ICD^3 : Towards a 3-Dimensional Model of Individual Cognitive Differences

Evan M Peck
Tufts University
evan.peck@tufts.edu

Beste F Yuksel
Tufts University
beste.yuksel@tufts.edu

Lane Harrison
UNC Charlotte
ltharri1@uncc.edu

Alvitta Ottley
Tufts University
alvittao@cs.tufts.edu

Remco Chang
Tufts University
remco@cs.tufts.edu

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 introduce the ICD^3 Model (Individual Cognitive Differences), whereby individual differences are evaluated in 3 dimensions: cognitive traits, cognitive states and experience/bias. Our proposed model systematically evaluates the effects of users' individual differences on information visualization and visual analytics, thereby responding to Yi's [72] call for "creating a standardized measurement tool for individual differences".

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 [24, 73], spatial ability [14], biases [40, 74, 76] and emotional state [4, 23, 34, 47, 56, 62] 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 [72].

In this position paper, we pursue this problem by introducing the ICD^3 Model (Individual Cognitive Differences) - a 3-dimensional model that encompasses the cognitive facets of individual indifferences. A necessary step in defining ICD^3 was to seek an underlying structure of previous research by identifying which factors are dependent and which are independent of one another. Doing so, we propose that individual differences can be categorized into three orthogonal dimensions: cognitive traits, cognitive states and experience/bias.

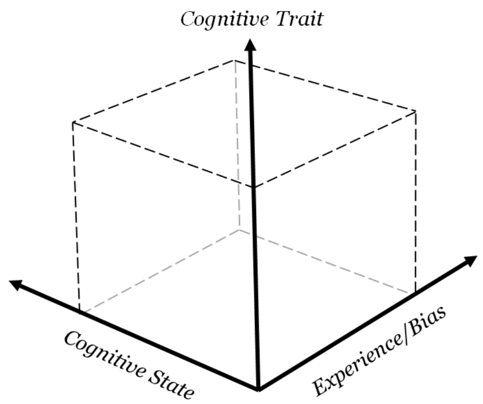

Figure 1: The ICD^3 categorizes individual cognitive differences in three orthogonal dimensions: Cognitive Traits, Cognitive States, and Experience/Bias

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 [15, 18, 24, 68, 73] 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 [4, 23, 34, 47, 56, 62], and the importance of combining workload with performance metrics has been noted for decades [28, 46, 71]. 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 [27].

Taken together, these three dimensions can create a model that encapsulates the cognitive aspects of individual differences (Fig. 1). 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). Thus, the model is only complete if all three dimensions are considered. By using ICD^3, evaluators can identify what factors must be controlled in an experiment and which should be included as independent variables. The community can also begin to evaluate visualizations using this 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. Evaluating visual forms and visual analytics systems share a common challenge with empirical evaluation in the field of HCI [63]: the results are often subjective and difficult to generalize to a large population in real-world conditions [25, 50]. To categorize evaluation approaches, Carpendale [9] carried out a comprehensive survey and divided the techniques into two groups: quantitative and qualitative evaluation methods.

Quantitative methods, such as laboratory experiments, seek to infer the quantifiable characteristics of a population by studying a few individuals. The challenges and concerns of using quantitative evaluation methods include the potential of Type I and Type II errors, internal validity (in that most findings are correlations and do not infer causality), external validity in generalizing the findings, and ecological validity in applying the findings to a real-world task, environment, or context.

For qualitative evaluation, the two primary mechanisms for gathering data are observations and interviews. There have been many proposed qualitative evaluation techniques: Nested Qualitative Methods, which argues for integration of qualitative methods such as the "think-aloud" protocol in both quantitative and qualitative studies; Inspection Evaluation Methods, which relies on an existing heuristic or theory such as perceptual theories [69] or expert guidelines [75]; and the Observational Methods, which promotes the use of exploratory methods to gain richer understanding of a new situation or group of users. For evaluating visualizations in which the user performs exploratory tasks, the Observational Methods are most frequently used with specific techniques like in-situ (or grounded) observations [31, 41], participatory observations [33, 54], and laboratory observations [30]. The key challenges and concerns to using qualitative evaluations include collecting data in an unobtrusive, objective, and timely manner; subjectivity in the sampled population; typical small sample sizes; and the coding and analysis of the collected data.

In addition to standard evaluation methodologies, visualization and visual analytics have additional considerations relating to perception and comprehensibility [26, 69] and the ability of a system to support higher level tasks [1]. Researchers have therefore suggested guidelines to determine how and when these evaluation methods can be used. Munzner [42] proposed a nested process in which she promotes the importance of identifying the key components of the tested visualization system and using the appropriate evaluation methodology for each component. Scholtz recommends an iterative and systematic approach to evaluating a visualization in different phases of its development and deployment [60, 61], which is similar in spirit to the MILCS concept proposed by Shneiderman and Plaisant [64]. Chang et al. [13] suggested that a mixed learning-based evaluation method can be more appropriate if the visualization is intended to improve a user's understanding of data, system, and domain. On the other hand, Kosara et al. [35] recommended that some aspects of the visualization cannot be evaluated using standardized metrics, and should instead be critiqued in the same manner as art and design.

The evaluation methods described so far have been in the category of secondary measurements. Some studies have attempted to measure visualization usage with more direct measurements. One notable technique suitable for evaluating complex, interactive visual analytics systems is insight-based evaluation, proposed by North et al. [43, 58, 59]. Since the most important criteria for a successful visual analytics system is to derive insight [8, 66] and to "answer questions that you didn't know you had" [50], an insight-based evaluation approach is highly appropriate for determining the effectiveness of the system. Unfortunately, the method proposed by North et al. relies on the user to track and self-report the number of insights experienced during the experiment. The results of such measurements are inherently subjective and therefore difficult to reproduce and generalize. As noted by Chang et al. [12], the key problem of self-reported insight is that the definition of insight is ambiguous and difficult to measure.

Clearly there has been a wide range of research in the area of visualization evaluation. Of particular interest are several pieces of work that directly report or suggest the use of brain imaging and individual differences for evaluating visualizations. Anderson et al. [2] 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 [53] proposed the use of multiple physiological measurements (heart rate, eye gaze, brain imaging, etc.)

for evaluating visualizations. At the same BELIV workshop, Yi [72] 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 highlights the importance of additional research in individual differences in visualization evaluation [36].

This body of research on directly measuring a user's cognitive and individual profile highlights a need for better evaluation methods to address the unique needs of visualization, but as of yet, there is no consensus on which methods best answer these needs. What is clear, however, is that the field of visualization does not yet have a systematic and objective way of measuring individual differences in user analysis of visualizations. The ICD^3 Model that we are proposing seeks to structure the existing research into a cohesive model.

3. DIMENSIONS OF INDIVIDUAL DIFFERENCES

In this section we discuss each of the three dimensions in the ICD^3 model: cognitive traits, cognitive states, and experience/bias. Figure 1 shows the three dimensions and how they could be represented graphically. Specifically, 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 [18] 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 [15] 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. [68] 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 [17] 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 [72] 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 [24] 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 [55] 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. [73] 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 [37, 39, 48]. 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 [10], and dual-task studies can be designed to evaluate mental demand through performance [38, 45].

Cognitive load theory breaks down this generic concept of workload into three more narrowly-defined categories [11]. 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 [71], 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 [70]. Accordingly, researchers have suggested the integration of performance and mental demand during evaluation [28, 46, 71]. Paas and Merrienboer constructed a two-dimensional model of performance and mental effort to define cognitive efficiency [46], and Huang et al. tailored the model to visualization evaluation by adding a third dimension - response time [28]. 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 [29].

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 [5]. Previous work has shown positive emotional states to enhance attention regulation, working-memory performance, open-ended reasoning, creativity, and "big picture" understanding [4, 23, 34, 47, 56]. Conversely, negative emotional states, such as anxiety, can disrupt visuospatial working memory [62]. Finally, emotions have a strong link to decision-making and cost-benefit analysis [6]. 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 [19, 67]. Although experience and bias could be discussed at length separately, here we discuss them together, since they are not orthogonal to each other [20]. 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 [32].

Experience is associated with the formation of effective reasoning strategies for given problem types [22, 57], many of which are applicable to reasoning with visualizations. For instance, the experiment in [19] 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 sensemaking model [49], 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 [16]. Perhaps the first to address experience directly is Kwon et al. [16], 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. [21] 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 [3], 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 [52, 67]. 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 [76] 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. [40], 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 [74] 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 [20, 27], 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. THE ICD^3 MODEL

In light of the three dimensions that we have discussed, we propose a structured model in order to describe individual cognitive differences when users interact with visualizations.

We therefore introduce the ICD^3 model: a three dimensional model of cognitive traits, cognitive states, and experience/bias. 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 the three different axes. This would allow for not just isolated cognitive factors, but for the *interaction* of the user's different cognitive abilities.

Figure 2 gives a hypothetical example of a user looking at percentage judgments in treemaps. The cognitive state in this example is the user's workload, their cognitive trait is their working memory capacity, and their experience/bias is how experienced they are with treemaps. Our ICD^3 model would show that if the user is an expert, has a low workload, and has a high working memory capacity, then they have higher performance and abilities with percentage judgment in treemaps. Conversely, if the user is overloaded with work, has a naturally low working memory capacity, and has no experience of treemaps, then they will be less effective in performing that task.

After defining the visualization, task, and cognitive factors, a set of experiments can then be run in which participant workload, working memory capacity, and experience is varied. For each interaction of factors, performance is recorded in the instance at the appropriate coordinates. Given enough data, we construct a descriptive topology of performance for a task and visualization.

Unfortunately, the interaction of cognitive facets is ordinarily much more nuanced than depicted in Figure 2. For the sake of simplicity, we chose working memory capacity, workload, and experience because their impact on performance is relatively straightforward. But in practice, we have little knowledge of how other 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 [7]. 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 [44], perform better in visualizations where they have had no previous experience than people with an internal locus of control (LOC) [73]. This demonstrates how trait and experience can interact to influence performance.

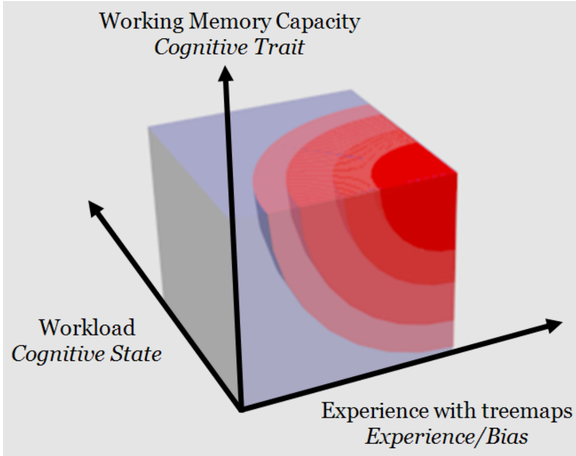

Figure 2: An example of how an ICD^3 model might be constructed. We map the interaction of workload, working memory capacity, and experience on performance of percentage judgments in treemaps. Darker red represents better performance.

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 two 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? Thus, a key attribute of the ICD^3 model is that limiting the scope of evaluation to any two of the three described dimensions 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

While instances of the ICD^3 model should be constructed for a explicit task and visualization, we imagine that the interaction of certain cognitive factors will be generalizable across visual forms (and tasks). In the next section, we explore the implications of the ICD^3 for design.

5. IMPLICATIONS FOR DESIGN

One important advantage of understanding individual users' cognitive states, traits, and biases as a cohesive structure is that this opens up the possibility of developing adaptive, mixed-initiative visualization systems [66]. As noted by

Thomas and Cook in *Illuminating the Path* [66], 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. [65], 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. [73] 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. FUTURE WORK AND 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 model, 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 [51], 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. As a result, the ICD^3 model takes a conservative approach by specifying an exact set of cognitive factors and requiring tests to be performed on a fixed task and fixed visualization. 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. CONCLUSIONS

We have introduced a model to capture the various cognitive aspects that affect visualization performance by dividing them into three dimensions: cognitive states, cognitive traits, and experience/bias. Furthermore, we have discussed how each of these dimensions are orthogonal to each other, meaning that during visualization interaction, a user may exhibit different values for states, traits, or experience/biases. Each of the dimensions are found to influence cognitive processes related to visualization, such as reasoning and perception. The ICD^3 model provides a sample space for experiments involving visualizations, so that we may form a better understanding of the cognitive underpinnings of visualization.

8. REFERENCES

[1] Amar, R., and Stasko, J. Knowledge precepts for design and evaluation of information visualizations. *IEEE Visualization and Computer Graphics 11*, 4 (2005), 432–442.

[2] Anderson, E., Potter, K., Matzen, L., Shepherd, J., Preston, G., and Silva, C. A user study of visualization effectiveness using eeg and cognitive load. In *Computer Graphics Forum* (2011), vol. 30, Wiley Online Library, pp. 791–800.

[3] Arias-Hernandez, R., Kaastra, L. T., Green, T., and Fisher, B. Pair analytics: Capturing reasoning processes in collaborative visual analytics. *System Sciences (HICSS)* (2011), 1–10.

[4] Ashby, F. G., Valentin, V., and Turken, U. The effects of positive affect and arousal on working memory and executive attention. In *Emotional Cognition: From Brain*

to Behavior, S. Moore and M. Oaksford, Eds. Amsterdam: John Benjamins, 2002, pp. 245–287.

[5] Bateman, S., Mandryk, R. L., Gutwin, C., Genest, A., Mcdine, D., and Brooks, C. Useful junk? The effects of visual embellishment on comprehension and memorability of charts. *Proc. CHI '10* (2010), 2573–2582.

[6] Bechara, A. The role of emotion in decision-making: Evidence from neurological patients with orbitofrontal damage. *Brain and Cognition 55* (2004), 30–40.

[7] Boddy, J., Carver, A., and Rowley, K. Effects of positive and negative verbal reinforcement on performance as a function of extraversion-introversion: Some tests of Gray's theory. *Personality and Individual Differences 7*, 1 (1986), 81–88.

[8] Card, S., Mackinlay, J., and Shneiderman, B. *Readings in Information Visualization: Using Vision to Think*. Morgan Kaufmann, 1999.

[9] Carpendale, S. Evaluating information visualizations. *Information Visualization* (2008), 19–45.

[10] Casner, C., and Larkin, J. Cognitive efficiency considerations for good graphic design. Tech. rep., 1989.

[11] Chandler, P., and Sweller, J. Cognitive Load Theory and the Format of Instruction. *Cognition and Instruction 8*, 4 (Dec. 1991), 293–332.

[12] Chang, R., Ziemkiewicz, C., Green, T., and Ribarsky, W. Defining insight for visual analytics. *IEEE Computer Graphics and Applications 29*, 2 (2009), 14–17.

[13] Chang, R., Ziemkiewicz, C., Pyzh, R., Kielman, J., and Ribarsky, W. Learning-based evaluation of visual analytic systems. In *BELIV '10* (2010), ACM.

[14] Chen, C. Individual differences in a spatial-semantic virtual environment. *Journal of the American Society for Information Science 51*, 6 (2000), 529–542.

[15] Chen, C., and Czerwinski, M. Spatial ability and visual navigation: An empirical study. *New Review of Hypermedia and Multimedia 3*, 1 (1997), 67–89.

[16] Chul Kwon, B., Fisher, B., and Yi, J. Visual analytic roadblocks for novice investigators. In *IEEE Visual Analytics Science and Technology* (2011), IEEE, pp. 3–11.

[17] Cohen, C., and Hegarty, M. Individual differences in use of external visualisations to perform an internal visualisation task. *Applied Cognitive Psychology 21*, 6 (2007), 701–711.

[18] Conati, C., and Maclaren, H. Exploring the role of individual differences in information visualization. *Advanced Visual Interfaces* (2009).

[19] Cox, J. R., and Griggs, R. A. The effects of experience on performance in Wason's selection task. *Memory & Cognition 10*, 5 (Sept. 1982), 496–502.

[20] Croskerry, P. Achieving quality in clinical decision making: Cognitive strategies and detection of bias. *Academic Emergency Medicine 9*, 11 (Nov. 2002), 1184–1204.

[21] Dou, W., Jeong, D. H., Stukes, F., Ribarsky, W., Lipford, H., and Chang, R. Recovering reasoning processes from user interactions. *IEEE Computer Graphics and Applications 29*, 3 (2009), 52–61.

[22] Fisher, C. W., Chengalur-Smith, I., and Ballou, D. P. The impact of experience and time on the use of data quality information in decision making. *Information Systems 14*, 2 (2003), 170âĂŞ–188.

[23] Fredrickson, B. What good are positive emotions? *Review of General Psychology 2*, 3 (1998), 300–319.

[24] Green, T., and Fisher, B. The impact of personality factors on visual analytics interface interaction. *IEEE Visual Analytics Science and Technology* (2010), 203–210.

[25] Greenberg, S., and Buxton, B. Usability evaluation considered harmful (some of the time). In *Proc. CHI '08* (2008), ACM, pp. 111–120.

[26] Healey, C., and Enns, J. On the use of perceptual cues & data mining for effective visualization of scientific datasets. In *Graphics Interface* (1998), Canadian Information Processing Society, pp. 177–184.

[27] Heuer, R. *Psychology of intelligence analysis*. United States Govt Printing Office, 1999.

[28] Huang, W., Eades, P., and Hong, S.-H. Measuring effectiveness of graph visualizations: A cognitive load perspective. *Information Visualization 8*, 3 (Jan. 2009), 139–152.

[29] Hullman, J., Adar, E., and Shah, P. Benefitting InfoVis with visual difficulties. *IEEE Visualization and Computer Graphics 17*, 12 (Dec. 2011), 2213–22.

[30] Isenberg, P., Tang, A., and Carpendale, S. An exploratory study of visual information analysis. In *Proc. CHI '08* (2008), ACM, pp. 1217–1226.

[31] Isenberg, P., Zuk, T., Collins, C., and Carpendale, S. Grounded evaluation of information visualizations. In *Proceedings of the 2008 conference on BEyond time and errors: novel evaLuation methods for Information Visualization* (2008), ACM, p. 6.

[32] Johnston, R. Analytic culture in the US intelligence community: An ethnographic study. *The Center for the Study of Intelligence 160* (2005), 72.

[33] Kang, Y., and Stasko, J. Characterizing the intelligence analysis process: Informing visual analytics design through a longitudinal field study. In *Visual Analytics Science and Technology (VAST), 2011 IEEE Conference on* (2011), IEEE, pp. 21–30.

[34] Klein, K., and Boals, A. Expressive writing can increase working memory capacity. *Journal of Experimental Psychology: General; Journal of Experimental Psychology: General 130*, 3 (2001), 520.

[35] Kosara, R., Drury, F., Holmquist, L., and Laidlaw, D. Visualization criticism. *IEEE Computer Graphics and Applications 28*, 3 (2008), 13–15.

[36] Kwon, B., Fisher, B., and Yi, J. Visual analytic roadblocks for novice investigators. *IEEE Visual Analytics Science and Technology* (2011), 3–11.

[37] Lohse, G. L. The role of working memory on graphical information processing. *Behaviour & Information Technology*, 16 (1997), 297–308.

[38] Matzen, L., McNamara, L., Cole, K., Bandlow, A., Dornburg, C., and Bauer, T. Proposed working memory measures for evaluating information visualization tools. In *BELIV '10* (2010).

[39] Miller, G. The magical number seven, plus or minus two: Some limits on our capacity for processing information. *Psychological Review 63*, 2 (1956), 81–97.

[40] Miller, S., Kirlik, A., Kosorukoff, A., and Tsai, J. Supporting joint human-computer judgment under uncertainty. *Human Factors 52*, 4 (2008), 408–412.

[41] Moggridge, B. *Design Interactions*. MIT Press, 2006.

[42] Munzner, T. A nested process model for visualization design and validation. *IEEE Visualization and Computer Graphics 15*, 6 (2009), 921–928.

[43] North, C. Toward measuring visualization insight. *IEEE Computer Graphics and Applications 26*, 3 (2006), 6–9.

[44] Organ, D. Extraversion, locus of control, and individual differences in conditionability in organizations. *Journal of Applied Psychology 60*, 3 (1975), 401.

[45] Paas, F., Tuovinen, J. E., Tabbers, H., and Van Gerven, P. W. M. Cognitive load measurement as a means to advance cognitive load theory. *Educational Technology 38*, 1 (2003), 63–71.

[46] Paas, F. G., and Van Merriënboer, J. J. The efficiency of instructional conditions: An approach to combine mental effort and performance measures. *Human Factors 35*, 4 (1993), 737–743.

[47] Phelps, E., Ling, S., and Carrasco, M. Emotion facilitates perception and potentiates the perceptual benefits of attention. *Psychological Science 17*, 4 (2006), 292–299.

[48] Pinker, S. A theory of graph comprehension. In *Artificial Intelligence and the Future of Testing*. 1990, pp. 73–126.

[49] Pirolli, P., and Card, S. The sensemaking process and leverage points for analyst technology as identified through cognitive task analysis. *Conference on Intelligence Analysis* (2005), 6.

[50] Plaisant, C. The challenge of information visualization evaluation. In *Proc. Advanced Visual Interfaces* (2004), ACM, pp. 109–116.

[51] Poh, M.-Z., Swenson, N. C., and Picard, R. W. A wearable sensor for unobtrusive, long-term assessment of electrodermal activity. *IEEE Transactions on Biomedical Engineering 57*, 5, 1243–1252.

[52] Reich, S. S., and Ruth, P. Wason's selection task: Verification, falsification and matching. *British Journal of Psychology 73*, 3 (Apr. 1982), 395–405.

[53] Riche, N. Beyond system logging: Human logging for evaluating information visualization. BELIV '10.

[54] Robinson, A. Collaborative synthesis of visual analytic results. In *IEEE Visual Analytics Science and Technology* (2008), IEEE, pp. 67–74.

[55] Rotter, J. Generalized expectancies for internal versus external control of reinforcement. *Psychological Monographs: General and pplied 80*, 1 (1966), 1.

[56] Rowe, G., Hirsh, J., and Anderson, A. Positive affect increases the breadth of attentional selection. *Proceedings of the National Academy of Sciences 104*, 1 (2007), 383–388.

[57] Salthouse, T. A., and Mitchell, D. R. Effects of age and naturally occurring experience on spatial visualization performance. *Developmental Psychology 26*, 5 (1990), 845–854.

[58] Saraiya, P., North, C., and Duca, K. An insight-based methodology for evaluating bioinformatics visualizations. *IEEE Visualization and Computer Graphics 11*, 4 (2005), 443–456.

[59] Saraiya, P., North, C., and Duca, K. Comparing benchmark task and insight evaluation methods on timeseries graph visualizations. In *BELIV '10* (2010).

[60] Scholtz, J. Beyond usability: Evaluation aspects of visual analytic environments. In *IEEE Visual Analytics Science And Technology* (2006), IEEE, pp. 145–150.

[61] Scholtz, J. Progress and Challenges in Evaluating Tools for Sensemaking. In *CHI '08 Workshop on Sensemaking* (2008).

[62] Shackman, A., Sarinopoulos, I., Maxwell, J., Pizzagalli, D., Lavric, A., and Davidson, R. Anxiety selectively disrupts visuospatial working memory. *Emotion 6*, 1 (2006), 40.

[63] Shneiderman, B. The eyes have it: A task by data type taxonomy for information visualizations. In *IEEE Visual Languages* (1996), IEEE, pp. 336–343.

[64] Shneiderman, B., and Plaisant, C. Strategies for evaluating information visualization tools: Multi-dimensional in-depth long-term case studies. In *BELIV '06'* (2006), ACM, pp. 1–7.

[65] Solovey, E., Schermerhorn, P., Scheutz, M., Sassaroli, A., Fantini, S., and Jacob, R. Brainput: Enhancing interactive systems with streaming fNIRS brain input. In *Proc. CHI '12* (2012), ACM Press, pp. 2193–2202.

[66] Thomas, J., and Cook, K. *Illuminating the path: The research and development agenda for visual analytics*, vol. 54. IEEE, 2005.

[67] Tversky, A., and Kahneman, D. Judgment under uncertainty: Heuristics and biases. *Science 185*, 4157 (Sept. 1974), 1124–1131.

[68] Velez, M., Silver, D., and Tremaine, M. Understanding visualization through spatial ability differences. In *IEEE Visualization* (2005), IEEE, pp. 511–518.

[69] Ware, C. *Information visualization: Perception for design*, vol. 22. Morgan Kaufmann, 2004.

[70] Wickens, C., and Hollands, J. *Engineering Psychology and Human Performance*. Prentice-Hall, Upper Saddle River, NJ, 1999.

[71] Yeh, Y.-y., and Wickens, C. D. Dissociation of performance and subjective measures of workload. *Human Factors 30*, 1 (1988), 111–120.

[72] Yi, J. S. Implications of individual differences on evaluating information visualization techniques. BELIV '10.

[73] Ziemkiewicz, C., Crouser, R., Yauilla, A., Su, S., Ribarsky, W., and Chang, R. How locus of control influences compatibility with visualization style. *IEEE Visual Analytics Science and Technology* (2011), 81–90.

[74] Ziemkiewicz, C., and Kosara, R. Laws of attraction: From perceptual forces to conceptual similarity. *IEEE Visualization and Computer Graphics 16*, 6 (2010), 1009–1016.

[75] Zuk, T., and Carpendale, S. Theoretical analysis of uncertainty visualizations. In *Proc. SPIE '06* (2006), vol. 6060, pp. 66–79.

[76] Zuk, T., and Carpendale, S. Visualization of uncertainty and reasoning. *Smart Graphics* (2007), 164–177.