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ScienceDirect
Procedia Manufacturing 3 (2015) 5527 – 5534
Procedia MANUFACTURING

6th International Conference on Applied Human Factors and Ergonomics (AHFE 2015) and the Affiliated Conferences, AHFE 2015

Web-based evaluation of information visualization

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Abstract

Information visualization is strongly related to human perception, human behavior, and in particular human interaction. It is a discipline that focuses on human to enable him gathering insights, knowledge, and solving various and heterogeneous tasks. The human-centered characteristic of information visualization requires valid and proper user studies that improve the system or validate their benefits. New methods, techniques, or approaches of information visualization are commonly evaluated. However, the evaluation is either time and cost consuming or they are made minimum resources that leads to results, which may not be valid. In particular the number of participants is commonly restricted and does not enable a valid assumption about the results. Thus performance measures plays a key role in information visualization, existing web-survey tools are not convenient. We introduce in this paper a new method that enables web-based evaluations of information visualization systems. Our main contribution is the enhancement of web-based survey tools with performance measures. Our approach enables the measurement of task-completion time, correctness of solved tasks, and includes a number of pre- and post-questionnaires.

Peer-review under responsibility of AHFE Conference

Keywords: Information Visualization; Web-based Evaluation; User Study; Human Perception; Evaluation Methods; Evaluation Tools

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Peer-review under responsibility of AHFE Conference
doi:10.1016/j.promfg.2015.07.718

1. Introduction

The increasing amount of digital data forces different disciplines to develop new approaches for information search, information exploration, knowledge acquisition, and in particular for heterogeneous analysis tasks. One of the most promising approaches that investigate the entire pipeline of search, exploration, and analysis is information visualization. Researchers from the area of information visualization designed and developed huge numbers of visual layouts and visual interaction methods. Although, the number of visual solutions for information search and acquisition increases, the problem of evaluating such new systems or methods still exists. Experts from the area of information visualization either (1) do not evaluate their approaches or (2) evaluate the systems without performing an a priori power analysis or (3) the process of evaluating the approaches is enormous time and cost consuming. This is due to the fact that visualizations are commonly designed for special group of users, e.g. analysts. Getting an adequate number of participants with the required skills and knowledge is not an easy task, in particular for research institutions or universities. Beside the mentioned problems or shortcomings in evaluating visualization tools, the complexity of evaluation increases dramatically with adaptive visualization that use machine learning and artificial intelligence methods to adapt the visual representation and interaction modalities on certain influencing factors, such as human, context, data, or environmental factors. Thereby the human-centered adaptation plays the most important role but is more difficult to evaluate due to the learning and the related changing character of the system. We introduce in this paper an approach for evaluating information visualization systems by considering the most relevant aspects of visualizations based on the reference model of Card et al. [1]. Thereby, we first identify the most relevant aspects based on the tasks and the purpose of the visualization tool. Thereafter, we introduce our approach that investigates in particular the posterior evaluation in experimental settings. Our main contribution is to provide a conceptual model for web-based evaluations that go one step beyond the state-of-the-art, namely to measure task-completion time, correctness, and used visual layouts in distributed web-based environments. Our approach enables to performed precise distance-evaluations with the character of controlled experiments. We will further illustrate the feasibility of our conceptual model with a prototype that has been already used in context of visualization for policy modelling.

2. Background and Related Work

In information visualization, the aspect of human perception and visual information processing plays an increasing role. How can data be transformed to interactive graphical representations that amplify cognition, support the information acquisition process, and consequently the acquisition of knowledge? [1] Visual Analytics investigates further the manipulation of data-analysis and transformation to provide unexpected patterns and thereby new insights [2]. In both research fields the way from data-oriented visualization to a more human-centered information presentation plays a key role. Moreover, the human as an implication and decision factor for information visualization was placed in the foreground of research [3]. The increased involvement of user's intentions and preferences in the process of information visualization got more important [2]. The visualization should enable the human to interpret faster, distinct graphical entities, or make fewer errors [1, p. 23]. In today's evaluation methods the two main factors for measuring the efficiency of visualizations are task completion time (faster interpretation) and task completion correctness (fewer errors).

The research field of Visual Analytics evolved from information visualization and other areas emphasizes knowledge generation as a process of reasoning facilitated by interactive visual interfaces [4]. Visual Analytics combines data analysis with interactive visualizations for an understanding and decision making on the basis of large and complex data [5]. Beside information visualization and Visual Analytics a new research area evolved and gained more and more attention: Adaptive visualizations that are synthesizing the areas of adaptive systems and information visualization. Adaptive visualizations are interactive systems that adapt autonomously the visual variables, visual structure, visualization method, or the composition of them by involving some form of learning, inference, or decision making based on one or many influencing factors like users' behavior or data characteristics to amplify cognition and enable a more efficient information acquisition [6, p. 110].

This section will introduce some main assumptions that are canonical for evaluating visualization systems. As visualization systems the areas of information visualization, Visual Analytics, and adaptive visualizations are meant, whereas the aspect of visualizing abstract data is the focus of the paper.

2.1. Background on Evaluating Visualizations

The interactive visualization of information enables human access to increasing amount of data for solving a variety of informational tasks. As we worked out in this thesis, information visualization and in particular adaptive visualization is a prospering area of Human Computer Interaction and helps users retrieving and acquiring information and knowledge [5, 1, 7]. Beside aspects like design and implementation or benchmarking techniques [8], the evaluation of information and adaptive visualizations plays an increasing role in today's research [9, 7, 10], due to the fact that information visualization builds the human interface to data, information, and knowledge. Komlodi and colleagues summarized the techniques on evaluating information visualization in the four main areas of *usability evaluation, controlled experiments comparing design elements, controlled experiments comparing two or more visualizations or tools,* and *case studies* [11, p. 2], [12]. Case studies, in which the users' task solving process is reported in their natural environment [11], are rarely used to evaluate visualizations. Thus, they are time-consuming and the results are not replicable [11]. Therefore, we will not investigate this type of evaluation in our paper.

Usability testing or evaluation can be distinguished in two approaches depending on the prototypes' development progress: *formative testing* and *summative* testing [13]. *Formative testing* is used in early stages of the development to discover usability problems. Additionally, heuristics have been used in the past to evaluate information visualizations [14]. Heuristics comprise a set of usability guidelines, due to which deficits concerning usability can be detected. These problems can be a starting point for further formative usability evaluations. In contrast to that *summative testing* aims at evaluating the application and reveal evidence for its goodness. The dominant method in summative testing are controlled experiments. This way confounding variables can be controlled by the experimental setting. However, well developed and reliable software is required, otherwise the evaluation may be unsuited to provide proper results. The conventional usability measures are *effectiveness, efficiency*, and *satisfaction*. According to the ISO standard [15] *effectiveness* describes the accuracy of goal achievement, *efficiency* measures the relation of effort and effectiveness with respect to goal achievement, and *satisfaction* comprises perceived comfort as well as absence of discomfort. Aside from quantitative measures qualitative user data has been assessed in the past to discover patterns in users' behavior [16].

As already mentioned, formative testing aims to improve the usability of visualizations during the development process, while summative testing compares different metrics of visualizations in controlled experiments [13, 11]. Komlodi et al. and Plaisant differentiate in the context of visualizations controlled experiments in comparing *design elements* and comparing *tools*. The comparison of design elements might include widgets or the mappings of data to certain visual layouts [11]. The comparison of tools is according to Plaisant the common type of study [11, pp. 2]. It includes typically different visualizations and enables a summative evaluation on different visualizations. This way of testing goes beyond usability aspects and may involve metrics like perceptual speed, visual working memory, or verbal working memory [10]. Perceptual speed in context of visualization is the speed of encoding visual information. Commonly, this is subdivided into *preattentive* information processing and *attentive* information processing [17, 18]. One important metric for the evaluation of visualizations can be the speed in which certain information is perceived by users. Based on the fundamental works of Treisman [17], Wolfe [18], Jun and colleagues introduced a visual information processing model for interactive visualizations [19]. The model divides the processing of visual information into three stages: *feature extraction, pattern perception* and *goal directed processing*. Feature extraction is a low level process to extract main features from sensory information and is more related to the preattentive stage of visual information processing. If the information of interest is found (pattern perception), the following action is related to goal directed processing [19]. Another relevant concept for the perceptual speed is the attentional weight, a value assigned to each visual entity [20]. The *attentional weight* is associated with the strength of the sensory evidence and the context [20]. The similarity-choice theory suggests that the bigger the attentional weight of an object, the higher is the probability of choosing that object. Therefore homogeneous objects, as in a textual representation, have equal attentional weights. When using adaptive

mechanism to visualize relevant objects differently, the probability of choosing them increases even more [21]. Within an application that uses visualization, the processing of visual information is faster and associated with less effort. Furthermore, visualizations can make use of visual variables [22] like color, shape, size etc. to guide users' attention. Therefore, goal directed processing would takes less time. With respect to visual information processing.

Another important construct is the visual working memory (VWM). As suggested by the biased competition hypothesis, VWM guides the allocation of attention [23]. It has been shown, that VWM is capable of storing an item during a task without influencing the task itself [23]. Other results show, while information that is present in the working memory, is also possible to interfere with attention and lead to a lower performance on the task [24]. Lavie and Fockert also evidenced that the working memory interferes with the guidance of visual selective attention [25]. They discovered in their fMRI-study, that single distractors influence the performance in visual search tasks. Somervell et al. discovered that visualizations with high density require more attentional capacity than those with low density. The performance in a simple game was higher, when the visual search tasks were performed with respect to a visualization with low density [26]. Prior research has shown that features like position and presence are encoded differently from color. The visual memory stores those features automatically, whereas features like surface attributes are associated with a higher amount of required attention [27]. An adaptive visualization provides more guiding features than a static visualization, thus a visual search task is done with lower cognitive load [10, 7]. The cognitive load can be assessed through various methods. One way to measure the cognitive load is to perform multiple tasks parallel. Another more direct way to assess the cognitive load is through EEG [28].

Verbal working memory refers to a measure of storage and manipulation capacity of verbal information [10]. In context of information visualization this subset of the working memory plays a secondary role [29, 10] and is often not considered in the evaluation process. With respect to the measurement of systems' intuitiveness, the verbalization ability and the verbal working memory play a role [30].

In summary, it can be said that there are established methods for evaluating information visualizations and proper metrics for evaluating their effectiveness, efficiency, and acceptance. The most common way to evaluate information visualizations with an advanced developing progress are summative evaluations, in particular by comparing the visualization tools in controlled experiments. Perceptual speed and visual working memory can be evaluated through the completion time of tasks compared to a baseline [29, 10] and refer to effectiveness and efficiency of the visualizations. Furthermore, the aspects of satisfaction or acceptance can be gathered and evaluated through appropriate questionnaires that may involve the verbal working memory [30].

In contrast to that the evaluation of adaptive visualizations are more complicated, due to the fact that the system learns from the user. To conduct an evaluation of adaptive visualization the participants have to work in long-term studies with the visualization system to train the underlying knowledge model.

The effect of this process is obvious: while the adaptive visualization systems learn from the participant, the participant learns by interacting with the system. It is therefore difficult to measure which way of "learning" had higher effects. As mentioned, the studies have to be designed as long-term studies to train the system. Ahn conducted a study, in which the participants had about 50 minutes time to train the system with their individual profile [7]. After the training three search session were started followed by questionnaires [7]. One main question arising from this procedure is how much did the participants learn during the training phase and how much did the system learn? A counterbalancing can be achieved by providing the same training session for an adaptive system and a non-adaptive system, but in this case "only" the adaptivity of the entire system can be measured without the effects that may occur by different levels of adaptation. Olson and Chun claimed that another problem with adaptive interfaces is that the spatial arrangement of items changes over time due to the adaptation effect [31]. This leads to losing the context in particular in repeated visual search tasks [31].

The effect of adaptive visualizations was evidenced by some user studies that measured the perceptual speed, visual working memory and verbal working memory [29, 32, 10]. Toker et al. evaluated for example the perceptual speed, visual working memory, and verbal working memory with two different but equivalent visualizations regarding their information content, a bar and a radar graph [32]. They performed their study in three main steps: a cognitive test containing questionnaires about the participants' working memory (visual and verbal) and perceptual speed, followed by search tasks, and concluded with post-questionnaire [32].

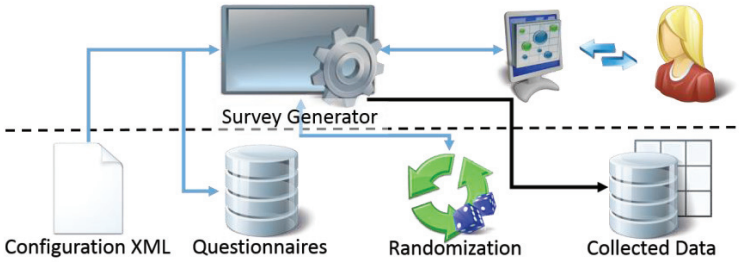

Fig. 1 Abstract architecture of the evaluation system: A configuration XML enables the design of the study and provides the information to a survey generator that make use of a pool of questionnaires and design the randomization if a within-subject design is chosen. Based on the configuration, the visualizations are loaded into the screen with the question bar. All collected data are saved into a database.

The tasks were subdivided into "common search task" and "complex search task" (double scenario tasks). A complex search task had more the characteristic of exploratory tasks based on the model of Marchionini [33, 34]. An example for their complex task was *"Find the courses in which Andrea is below the class average and Diana is above it?"* [32, p. 277]. Their study measured three main aspects, *task completion time*, *visualization preference*, and *ease-of-use*. The task-completion-time was recorded by their software, the visualization preference was asked with a five-item question (from like to dislike), and the ease-of-use with five-item questions about the "understanding" of each visualization (from easy to understand to difficult to understand). The results of their study showed that bar graphs lead to faster task-completion- time for simple tasks. In more complex tasks no significant difference between the visualizations could be observed. Further, the results showed a high effect of perception speed on task-completion-time when dealing with simple tasks. They discovered an interaction between the task and the visualization regarding the relation between perception speed and task-completion-time [32]. Although bar graphs lead to quicker task completion in accordance with other studies [35], the task-completion-time was more affected by perception speed when participants used radar graphs [32]. Expertise had no influence on the performance in the simple task condition. Further, a positive effect of perception speed on task-completion-time was also revealed in the context of complex tasks [32]. However, there was no interaction. In contrast to simple tasks, expertise had an influence on task-completion-time. This effect was also present, when the expertise was related to the other visualization [32].

Based on the introduced studies and theoretical foundations, it is obvious that the evaluation of adaptive visualizations should be performed as controlled experiments with different conditions, on design or tool level. The main question remains how to train the user model without providing a learning effect for the participants? Further, it is more than relevant to evaluate the different aspects of adaptation and their effect to task completion and acceptance. Thus, commonly the evaluation of adaptive metrics is performed only on the visual layout level [29, 10, 32]. Another main aspect is the measurement of the task completion with different level of task complexity according to the exploratory search definitions [33, 34]. Further it should be expected from adaptive visualizations compared to static ones that the cognitive load is reduced, due to the adaptive characteristics.

2.2. Related Work

The main aspects on how visualizations should or can be evaluated were addressed in the previous section. We focused there more on the general way of how visualizations can be evaluated without considering the aspect of web-based evaluation. This part of the paper will introduce the most common and well known web-based evaluation and survey tools as distance evaluation methodology based on the work of Leland [37].

SurveyMonkey (www.surveymonkey.com) offers in its commercial version unlimited questions and answers that are commonly defined and verbalized by the evaluation examiner. The main advantage of this tool is the integration with IBMs SPSS statistical software and the text analysis methods. However, the interaction, the consumed time for solving tasks etc. are not supported, just like Zoomerang (www.zoomerang.com). SurveyGizmo

(www.zoomerang.com) offers a full customizable survey tool for web-based questionnaires. Questions can be used from a pool of questions or defined by the examiner. However, this tool does not support the measurement of task-completion-time or task correctness based on real usage of web-based software. More advanced tools like Qualtrics (www.qualtrics.com), Key Survey (www.keysurvey.com), QuestionPro (www.questionpro.com), LimeSurvey (www.limesurvey.com), or AttraktDiff [36] offer various functions for detailed analysis based on questionnaires. The main shortcomings of the web-based evaluation tools is commonly the lack of integrating a software or a visualization and measure interaction costs, time, and gather the correctness of the provided answers. In general there exist to our knowledge no system that combines the surpluses of web-based surveys with performance measures to evaluate information visualization tools. It is obvious that web and web-based technologies enable to evaluate a huge number of participants and provide sufficient power for analyzing visualizations. However, the main measures of performance are not supported.

3. The Evaluation System

To face the shortcomings of the existing online survey tools and measure beside acceptance and satisfaction, the performance of information visualization in terms of efficiency and effectiveness, we introduce in this section a web-based evaluation tool that enables the measurement of performance.

3.1. General Architecture

Our approach consist of the following main components (see Figure 1). The Configuration XML contains all information about the study. Thus commonly information visualization tools are compared with other visualizations or another baseline, information about the group design can be entered here. Based on the amount of conditions an appropriate randomization is chosen and defined. We also integrated a pool of questionnaires in a database. This pool enables to choose a number of questionnaires either for each condition or for the entire evaluation scenario. Beside the questionnaires, tasks can be defined for each condition. These are the tasks that should be solved by the participants with the underlying information visualization tool. The task consists commonly of a question that should be answered by the participants with multiple-choice responses (see Figure 2b). The configuration file includes thereby the corresponding correct answers of each tasks. At the moment, when a task is shown on the screen and the visualization is loaded completely a timer starts to measure the time for task competition. The task correctness is derived from the given answers and click cost are measured as an enhancement for performance. Before and after each condition, questionnaires can be included to gather measures about perceived effort, satisfaction, and further subjective feelings about the usage with a visualization systems.

3.2. Procedure

As described in the previous part, the entire procedure of the evaluation can be described in the configuration file. It possible to choose the amount of conditions, the randomization procedure (e.g. Latin Square or cross-evaluation), the visualizations that should be evaluated, the tasks to be solved, including the correct answers, the time for each task, collected data, e.g. interactions of users, and a variety of questionnaires.

Commonly a study starts with a unique participant's number that is used for the randomization and for a session. In case of closing the browser or being absent (no mouse move within 10 min) the system stops the evaluation and asks for refreshing the browser. In that case the participant's number indicates which tasks are already solved so that the participant can continue with the evaluation. Thereafter commonly socio-demographic questionnaires are used to determine if there are significant differences in age, computer literacy, and gender among the different experimental orders to re-randomize automatically the participants.

Further information about visual impairments and experience with information visualizations are gathered. Thereafter the participants get an instruction on the screen (see Figure 2a) on how to use the visual interface and starts with the evaluation. In our procedure we conduct our evaluations with commonly ten tasks per condition and

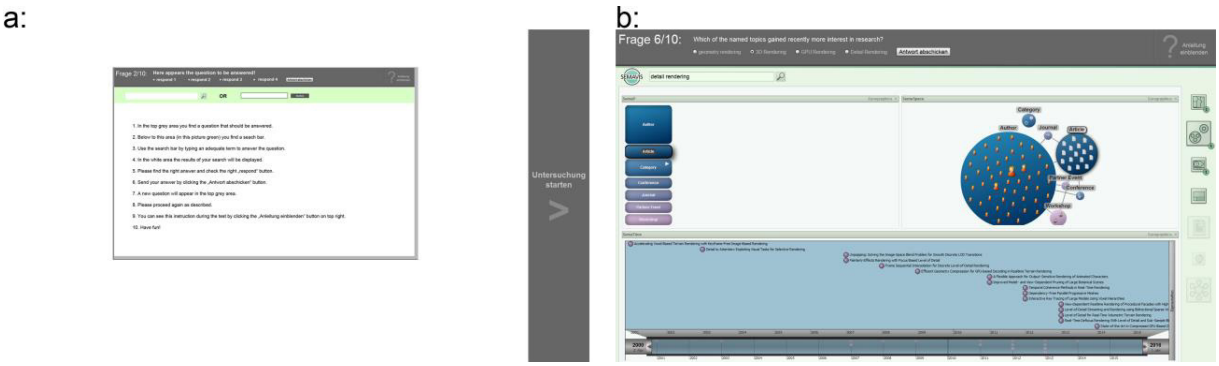

Fig. 2. Screenshots of the evaluation system: a: illustrates the instructions on how to use the different visual interfaces in a study and b: illustrates a visual interface with a task on top of the screen (grey area) and four possible responses. The button on this area sends the answer and illustrates the next task.

two questionnaires for gathering subjective measures: the INTUI questionnaire for measuring the intuitiveness [30] and the AttrakDiff questionnaire [36] for measuring satisfaction, user experience, and in particular hedonic values. The system offers the possibility to enhance the questionnaires for measuring different further aspects. The questionnaires are appears after each condition. It is further possible to conclude the evaluation with a questionnaire that gathers the overall opinion about the different visual interfaces. We experienced that commonly the first visualized tools get less scores on the used questionnaires. But if a short questionnaire is added at the end of the evaluation, after they have seen all the visual interfaces, the participants will give differing scores. We therefore recommend to sum up the evaluation with a questionnaire that scores all visualizations at the end of a session.

4. Conclusion

We discussed in this paper which aspects are important for evaluating information visualization and which problems may occur, e.g. with adaptive visualizations. It is important to measure beside acceptance or any other subjective values, the real task completion time. The efficiency measure can be enhanced with click-cost measurement. Another important factor is the effectiveness of information visualization. This can be measured best with real tasks and real data by obtaining the correctness of the solved tasks. Further omitted tasks should be observed, thus complex task may be omitted by users. Subjective values can already be measured through the different existing web-survey tool. But our reviewing on existing web-based survey tools revealed that performance measures in terms of efficiency and effectiveness are not provided.

We therefore introduced an approach on web-based (distance) evaluation of information visualizations that enable to measure efficiency by task-completion-time and click cost, and effectiveness by task correctness and number of omitted tasks. Our approach enables further valid randomization methods for any number of conditions and interventions.

Acknowledgements

This work has been carried in the FUPOL project, partially funded by the European Union under the grant agreement no. 287119 of the 7th Framework Programme.

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