Position Paper: Towards a 3-Dimensional Model of Individual Cognitive Differences

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ABSTRACT

The effects of individual differences on user interaction is a topic that has been explored for the last 25 years in HCI. Recently, the importance of this subject has been carried into the field of information visualization and consequently, there has been a wide range of research conducted in this area. However, there has been no consensus on which evaluation methods best answer the unique needs of information visualization. In this position paper we propose that individual differences are evaluated in three dominant dimensions: cognitive traits, cognitive states and experience/bias. We believe that this is a first step in systematically evaluating the effects of users' individual differences on information visualization and visual analytics.

1. INTRODUCTION

In recent years, strides have been made toward understanding the impact of individual differences on performance when interacting with visual analytic systems. Research has shown that factors such as personality [18, 53], spatial ability [9], biases [29, 54, 55] and emotional state [3, 17, 23, 34, 41, 45] impact a user's performance. Though progress is undeniable, a common limitation is that every cognitive factor that affects visualization performance is not considered or properly controlled. For instance, studies that focus on personality factors alone do not consider how differences in working memory, perceptual ability, and previous experience can also affect visualization performance. Indeed, as stated by Yi in his position statement in 2010, the visualization community has yet to employ a comprehensive and standardized model for measuring individual differences such that researchers can better understand how factors in individual differences interact with each other and with existing evaluation techniques [52].

We acknowledge that one position paper cannot solve all of the problems described above. However we propose a first-step towards a solution by exploring existing literature and identifying which cognitive factors are independent of one another. We believe that individual differences can be categorized into three orthogonal dimensions: cognitive traits, cognitive states, and experience/bias.

Cognitive traits are user characteristics that remain constant during interaction with a visual analytic system. Factors such as personality, spatial visualization ability, and perceptual speed are all examples of cognitive traits. These have been shown to correlate with a user's ability to interact with a visualization [10, 12, 18, 49, 53] and can be generalized to predict the behavioral patterns of users with different cognitive profiles.

Cognitive states, on the other hand, are the aspects of the user that may change during interaction and include situational and emotional states, among others. Research has shown that a user's performance can be significantly altered by changes in their emotional state [3, 17, 23, 34, 41, 45], and the importance of combining workload with performance metrics has been noted for decades [20, 33, 51]. Although cognitive states are difficult to measure because of their volatility, they provide important contextual information about the factors affecting user performance that can not be described through cognitive traits alone.

Cognitive states and traits can describe a significant portion of a user's cognitive process but they are not comprehensive; *experience and biases* can also affect cognition. Intuitively, we think of experience and bias separately, but they both describe learned experiences that can affect behaviour when familiar problems arise, and are therefore not orthogonal. Although there has been little work about the impact of experience/bias on interaction with visual analytics systems, previous studies have shown that learned behavior such as confirmation bias can significantly affect performance and decision-making [19].

Taken together, we believe that these three dimensions can encapsulate the cognitive aspects of individual differences. Similar to how analyzing state and trait alone would disregard potential performance gains from expertise, ignoring any one dimension of the model would also result in an incomplete description of performance. For example, analyzing only expertise and traits ignores changes that may be triggered by workload or emotions (cognitive state).

By being aware of which cognitive aspects impact individual differences, evaluators can identify what factors must be controlled in an experiment and which should be included as independent variables. The community can also begin

BELIV 2012 Seattle, WA USA

to evaluate visualizations using a common platform and be able to better reproduce and extend each other's research.

2. BACKGROUND

Evaluation has been an active area of research in visualization in recent years. Several researchers have worked toward developing standard evaluation methodologies and secondary measures to evaluate perception and comprehension [24, 30, 43, 44]. In this section, we focus on those that directly report or suggest the use of brain imaging or individual differences for evaluating visualizations.

Anderson et al. [1] demonstrated the use of EEG to measure the user's cognitive load when viewing different boxplot designs. In a position statement presented at BELIV 2010, Riche [39] proposed the use of multiple physiological measurements (heart rate, eye gaze, brain imaging, etc.) for evaluating visualizations. At the same BELIV workshop, Yi [52] proposed studying individual differences when evaluating visualizations. Yi argued that understanding how users differ in personality and cognitive factors is important in evaluating visualizations. In a follow-up research project, he demonstrated that there is a significant difference between novice and expert users when using a visualization to solve analytical tasks and pinpoints the importance of additional research in individual differences in visualization evaluation [25].

The emergence of this body of research ultimately highlights the need for better evaluation methods that address the unique needs of visualizations, but there is no consensus on which methods address these needs. What is clear, however, is that the field of visualization is yet have a systematic and objective way of measuring individual differences in user analysis of visualizations. This position paper seeks to address this by organizing the existing research into a cohesive structure.

3. DIMENSIONS OF INDIVIDUAL DIFFERENCES

In this section, we discuss three dimensions that influence individual cognitive differences: cognitive traits, cognitive states, and experience/bias. While there may be more dimensions, we believe that these three serve as a minimum set that needs to be considered. We illustrate how the components of these dimensions affect performance, and tie these to related experiments in visualization.

3.1 Cognitive Trait

Cognitive traits such as spatial ability, verbal ability and working memory capacity vary considerably among individuals and have been demonstrated to significantly affect perception, learning and reasoning. Consequently, it has been shown that cognitive factors can affect a user's performance when using a visualization. We propose using these factors to measure the stable traits that make up a user's basic cognitive profile.

Several studies have demonstrated the effect of basic cognitive abilities on user performance in visualization tasks. For example, Conati and McLaren [12] found that perceptual speed, the speed at which users compare two figures, correlates with accuracy on an information retrieval task. Another commonly studied cognitive factor that has been shown to impact interaction in a visualization is spatial ability, and refers to the ability to reproduce and manipulate spatial configurations in working memory. Chen and Czerwinski [10] found correlations between spatial ability and the visual search strategies users employed in a network visualization. Participants with high spatial ability performed better in search tasks and navigated an interactive node-link visualization of a citation network more efficiently. Velez et al. [49] tested the correlation of speed and accuracy with a number of factors related to spatial ability, including spatial orientation, spatial visualization, visual memory and perceptual speed. These factors affected users' speed and accuracy in the comprehension of three-dimensional visualizations, similar to those found in scientific visualization applications. Similarly, Cohen and Hegarty [11] found that a user's spatial ability affects the degree to which interacting with an animated visualization helps when performing a mental rotation task.

An interesting aspect of these findings is that an individual's spatial ability not only affected performance, but also how they approached tasks. If people with varying cognitive abilities employ different strategies, an evaluation methodology will need to take these strategies into account to fully understand user behavior.

Perceptual and spatial abilities are not the only cognitive factors that have been shown to have an effect. Yi [52] proposed that one must investigate beyond a users' basic spatial ability to better understand the variability in visualization evaluation. Many personality factors relevant to visualization use are both reliably measurable and consistent over a user's lifetime, making them potential candidates for understanding a user's stable traits. For example, the Five Factor Model, a common model in personality psychology, categorizes personality traits on five dimensions: extraversion, neuroticism, openness to experience, conscientiousness and agreeableness. Green and Fisher [18] studied how varying scores on the Five Factor Model as well as locus of control impacts the way users interact with visualizations. Locus of control [40] is the degree to which a person feels in control of (internal locus of control) or controlled by (external locus of control) external events. The authors found individuals with an external locus of control performed better at complex inferential tasks when they used a visual analytics system than when they used a web-based interface with a list-like view. The study also revealed a correlation between neuroticism and task performance. Ziemkiewicz et al. [53] found that users with a more internal locus of control showed greater difficulty adapting to visual layouts with a strong metaphor of containment (i.e. a layout with many containers) versus a more traditional list-like menu.

The results of these studies suggest that cognitive traits may account for some of the observed individual variability in visualization use. Understanding this variability will help to improve the generalizability of evaluation findings. Therefore, it seems prudent to include this in a model of individual differences in user research.

3.2 Cognitive State

Cognitive state refers to the current condition of a person's mental processes. Unlike cognitive traits, cognitive state can change from moment to moment during interaction with a visualization, impacting performance, understanding, or retention.

Cognitive load is the most studied cognitive state in visualization evaluation, as it often has a direct impact on performance. In particular, working memory has been labelled as an information bottleneck in visualization because it is limited by both size and duration [26, 28, 35]. When multiple visual elements compete for space, there is a loss of information and often a decrease in performance. Speed and accuracy regularly suggest mismatches between visual design and perceptual affordances [7], and dual-task studies can be designed to evaluate mental demand through performance [27, 32].

Cognitive load theory breaks down this generic concept of workload into three more narrowly-defined categories [8]. Germane load describes the memory needed to the process and understand new schemas, intrinsic load refers to the amount of memory necessary for a given task (and cannot be modified by instructional design), and extraneous load is determined by the memory needed to absorb information and can be modified based on presentation. This last category is what researchers typically refer to when comparing the workload demands between visualizations.

Unfortunately, an increased load on working memory is not always reflected in behavioral metrics [51], and it is possible for one person to exert significantly more mental effort than another to achieve the same level of performance in a visualization [50]. Accordingly, researchers have suggested the integration of performance and mental demand during evaluation [20, 33, 51]. Paas and Merrienboer constructed a two-dimensional model of performance and mental effort to define cognitive efficiency [33], and Huang et al. tailored the model to visualization evaluation by adding a third dimension - response time [20]. However, this extra exertion is not necessarily an indication of poor design. Hullman et al. proposed that "visual difficulties" may introduce beneficial obstructions that aid information processing and engagement [21].

Moving away from cognitive load, emotional states triggered by visual imagery or from other external sources can also impact interaction with a visualization. Bateman et al. suggested that emotional responses to "chart-junk" may have favorably impacted the recall of information [4]. Previous work has shown positive emotional states to enhance attention regulation, working-memory performance, open-ended reasoning, creativity, and "big picture" understanding [3, 17, 23, 34, 41]. Conversely, negative emotional states, such as anxiety, can disrupt visuospatial working memory [45]. Finally, emotions have a strong link to decision-making and cost-benefit analysis [5]. Observing these subtle (or not so subtle) nudges to performance is necessary to fully describe the interaction between a person and a visualization.

These studies represent a small subset of work from the psychology literature that has addressed cognitive state and performance. For example, cognitive load is an umbrella term that needs to be narrowed in order to be predictive of performance (for example, visuospatial working memory v. verbal working memory). Additionally, the effect of emotional state on visualization performance has been largely unexplored. Considering these factors will help construct more accurate models of performance in visual analytic systems.

3.3 Experience and Bias

Whereas cognitive state refers to current mental processes, and cognitive trait to stable aspects such as personality, neither of these capture how experience and bias can affect visualization performance. Here we cover a sample of the extensive work on the effects of experience and bias on cognitive performance from the fields of psychology and decision science. We then relate them to recent work in visualization that has begun to explore the role of experience and bias in visualization.

Both experience and biases form through previous interactions with a given problem, and are often utilized when a similar problem is encountered later on [13, 48]. Although experience and bias could be discussed at length separately, here we discuss them together, since they are not orthogonal to each other [14]. For instance, while extensive experience assists with avoiding biases common to novices, experience has also been shown to introduce biases that novices do not encounter, such as the failure to appropriately weight information that contradicts previous findings [22].

Experience is associated with the formation of effective reasoning strategies for given problem types [16, 42], many of which are applicable to reasoning with visualizations. For instance, Cox et al. [13] explored the relationship between experience and performance on a hypothetico-deductive task, and found that participants who had experience with similar problems were able to utilize previously formed reasoning strategies on the new task. Such tasks parallel the hypothesis testing techniques described in Pirolli and Card's sense-making model [36], which has been utilized widely in the design of visual analytics systems.

While the effect of experience on cognitive processes has been studied extensively, there is relatively little work in the visualization community which has explicitly examined and discussed how differences in experience affects performance in interactive visualizations [25]. Perhaps the first to address experience directly is Kwon et al. [25], who identify common roadblocks novice analysts face when using a complex visual analysis system. Other visualization work has explored experience's effects on visualization somewhat indirectly. For instance, Dou et al. [15] explore the how well novice users were able to infer the reasoning processes of expert analysts based on a visualization of the experts' interaction logs. Arias-Hernandez et al. describe pair analytics [2], an analysis process which pairs one analyst with visualization experience with another who has experience in the data domain.

Bias refers to a predisposition to behave a certain way for a given task [38, 48]. Similar to experience, there is little work in the visualization community that discusses the relationship between visual analysis and different types of cognitive biases. Notably, Zuk and Carpendale [55] discuss bias and uncertainty in depth, focusing on the many ways in which bias can affect reasoning with uncertain data and how visualization may aid users in debiasing. Another example of debiasing comes from Miller et al. [29], who describe an experiment in which a system consisting of a statistical model and corresponding visualization was used to assist users in avoiding regression bias. Their results showed that the visualization approach outperformed both no-visualization and algorithmic approaches, supporting the notion that visualization and interaction help users manage biases effectively. Ziemkiewicz and Kosara [54] found that visualizations can be subject to perceptual biases, which can adversely influence how users recall spatial relationships between visual elements. Many other types of cognitive biases exist which significantly impact reasoning and task performance [14, 19], yet the relationships between these and visualization is largely unexplored.

The experiments described here underscore the argument that experience and bias can significantly influence visualization performance. However, since cognitive states and traits also affect performance, it is imperative that we explore the relationship between these three dimensions.

4. TOWARDS A MODEL OF INDIVIDUAL COGNITIVE DIFFERECES

In light of the three dimensions that we have discussed, we believe that a multi-dimensional structured model would be useful in order to describe individual cognitive differences when users interact with visualizations. Each orthogonal dimension would represent an individual difference of a user, thereby allowing researchers to describe or perhaps even predict a user's ability to interact with a visualization by knowing where that individual lies along each axis. Thus, constructing a model of individual differences would allow for the evaluation of not just isolated cognitive factors, but for the *interaction* of a user's different cognitive abilities.

Unfortunately, the interaction of cognitive facets is nuanced. We often have little knowledge of how combinations of state, trait, and experience/bias influence interaction with a visualization. For example, some studies have shown that extraverts and introverts perform differently when they receive positive or negative feedback about a task, thus modifying their cognitive state [6].

Introverts tend to perform well when given positive feedback and worse when given negative feedback. Reciprocally, extraverts perform worse than intraverts given positive feedback, but their performance improves under negative feedback. This exemplifies why it is important to consider the interaction of state and trait. However, other studies have suggested that people with an external locus of control (LOC), which is correlated with extraversion [31], perform better in visualizations where they have had no previous experience than people with an internal LOC [53]. This demonstrates how trait and experience can interact to influence performance.

Each of these examples provide a two dimensional snapshot of how cognitive dimensions can impact performance. But how do we combine the knowledge of these studies? How would performance be impacted when an experienced intravert is given negative feedback, or an inexperienced extravert is given positive reinforcement during a task? Limiting the scope of evaluation to any two of the three dimensions we previously identified leaves an incomplete and potentially misleading model of performance:

- Analyzing state and trait without experience ignores performance gains by expertise
- Analyzing state and experience without trait ignores interaction differences that are driven by personality or inherent cognitive strengths (e.g. spatial ability)
- Evaluating experience and trait without state disregards the moment-to-moment cognitive changes in the user that could be driven by emotion or workload

In the future, any models will need to have the specificity to describe the impact of cognitive factors on a particular task and visualization. However, we imagine that the interaction of certain cognitive factors will be generalizable across visual forms (and tasks). In the next section, we explore the potential implications of constructing models that describe individual cognitive differences.

5. IMPLICATIONS FOR ADAPTIVE SYSTEMS

One important advantage of understanding a user's cognitive states, traits, and biases as a cohesive structure is that this opens up the possibility of developing adaptive, mixed-initiative visualization systems [47]. As noted by Thomas and Cook in *Illuminating the Path* [47], an important direction in advancing visual analytics research is the development of an automated, computational system that can assist a user in performing analytical tasks. However, with few exceptions, most visualization systems today are designed in a "one-size-fits-all" fashion without the ability to adapt to different users' analytical needs into the design.

There is mounting evidence that successful adaptive systems can significantly improve a user's ability in performing complex tasks. In the recent work by Solovey et al. [46], the authors show that with the use of a brain imaging technology (fNIRS) to detect a user's cognitive states, the system can adapt the amount of automation and notably improve the user's ability in performing a complicated robot navigation task. Ziemkiewicz et al. [53] demonstrate that the impact of locus of control (LOC) on visualization can be significant. When the user is given a hierarchical visualization that correlates with the user's LOC, a user's performance can be improved by up to 52% in task completion time, and 28% in accuracy.

It is clear that adaptive systems offer new possibilities for visualization research and development, but more work is necessary to model *how* and *when* a system should adapt to a user's needs. As noted earlier, only emphasizing one or two of the three proposed dimensions can lead to a system incorrectly assessing the user's analysis process and provide the wrong adaption. By examining all three dimensions in a cohesive fashion, it becomes possible for a system to predict a user's performance and realize the potentials of an adaptive, mixed-initiative system as proposed by Thomas and Cook.

6. CHALLENGES

Creating a precise model of individual differences is a daunting task. From the outside, it can appear that even the slightest deviations between people can influence performance in a visualization, whether it is as obvious as taking a formal course in visualization or as subtle as reading emotionally-charged news articles between analysis tasks. Cognitive states may interact with and manipulate each other - for example, emotional state has been shown to impact working memory - and people simultaneously bring many traits and experiences to the table each time they see a visualization. Furthermore, there are almost certainly cognitive traits, states, and experiences that impact interaction significantly more than others.

While we don't believe that these problems impact the orthogonality of our proposed dimensions, it illuminates the potential dependency of factors within each dimension, increasing the difficulty of predicting human interaction. We highlight at least two future areas of research that will be critical to addressing these challenges.

First, discovering new and unobtrusive methods to capture cognitive state, trait, and experience/bias will ultimately drive research in individual cognitive differences. For example, recent advances in non-intrusive physiological sensors that detect emotional states, such as the Affectiva Q-Sensor [37], will enable future studies into the impact of emotional state and visualization performance. In real-world scenarios, it is unrealistic to expect users to be subjected to a deluge of forms and intrusive monitoring equipment. The simple act of filling out personality surveys or applying brain sensing equipment is enough to potentially modify cognitive state (or introduce biases) before interaction. It should be a central goal to record as many cognitive factors as possible, in as little time as possible, with as little disruption as possible.

Second, finding dominant individual cognitive factors both within dimensions and between dimensions should limit the sheer volume of cognitive tests necessary to describe interaction. For example, if participants have a low working memory capacity, their locus of control might not matter given a certain task and a visualization. If this is true, then having a participant fill out a survey to determine locus of control may be unnecessary. Similarly, we suspect that a person's experiences and biases may impact performance more than many other cognitive traits and states. Thus, if we know a person is an expert at a simple task, emotional state might be irrelevant. Identifying these dominant factors should reduce the number of interactions between cognitive factors.

The generalizability of cognitive states, cognitive traits, experiences/biases on performance in visualization has yet to be seen. By identifying important factors or important interactions between factors, we hope to construct new metrics in the future that are more predictive of interaction with a visualization.

7. CONCLUSION

By surveying the existing literature, we have made initial steps towards identifying dominant cognitive dimensions that affect visualization performance: cognitive states, cognitive traits, and experience/bias. We hope that by identifying these dimensions, we will move towards the development of a model of individual cognitive differences, eventually leading to a better understanding of the cognitive underpinnings of visualization.

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