Intelligence and Analytics: From Big Data to Big Impact. *MIS*, 36(4), 1165–1188.

Chi, E. H. (2000). A Taxonomy of Visualization Techniques using the Data State Reference Model. In Information Visualization, 2000. InfoVis 2000. IEEE Symposium, 69–75.

Steyn, J., Van Belle, J.P. (Eds.). 2015. Beyond development. Time for a new ICT4D paradigm?
Proceedings of the 9th IDIA conference, IDIA2015, Nungwi, Zanzibar: 148-162
ISBN: 978-0-620-68395-1

Chiang, R. H. L., Goes, P., & Stohr, E. A. (2012). Business Intelligence and Analytics Education, and Program Development: A Unique Opportunity for the Information Systems Discipline. ACM Trans. Manage. Inf. Syst., 3(3), 12:1–12:13.

DASIK. (2014). Retrieved July 7, 2015, from http://www.dasik.org/dasik-modules/bi

Elias, M. (2012). *Enhancing User Interaction with Business Intelligence Dashboards*. *Doctoral Thesis*. Ecole Centrale Paris.

Elias, M., Aufaure, M., & Bezerianos, A. (2013). Storytelling in Visual Analytics tools for Business Intelligence. In *Proceedings of the 14th IFIP TC13 International Conference on Human-Computer Interaction (Cape Town, South Africa, September 2-6, 2013). INTERACT 2013*. Springer Berlin Heidelberg.

Elias, M., & Bezerianos, A. (2011). Exploration Views : Understanding Dashboard Creation and Customization for Visualization Novices. In *Proceedings of the 13th IFIP TC13 International Conference on Human-Computer Interaction (Lisbon, Portugal, September 5-9, 2011). INTERACT 2011*. Springer Berlin Heidelberg.

Fan, W., & Bifet, A. (2013). Mining Big Data: Current Status, and Forecast to the Future. ACM SIGKDD Explorations Newsletter, 14(2), 1–5. doi:10.1145/2481244.2481246

Few, S. (2012). Criteria for Evaluating Visual EDA Tools. Visual Business Intelligence Newsletter. Perceptual Edge.

Grammel, L., Tory, M., & Storey, M. (2010). How Information Visualization Novices Construct Visualizations. IEEE Transactions on Visualization and Computer Graphics, 16(6), 943–952.

Gupta, B., State, C., & Goul, M. (2015). Business Intelligence and Big Data in Higher Education: Status of a Multi-Year Model Curriculum Development Effort for Business School Undergraduates, MS Graduates, and MBAs. Communications of the Association for Information Systems, 36(1), 449-476.

Hart, S. G. (2006). NASA-TASK LOAD INDEX (NASA-TLX): 20 YEARS LATER. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting,* 904–908. SAGE Publications.

Heer, J., Ham, F., Carpendale, S., Weaver, C. & Isenberg, P. (2008). Creation and Collaboration: Engaging New Audiences for Information Visualization. In Information Visualization, Springer-Verlag, Berlin-Heidelberg, 92–133.

Heer, J., Shneiderman, B., & Park, C. (2012). A taxonomy of tools that support the fluent and flexible use of visualizations. Interactive Dynamics for Visual Analysis, 10(2), 1–26.

Hilbert, M. (2013). Big Data for Development: From Information-to Knowledge Societies. Available at SSRN 2205145, 1–39.

Huron, S., Jansen, Y., & Carpendale, S. 2014. Constructing Visual Representations: Investigating the Use of Tangible Tokens. IEEE Trans. Vis. Comput. Graph. 20(2), (October 2013) 2102-2111.

Huron, S., Carpendale, S., Thudt, A., & Tang A. (2014). Constructive Visualization. In *Proceedings of The 2014 Conference on Designing Interactive Systems, Vancouver, Canada, June, 2014, DIS '14*. ACM. 433–442.

Jooste, C., Van Biljon, J., & Mentz, J. (2014). Usability evaluation for Business Intelligence applications : A user support perspective. South African Computer Journal, (53), 32–44.

Kienle, H. M., & Muller, H. A. 2007. Requirements of Software Visualization Tools: A Literature Survey. In Proceedings of the 4th IEEE International. Workshop on Visualizing Software for Understanding and Analytics (Banff, Alberta, Canada, June June 24-25). VISSOFT 2007. IEEE 2–9.

Letouzé, E. (2012). Big Data for Development: Challenges & Opportunities. Global Pulse Is a United Nations Initiative, (May), 47. Retrieved from http://www.unglobalpulse.org/sites/default/files/BigDataforDevelopment-UNGlobalPulseJune2012.pdf

Liu, S., Cui, W., Wu, Y., & Liu, M. (2014). A Survey on Information Visualization: Recent Advances and Challenges. Vis. Computing. 30, 12 (January). 1373-1393.

Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., Roxburgh, C., & Byers, A. H. (2011). Big Data: The Next Frontier for Innovation, Competition, and Productivity. Retrieved from (http://www.mckinsey.com/insights/mgi/research/ technology_and_innovation/big_data_the_next_frontier_for_in novation.

Muriithi, G. M., & Kotzé, J. E. (2013). A conceptual Framework for Delivering Cost Effective Business Intelligence Solutions as a Service. ACM International Conference Proceeding Series, 96–100.

Nofal, M. I., & Yusof, Z. M. (2013). Integration of Business Intelligence and Enterprise Resource Planning within Organizations. Procedia Technology, 11, 658–665.

Pantazo, K., Kuhail, M.A., Lauesen, S., & Xu, S. 2013. uVis Studio: An Integrated Development Environment for Visualization. In Proceedings of the SPIE8654 Conference for Visualization and Data Analytics 2013 (Burlingham, USA, February 3, 2013). SPIE8654. IEEE Trans. Vis.

Patterson, R. E., Blaha, L. M., Grinstein, G. G., Liggett, K. K., Kaveney, D. E., Sheldon, K. C., & Moore, J. A. (2014). A human cognition framework for information visualization. Computers & Graphics, 42, 42–58.

Pitula, K., & Radhakrishnan, T. (2011). On eliciting requirements from end-users in the ICT4D domain. Requirements Engineering, 16(4), 323–351.

Global Pulse. (2015) Retrieved July 9, 2015, from http://www.unglobalpulse.org/about-new.

Ritsos, P. D., & Roberts, J. C. (2014). Towards more Visual Analytics in Learning Analytics, 9–13.

Sabherwal, R., & Becerra-Fernandez, I. (2013). Business Intelligence: Practices, Technologies and Management. John Wiley & Sons, Inc.

Sallam, R. L., Hostmann, B., Schlegel, K., Tapadinhas, J., Parenteau, J., & Oestreich, T. W. (2015). Magic Quadrant for Business Intelligence and Analytics Platforms.Gartner Group Inc.

Schröter, B. H. (2015). Helping Novices Explore Data: Facilitating Mental Model Creation of an Information Visualization System by Displaying Information Flows. Master's Thesis. Technische Universiteit Eindhoven.

Tobiasz, M., Isenberg, P., & Carpendale, S. (2009). Lark: Coordinating co-located collaboration with information visualization. IEEE Transactions on Visualization and Computer Graphics, 15(6), 1065–1072.

Toker, D., Conati, C., Steichen, B., & Carenini, G. (2013). Individual User Characteristics and Information Visualization: Connecting the Dots through Eye Tracking. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (Paris, France) ACM*, 295–304.

Wang, Y., & Harbert, R. J. (2015). Business Intelligence and Analytics Education : Hermeneutic Literature Review and Future Directions in IS Education. In *Proceedings of the 21st Americas Conference on Information Systems AMCIS (Puerto Rico, August 13),* 1–10.

Wixom, B., & Goul, M. (2014). The Current State of Business Intelligence in Academia : The Arrival of Big Data The Current State of Business Intelligence in Academia: The Arrival of Big Data. Communications of the Association for Information Systems, 34(1), 1–10.

Yigitbasioglu, O. M., & Velcu, O. (2012). A Review of Dashboards in Performance Management: Implications for Design and Research. International Journal of Accounting Information Systems, 13(1), 41–59.