Towards the Personal Equation of Interaction: The Impact of Personality Factors on Visual Analytics Interface Interaction

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ABSTRACT

These current studies explored the impact of individual differences in personality factors on interface interaction and learning performance behaviors in both an interactive visualization and a menu-driven web table in two studies. Participants were administered 3 psychometric measures designed to assess Locus of Control, Extraversion, and Neuroticism. Participants were then asked to complete multiple procedural learning tasks in each interface. Results demonstrated that all three measures predicted completion times. Additionally, results analyses demonstrated personality factors also predicted the number of insights participants reported while completing the tasks in each interface. We discuss how these findings advance our ongoing research in the Personal Equation of Interaction.

KEYWORDS: visual analytics, cognition and perception theory, embodied cognition, visualization taxonomies and models

INDEX TERMS: H.1.2 [Models and Principles]: Human Information Processing J.4 [Social and Behavioral Sciences] : Psychology - Experimentation

1 INTRODUCTION

The primary purpose of visual analytics is commonly defined as the facilitation of analytical reasoning through use of interactive visual interfaces [1]. Facilitating analytical reasoning, however, requires a comprehensive and operational understanding of the cognitive processes that make up analytical reasoning. Complex cognition includes a plethora of smaller processes that work together, including perceptual cognition, categorization, problem-solving, decision-making, judgement, and reasoning. These processes feed and inform each other throughout each stage of the analytical task; simply supporting each process individually is not enough. Visual analytics must also support the temporal and cognitive flow of reasoning. And yet, an operational understanding of analytical cognition has, to date, proven elusive.

For example, as is often the case with behavioral experimentation generally, studies of cognition tend to involve small, simple, normative or "toy world" tasks, while interaction in the real world tends to be more complex, harder to predict, and thus harder to measure. Additionally, these evaluations focus on the more binary of cognitive processes. Especially in visualization studies, the cognitive variables measured are usually facets of vision, given attention, and tactile manipulation. While visual and motor effectiveness are important to interface interaction, they are only part of the story.

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Complex cognition is not binary nor necessarily sequential. Reasoning, in particular, uses a variety of heuristics, from quick elimination heuristics like Gigerenzer's Take-the-Best [2] or satisficing [3] to much more complicated processes such as iterative reasoning, deductive analyses, or rule inferencing. Which heuristics are used and in what order depend on the task, the environment, and the user. These heuristics are often used combinatorially, feeding and informing the analysis until a solution or hypothesis has been satisfactorily reached.

Unfortunately, at this time, analytical reasoning behaviours can be described in part and in whole, but not necessarily predicted. There are no unifying theories of reasoning. And this difficulty of prediction is compounded by three types of user individual differences: institutional, environmental, and inherent.

How humans work through reasoning tasks is impacted by institutional differences. Cognition is a social activity [4], and domain-specific knowledge, jargon, learned methodologies, and other cultural factors can influence how analysis tasks are approached and what heuristics are used in solving them. In addition, these domain or expert cultures tend to have similar inherent differences; members of an expert cohort may share personality or learned proclivities [5, 13].

Environmental differences – such as differences in the interface or tool used during visually enabled interaction – frame the task and can help or hinder the reasoning process. These differences are naturally of particular interest to visual analytics design, as effective interfaces can facilitate analytical reasoning.

In this paper, we will higlight the impact of inherent indvidual differences. Individual differences of whatever variety are obviously not the only factors which demonstrably impact user interactive performance. But as we will show, individual differences – and inherent differences in particular – can predict certain types of performance. Further, these differences seem to influence performance differently, depending on the cognitive task being undertaken. Another reason to study inherent differences is that they, unlike environmental and to some degree institutional differences, are variables over which interface designers have no control.

In our research toward the Personal Equation of Interaction, our goal is to know and understand the impact of these variables, as well as to develop a battery of predictive measures to aid in the development of interfaces which cater to the individuality of the user or user domain. The creation of the Personal Equation of Interaction at this current time is focused on inherent individual differences. Inherent differences are those of learning style, personality factors, self-beliefs, and other cognitive "presets" which the user brings to the interface. We will demonstrate that these inherent differences can and do demonstrably impact interaction outcomes. Further, we can show that, if the inherent differences are known, interaction performance can be predicted, and so could, if part of a robust user profile, be used to develop design requirements for expert systems design as well as real-time interface individuation.

Inherent individual differences in problem-solving approaches can affect task orientation and motivation when a user is engaged in goal-oriented behaviors [6]. In particular, personality factors similar to the ones evaluated in the studies reported here have been shown to impact cognition and cognitive performance in other learning environments. For example, personality factors predicted preferences in visual perception of landscapes [7]. In an HCI study, Palmer found that interactive behaviors in information search can be categorized by personality factors [8]. In reasoning research, individual differences have been found to impact rationality and metareasoning [9]. These are just a few examples in a broad literature of how personality factors and other individual differences demonstrably affect complex cognition. The findings we currently report are part of this body of work. The question is not whether individual differences impact cognition, but how and when. We hope, in the creation of the Personal Equation, to answer several of these questions.

Furthermore, we can use individual differences to improve our understanding of visually enabled analysis across knowledge domains. Research has demonstrated that users in a particular domain can share personality characteristics and learning preferences, both inherent and institutional. This implies that traits common to the user group can be aggregated into specific user profiles, informing superior design requirements and aiding in evaluation protocols. A personal equation of interaction could both a) provide guidelines for individuated interface designs which could broadly accommodate differences in learning style, reasoning heuristic preferences, and perceptual behaviors and b) develop profiles of expert or non-expert user groups, deliniated by either knowledge domain or cognitive task, that would inform the interface design for specific user or task domains.

As we discussed previously, individual differences have been found to have a bearing in traditional learning environments [e.g. 11]. And in an earlier study [10] we found that certain aspects of trait anxiety had an impact on task efficiency in both inferential and procedural tasks. Also, Rotter's Locus of Control [12] predicted inferential task efficiency; we will review this finding in Section 3. For user group profiles, characteristics of user domains has been done in a limited fashion [e.g. 13]; this research would further these aims.

Learning is not generic. Learning heuristics and processes vary depending on human individuality, the learning environment, and the learning tasks. In other work, we discussed the impact of locus of control on inference learning in the form of category reasoning [10]. The tasks used in these current studies are procedural. Procedural learning, broadly defined, is the "knowing how" of any sequential task. It is sometimes called skill learning, as it is the learning most common to motor and iterative tasks that require repetition to master [14]; it is also referred to as script learning, which captures the idea that there is a "recipe" or "roadmap" to be followed. Procedural learning is thought to be either top-down (i.e. CLARION) [14], or, more commonly, to be bottom up, first assimilating the necessary declarative facts and then the use of that information into the deconstruction of the task procedure [15]. Procedural learning, due in part to repetition, can become "automatic," requiring little conscious focus. *For the purposes of these current studies, procedural learning is the ability to learn to manipulate an interface well enough to find and identify target information, or to answer straightforward questions about the target information.*

Procedural or script learning is integral to interface interaction at every level. Some research has been conducted with an eye toward procedural or target-finding tasks. But, as Plaisant has outlined [16], many of these studies are tool evaluations of specific interfaces, and are designed to designate one interface as "better" than another, or done without an understanding of the learning which underlies task performance.

Individual differences in reasoning ability have been found to impact procedural learning in non-interface task environments [e.g. 17]. These current studies evaluate inherent differences in computer-mediated procedural tasks.

In another vein, visualizations are generally considered preferable to other interfaces in generating "insight" [18]. But this claim to date has been poorly supported by empirical research. Further, research has focused on the visualization and insight generation, but not necessarily on the tasks that support insight generation, or the degree to which user individuality impacts the frequency of insight. *In this study, we evaluate the insight generation by comparing the number of reported insights in the two interfaces while completing two types of procedural task: script learning, which involves the use of sequential instructions and interface learnability, and target identification, which can involve hunting for information through several layers of hierarchical organization.* In addition, we explore the impact that individual differences have on the number of insights generated in both interfaces across task.

The current studies were designed to explore 2 broad research questions. The first question was whether and to what degree Locus of Control, Big Five Neuroticism, and Big Five Extraversion would have a significant relationship with the outcome variables in task performance. It was hypothesized that some whole measures or highly-predictive clusters of items would trend with the outcomes. Based on previous work [10], we expected that the Locus of Control whole score would be one predictor, and that more extraverted and neurotic participants would be quicker in task completion. And based on behavioral literature[e.g. 24], we hypothesize that participants with an external locus would be quicker in identifying target information.

The second question was whether and to what degree Locus of Control, Big Five Neuroticism, and Big Five Extraversion would have a significant relationship with the number of insights reported; it was hypothesized that, given the interrelationship between these constructs, whole score or individual items, would be found to predict insight generation in both interfaces. Based on previous locus of control literature [e.g. 22, 24], we predicted that participants with an internal locus might be more apt to self-report more insights.

The answers to these questions will aid in the creation of the Personal Equation on Interaction, by identifying influential psychometric items for interactive behaviors and reported insights, which, in the long term will aid in the creation of predictive measures depending on the type of analytical task being undertaken.

2 Comparative Studies

Two studies were conducted. Each study employed a within-participants design, and compared procedural learning behaviors in an information visualization and a web table. Study 1 tested procedural learning performance with a series of 5 questions in each interface. Study 2 tested procedural learning performance, with a total 6 questions in each interface (3 training and 3 task). The procedural task completion times in both studies were combined for the purpose of analysis. The design and findings of Study 2 have also been reported and discussed in [10].

2.1 Interfaces

Both studies asked participants to interact with two interfaces built to display genomic information. These interfaces were chosen as artifacts because both interfaces were fed by the same underlying dataset (GenBank), both interfaces supported the types of tasks we wanted to study, and the presentation and organization of data and interaction methodology was demonstrable different. One interface is the web-based National Center for Biotechnology Information (NCBI) MapViewer for genomic information, which is publically available and can currently be found at http://www.ncbi.nlm.nih.gov/mapview. MapViewer is a multiple-row-based hierarchical representation, and uses standard GUI manipulation, such as menus and hyperlinks. (See Figure 1.)

The other interface is an interactive data visualization (GVis) of genomic relationships [19] which is not available publically. (See Figure 2.) GVis primary purpose is to represent relevant relationships (such as mapped genomes or the phylogenic organization) between two organisms. Users manipulate the interface through direct interaction, "drilling down" through each hierarchy of subcategory directly by pressing and holding down a mouseclick near the information of interest.

2.2 Psychometric measures

These psychometric measures we have chosen have been shown to capture the impact of these inherent constructs on human cognitive performance and motivation as discussed in the behavioral literatures (as discussed briefly in Section 1). Our purpose was to explore what impact they might have on analytical performance enabled by a visual interface.

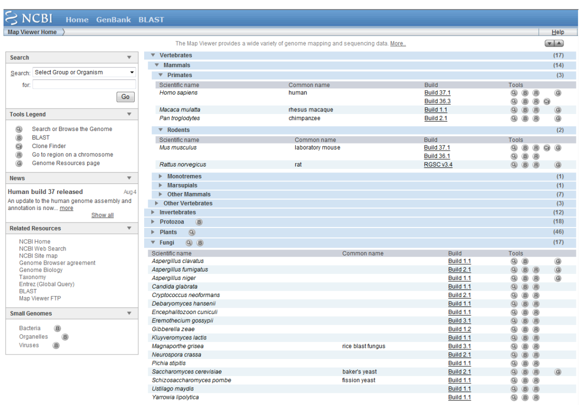

Figure 1. NCBI MapViewer

Three psychometric measures were administered: the Locus of Control Inventory, as well as the Neuroticism and Extraversion subscales of the IPIP Mini Big Five Personality Inventory.

The Internal-External Locus of Control Inventory (LOC) [12] is a 39-item forced choice measure designed to evaluate the degree to which participants attribute life events to some action of their own, or to some uncontrollable action outside of themselves. Lower LOC scores are associated with an "internal locus" of control, an inherent belief that events and outcomes are under a person's control, and thus, success or failure depends largely on personal behavior and attitudes. Higher scores indicate an "external locus," an inherent belief that events and outcomes are influenced by external factors such as, unforeseen circumstances, a higher power, or "good luck." Rotter postulated that these loci were traits remaining stable over a person's lifetime [12]. Research demonstrates that locus of control has an impact on a wide variety of human outcomes, including academic and workplace performance[21,22].

The Neuroticism and Extraversion subscales of the IPIP 20-item Mini Big Five Personality Inventory [20] ask participants the degree to which each listed characteristic applies to them. The Big Five factors have a long history in psychology and decades of literature on their scope and impact. Briefly, Extraversion defines the degree to which a person is open-minded, action-oriented and seeks the society of others. Neuroticism is distinguished by negativity and a propensity to be moody. In previous work [10], as well in other literature (e.g. [23]), these traits have a demonstrated relationship to each other, and, in the case of Neuroticism, to locus of control.

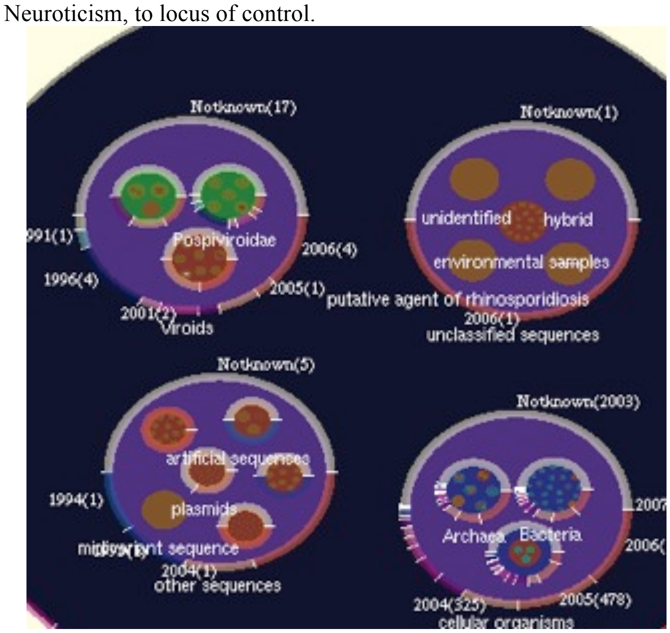

Figure 2. The main view of GVis.

2.3 Participants

In total, 106 participants agreed to complete the study: 50 in the first study, 56 in the second study. 94 participants reported being right-handed; 11 were left-handed. Most (101) were undergraduates and received course credit for participation. Students reported having 22 different majors or academic concentrations, including Business, Nursing, Computer Science, and Psychology.

The vast majority of all participants 101 (96%) had taken fewer than 4 biology or biology-related classes. Novices were recruited specifically to better evaluate procedural learning with novel information; experts would have had a more advanced understanding of the knowledge ontology, which would have weakened the comparison between interface metaphors.

All participants were asked to rate their ability and comfort level with a computer and mouse on a 5-item Likert-like scale. They were also asked to identify whether they had previous experience with the computer interfaces being investigated. 97 reported being comfortable or very comfortable with a computer; 79 reported having "very good" or "expert" computer ability. No one reported a computer comfort or ability level less than a 3 or "OK." Almost all (104) participants had used a web-based application before. 35 participants reported having used a data visualization previously. None of the participants reported having a medical condition that might interfere with their use of a computer or mouse. 2 participants reported being color-blind.

2.4 Study Protocols

After signing the informed consent, participants were asked to fill out an online self-report questionnaire that included the 3 psychometric measures and basic demographic information, with particular emphasis on self-perceived ability, experience and comfort with computers and computer interfaces. Participants in the first study were allowed to complete the questionnaire online before their session in the lab. All data were collected for post-hoc analysis with task performance data.

In both studies, after completion of the self-report measures, participants began the procedural learning tasks in one of the two interfaces. The order of interface was counterbalanced for order effects; half of the participant used GVis first, and half used MapViewer first.

In the first study, the tasks started with a brief demonstration of interface and interaction techniques, such as the use of hyperlinks or how to zoom into the visualization. After the demonstration, a short tutorial was administered to introduce participants to essential tools and concepts in the interface, and to allow participants to experiment with what was being learned. In some cases, step-by-step instructions were given. A researcher was on hand throughout the study to answer any questions. Following the tutorial was a series of 3 tasks designed to test procedural performance in finding target information: the participant was asked to identify a target located somewhere within the presented informational hierarchy. The question provided what base categorization or subclass the information was located within, but did not provide step-by-step instructions. Participants were also told to find the item as quickly as possible, as the task was being timed. As soon as the target was located on screen, the participant pushed a "Found It" button on the screen. The time taken from the presentation of the question on-screen to the moment the button was pushed was recorded as *completion time*.

In the second study, participants were asked to demonstrate script learning or tool skill by answering 5 hunt-and-find questions. All tasks were open response. Each question included step-by-step "cues" to assist in finding the answer to each question. A cue was the next step or concept on the current page or in the current view to look for. Participants were given little or no help from the researchers while working through the question, but were allowed or encouraged to experiment with different interaction paths within the interface in order to find the answer. If the answer given was incorrect, the error was recorded and the researcher asked the participant to try again, until the correct answer was given. The total time from the initial reading of the question to the indication of the correct answer was recorded as the completion time. Participants were not told explicitly that they were being timed.

A third recorded outcome variable was insight. Participants were asked after finishing each task in both studies to indicate whether they had "learned anything unexpected while finding the solution." Insight was defined as "unexpected" to prompt for only new knowledge that the participant considered to be novel or surprising. If the participant reported a new insight, they were asked to describe what they had learned.

After each participant had answered the questions in both interfaces, they were asked to specify which interface they liked better, and to give each interface a letter grade ('A' (superior) through 'F' (failing)). A short debriefing ended the study session, and there were no follow-up sessions.

3 Results

In Study 1, the mean completion times for the procedural learning tasks in the MapViewer (M = 684.77, SD = 235.46) were more efficient than the completion times in the GVis (M = 684.77, SD = 288.49). In Study 2, the MapViewer procedural completion times were also faster (M = 133.54, SD = 84.00) than those in the GVis (M = 161.64, SD = 111.40).

Overall, participants preferred interacting with the visualization to interacting with the web table. This preference was indicated by post-study feedback. For example, when asked to give each interface a letter grade, from A (superior) to F (failing), 75 (73%) gave the GVis an A or B; 57 (56%) gave an A or B to the MapViewer. Additionally, when asked, 64(61%) reported that they both preferred the visualization; 39 (37%) preferred the web table.

3.1 Completion times and personality factors

The completion times for each condition for the procedural learning tasks in each study were merged into a single statistic, with $N = 106$. Participants completed tasks more quickly in MapViewer ($M = 383.15$, $SD = 32.38$) than in GVis ($M = 426.86$, $SD = 32.15$). A paired t-test between total completion times in GVis and completion times in MapViewer was significant ($t(100) = 2.11$, $p = .037$, suggesting that the differences in completion times was due to more than random chance.

A one way Analysis of Variance (ANOVA) was used to test for the impact of Locus of Control (LOC) across interface completion times. The ANOVA for GVis was significant ($F(14, 88) = 1.89$, $p = .039$) but the comparison for MapViewer was not ($p = .099$). In addition, LOC predicted completion times in both interfaces; a Pearson's correlation between LOC and completion times was significant (GVis: $r(105) = .234$, $p = .02$, MapViewer: $r(105) = .254$, $p = .01$). (See Figures 3a and 3b.) These findings suggest that participants with a more internal locus (those who believe they have control over personal life events) take less time finding target information than those with a more external locus. This correlational finding is the opposite of findings reported in an earlier study [10]. This previous study used inferential tasks, and found that participants with a more external locus (those who did not believe that they were in control) tended to solve a series of inferential tasks more quickly than those with a more internal locus. These tasks were more cognitively complex than the current studies, and asked the participants to compare and contrast multi-dimensional objects and make decisions about similarities and differences. We will discuss this further in the Section 4.

ANOVAs to test for the impact of Neuroticism in both interfaces were significant: GVis: ($F(16, 86) = 3.42$, $p < .001$), MapViewer: ($F(16, 85) = 5.14$, $p < .001$). Neuroticism also was negatively correlated with completion times in both interfaces. GVis: ($r(103) = -.47$, $p < .001$, MapViewer: $r(102) = -.54$, $p < .001$). (See Figures 3a and 3b.) ANOVAs to test for the impact of Neuroticism in both interfaces were significant: GVis: ($F(16, 86) = 3.42$, $p < .001$), MapViewer: ($F(16, 85) = 5.14$, $p < .001$). Neuroticism also was negatively correlated with completion times in both interfaces. GVis: ($r(103) = -.47$, $p < .001$) MapViewer: ($r(102) = -.54$, $p < .001$).

Differences in interface completion times and Extraversion were significant across both interfaces: GVis: ($F(14, 88) = 5.37$, $p < .001$). MapViewer: ($F(14, 87) = 4.12$, $p < .001$). These faster participants also tended to be more emotional and sociable. A summary of these findings can be found in Figure 5.

3.2 Task Errors and Personality Factors

The two studies measured tasks errors differently, and so must be analyzed separately. In Study 1, procedural tasks asked participants only to indicate when they had located the target information, so no errors were made or recorded. In Study 2, error was defined as giving the wrong answer to a question. Upon making an error, participants were asked to continue to try until they correctly solved the task. Each incorrect solution was recorded as an error.

Kolomogorov-Smirnov Z was significant in both interfaces (GVis: $p < .001$, MapViewer: $p < .001$). Levene's test of homogeneity was significant in for GVis ($p = .004$), but not MapViewer ($p = .30$), suggesting that sample distributions were not uniformly normal. Due to these two findings, we opted to conduct non-parametric tests for the purposes of the following analyses.

Participants made more errors in GVis ($M = 1.21$, $SD = 1.07$), than they did in MapViewer ($M = .69$, $SD = 1.07$). Friedman's chi square was significant (X^2 (1) = 5.45, $p = .02$) Kendall's tau was conducted between errors in each interface and psychometric scores; no significant associations were found.

Generally speaking, only the difference in interface had a significant impact on how many errors were made; participants were more effective in the MapViewer interface. A summary can be found in Figure 5.

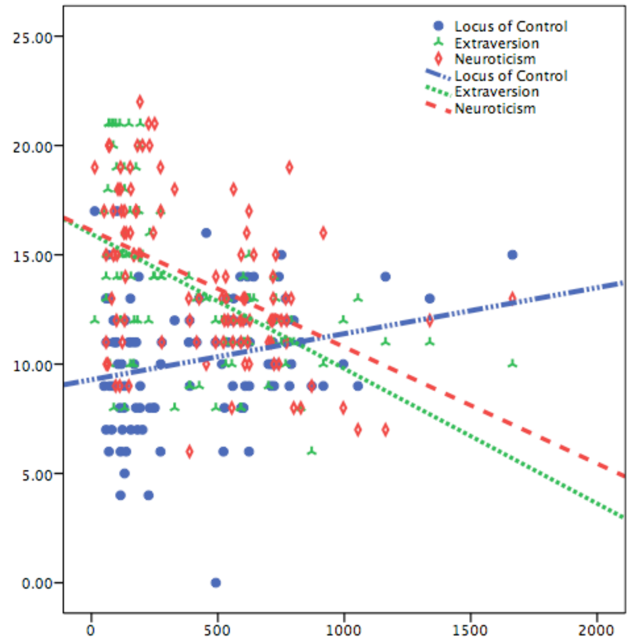

Figure 3a. Correlations of GVis Total Completion Times (in seconds) across procedural tasks and the Locus of Control, Extraversion, and Neuroticism scores.

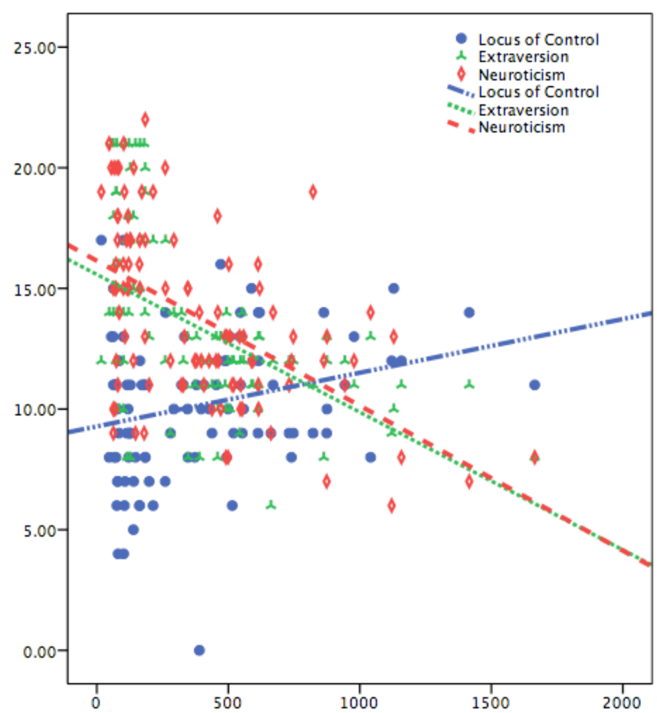

Figure 3b. Correlations of MapViewer Total Completion Times (in seconds) across procedural tasks and the Locus of Control, Extraversion, and Neuroticism scores.

3.3 Insight generation and personality factors

Participants reported having more "unexpected" insights in the GVis ($N = 73$) than in the web-based MapViewer ($N = 70$). The distribution of the combined insights reported across both interfaces was not normal according to the Kolomogorov-Smirnov (GVis: $p < .001$, MapViewer: $p < .001$). Levene's test of homogeneity was significant for GVis ($p < .001$), but not MapViewer ($p = .373$). As the distribution was not normal, a Friedman's chi square was run between the mean number of insights generated in both interfaces, and was not significant: Friedman's X^2 (1) = 1.59, $p = .208$. Kendall's Coefficient of Concordance = .015. This suggests that interface type did not have a significant impact on the number of insights generated.

In an investigation of the impact of Locus of Control (LOC) on insight generation, a Friedman's chi square was run between LOC scores and the mean number of insights generated in both interfaces and was significant. GVis: Friedman's X^2 (2) = 174.36, $p < .001$. Kendall's Coefficient of Concordance = .83. MapViewer: Friedman's X^2 (1) = 101.04, $p < .001$. Kendall's Coefficient of Concordance = .96.

As the sample was large ($n > 50$), Spearman's rho was conducted to evaluate correlations between the psychometric scores and completion times. Locus of Control predicted the number of generated insights (GVis: $R(103) = .20$, $p < .04$; MapViewer: $R(101) = .239$, $p = .016$). Because both studies had a within participants design, a Kendall's tau-b was conducted. LOC was not associated with the number of generated insights in both interfaces (GVis: $p = .59$, MapViewer: $p = .46$).

These findings demonstrate that LOC had some impact on the number of insights the participants reported; persons with a more external locus tended to report a greater number of insights (Figure 4 (top)).

We also explored the impact of Big Five personality traits Extraversion and Neuroticism on insight generation in both interfaces. A Friedman's chi-square between mean Extraversion scores across interfaces was significant. (GVis: Friedman's X^2 (1) = 105.0, $p < .001$. Kendall's Coefficient of Concordance = 1.0. MapViewer: Friedman's X^2 (1) = 105.0, $p < .001$. Kendall's

Coefficient of Concordance = 1.0). Extraversion was associated with insight generation (GVis: τ = -.15, p = .051, MapViewer: τ = -.18, p = ,027), and predicted the number of insights in both interfaces (GVis: R(103) = -.554, p < .001; MapViewer: R(101) = -.543, p < .001). These findings suggest the more insights were reported by participants that were less extraverted (Figure 4 (middle)).

A Friedman's chi-square between mean Neuroticism scores across interfaces was significant: (GVis: Friedman's X^2 (1) = 105.0, p < .001. Kendall's Coefficient of Concordance = 1.0. MapViewer: Friedman's X^2 (1) = 105.0, p < .001. Kendall's Coefficient of Concordance = 1.0). Neuroticism was not significantly associated with insight generation (GVis: p = .716, MapViewer: p = .37), but did predict the number of generated insights in both interfaces (GVis: R(103) = -.415, p < .001; MapViewer: R(101) = -.509, p < .001). These findings suggest that more neurotic participants did not report as many insights as those who had lower Neuroticism scores (Figure 4 (bottom)). A summary is in Figure 5.

4 Discussion

The findings of these studies demonstrate that, even when the procedural tasks are somewhat different, inherent personality differences can predict interaction and behavioral outcomes across the interfaces. Aside from generally evaluating interface learnability, which we did in both studies, we studied procedural learning tasks in two slightly different ways. The first study focused on target identification; participants were asked to find an organism label on the screen: for GVis, this label was attached to a spherical glyph, for MapViewer, very often the label was also a textual hyperlink. Once the label had been obtained, the participant pushed the 'Submit' button and the task was done.

In the second study, we asked participants trivia questions whose answers had to be hunted through the interface. If they gave the wrong answer, we requested that they keep looking. Like the first study, nothing other than an ability to use the interface and identify target labels was required. In both of these tasks, participants found the targeted information more quickly in the web table MapViewer; in Study 2, they also made fewer errors in MapViewer. Given the wide commercial use of web tables, it seems reasonable that most participants brought some prior knowledge of the interaction metaphor to the MapViewer tasks that they did not have for the data visualization. However, participants still strongly preferred GVis to MapViewer, even if they were not as effective in task performance. This may have been due to the novelty of GVis; most participants had never seen anything like it before. It also may have been due to data organization; many participants, in post-study open response, indicated a clear preference for GVis' organization and interaction.

Locus of Control proved to be an influential personality trait no matter what the interface or task. The faster participants in both interfaces were persons who had a more internal locus of control, which is typified by a belief in personal control over life events. This finding is in close agreement with much of the available literature on locus of control. Persons were a more internal locus have been found to have better problem-solving skills [21], to be more resolved to solve a task when it became difficult [22], and to be more likely to develop an intrinsic (internal) motivation to finish a difficult task [22]. Thanks in part to positive behaviors like these, internal locus has also been found to lead to superior

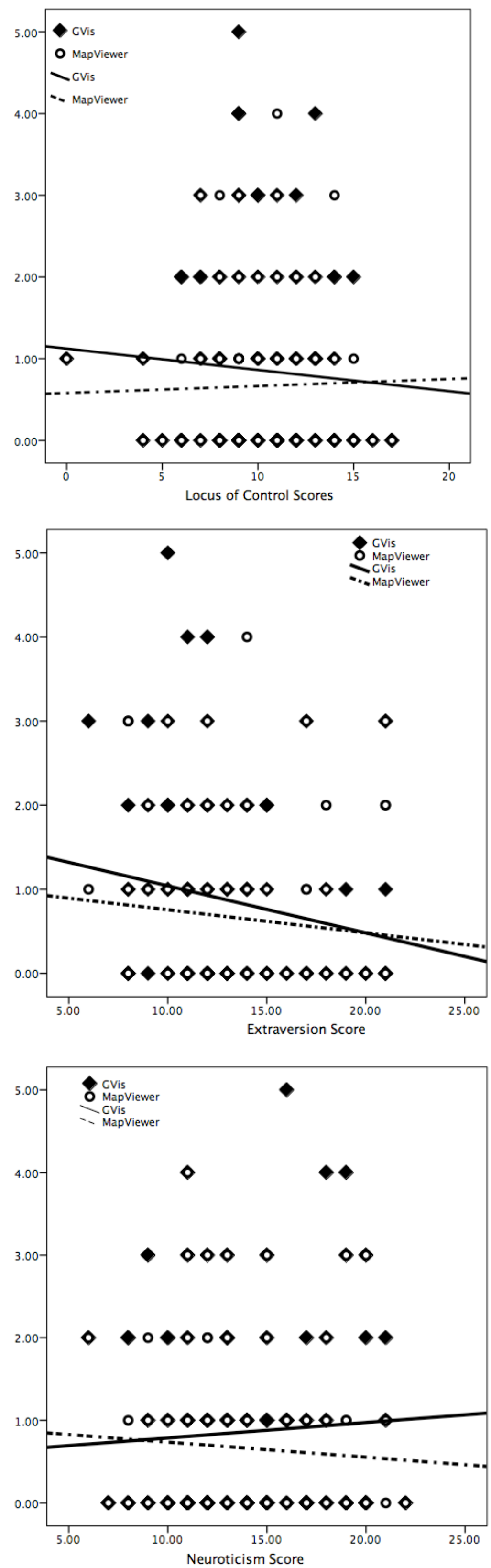

Figure 4. Scatter plot overlay the correlation of generated insights and Locus of Control (top), Extraversion (middle) and Neuroticism (bottom).

outcomes in academics [24], hospital recovery, and organizational environments.

What is intriguing is that, while an internal locus led to faster procedural task outcomes, this is not necessarily the case when the task becomes more cognitively difficult. In a previous paper [10], we studied inferential learning. The tasks required participants to evaluate a multi-dimensional exemplar, and draw a conclusion about other organisms based on similarities or differences. We reported that participants who had a more external locus – those who believe that they are not in control, and who tend to believe in luck as a cause of events – solved inferential tasks in GVis more quickly than those with an internal locus. For a discussion of these results, please see [10]. The results in [10] do not contradict our current findings, but rather expand on them. In these studies, we used a larger N, which likely made our analyses more sensitive to changes in participant scores. Further, we focused on only 3 constructs that seemed more highly predictive, unlike [10] which used 6 psychometric measures.

For one type of learning task performance to be predicted by the degree of internal locus and another type to be predicted by the degree of external locus lends credence to our introductory statement that, depending on task, inherent individual differences can predict interface performance. Yet while locus of control has been shown to be influential in a wide variety of human performance, as previously discussed, to date, it has not been considered by interface designers and evaluators. Based on our research, as well as a broad locus of control literature, we consider locus of control to be one construct in the Personal Equation of Interaction.

In addition to Locus of Control, the Big Five personality factors of Neuroticism and Extraversion also predicted procedural task performance. The more extraverted or neurotic the participant, the more quickly he or she was able to identify target information. This is interesting, but little in the behavioral literature explains these correlations; for us, it is a subject of our ongoing research. Further, Neuroticism in these studies was found to be negatively correlated with Locus of Control ($r(105) = -.284$, $p = .003$). This does have some precedent in the literature. For example, Judge et al. [23] evaluated several personality factors, including Locus of Control and Neuroticism, and found that they were interrelated and could be shown to be a part of the same construct. This means that items from these measures trended together and were statistically predictive of the same personality factor(s). Research like this affirms psychometric constructs can and do work together, Further, it lends credence to an approach that seeks to find items or clusters of items which could work together in the prediction of interaction efficacy.

Insights were also predicted by personality as in factor scores. This is compelling because it suggests that the impact of a predictive Personal Equation may go further than efficacy or efficiency; it may extend to being able to predict some learning or problem-solving outcomes as well. Much depends on how the word "insight" is defined. In the visualization and visual analytics literature, insight is often undefined. When defined, it is often broadly defined, as in [25]. This makes "insight" difficult to use as an evaluative interaction outcome, and thus, as briefly discussed earlier, leaves certain claims about the superiority of visual analytics interfaces unproven. Recently, "insight" has been defined within two categories: knowledge-based insight, and spontaneous insight [19]. Spontaneous insight is a sudden solution to an unsolvable problem, and has often, in the psychological literature, been referred to as an "aha!" moment. Spontaneous insight was not evaluated in these studies.

In these studies, we evaluated the number of knowledge-based insights reported across task and interface, which are generally defined as items or concepts learned or added to the user's knowledge base. In evaluating the knowledge-based insights reported, we categorized insights on the basis of content: insights about how to use the interface itself were separated from insights about the informational content presented and manipulated.

In both interfaces, roughly twice as many knowledge-based insights were reported about interface learnability (GVis: N = 51, MapViewer: N = 47) as were reported about the informational content (GVis: N = 22, MapViewer: N = 23). In both interfaces, the greatest number of interface learning insights was reported in the first question, which suggests that learnability started early. As the task set proceeded, the reported count of each insight type tended to even out somewhat, which is not unexpected; users started paying attention to content once manipulating the interface was less of an issue or became more automatic.

Overall, whether learning about the interface or the interface content, personality factors predicted reported learning as well as other interaction outcomes. These findings have immediate implications. For example, these studies have demonstrated that users who tend to be more extraverted and neurotic are also more likely to believe that they are in control of the task situation (internal locus). By extension, this also means highly neurotic or extraverted users tend to be better at interface manipulation and target identification. If the personality factors of the user were known beforehand, we could reasonably predict how quickly he or she would be able to learn a novel interface and find pertinent information. For even when the interaction metaphor was completely unfamiliar, as it was in the GVis visualization, neurotic/extraverted participants were able to learn to manipulate the data more quickly.

	Completion times	Errors	Insights
Interface	faster times in MapViewer	fewer errors in MapViewer	more insights in Gvis
Locus of Control	internal locus faster times	none	external locus more insights
Extraversion	more extraverted faster times	none	less extraverted more insights
Neuroticism	more neurotic faster times	none	less neurotic more insights

Figure 5. A summary of the findings in Section 3.

However, what these findings do not do is demonstrably differentiate between interface and interactive techniques. The three evaluated personality factors impacted both interfaces similarly. Given the cognitive simplicity of the tasks, this is perhaps unsurprising. Ongoing research has been designed to evaluate learning styles which tend to guide focused attention and information organization during task, and where behavior research suggests more delineating personality factors for visualization technique might be found.

A last note is on the use of novices in evaluations using an expert system; most of the participants had little or no knowledge of biological concepts. However, the participants were still capable of ably find target information in both interfaces. Yet even with the more familiar archetype of the web interface, participants preferred the visualization.

The intent of these studies was never to evaluate the efficacy of GVis *per se*; a formal evaluation of GVis as an expert system is reported in other literature [19]. The aim of these studies was to evaluate human cognition during learning interaction using both interfaces as working artifacts of a kind. In addition, we explored whether individual differences in personality factors and self-beliefs could have a large enough impact on interaction outcomes to warrant their inclusion in the Personal Equation of Interaction.

For these reasons, we recruited non-experts who were unfamiliar with the knowledge domain. Expertise would have biased the user's interaction; they would have had an expert knowledge of the genomic hierarchies, and thus known where to look for the requested information. This would have proven a poor evaluation of how each interface promoted learning.

5 Conclusion

The Personal Equation of Interaction is still very much a work in progress. In the short-term, it serves as an open discovery and proof of concept. We have shown that inherent differences impact interaction. Our ongoing research seeks to better define what differences impact what type of analytical task (for it seems reasonable to assume that one inherent set of differences will only generalize to one type or set of task constraints). For example, we are currently narrowing our task sets to study multiple decision points in specific types of category or inference reasoning. And further, we hope to explore whether that impact is temporally static or dynamic throughout the analytical process.

In the longer term, we intend to isolate predictive matrices and validate a battery of measures that will successfully inform interface design based on the types of cognitive task undertaken. Ultimately, this is the Personal Equation of Interaction. These measures will likely involve more than personality factor matrices; other areas of exploration include perceptual logics and use of decision-making heuristics. In addition to informing design, the Personal Equation could be used to provide real-time interface adaptation to accommodate user needs and preferences, and provide a basis for robust group profiles of users who share common differences, such as experts or users of a particular visualization technique. Visual analytics seeks to facilitate analytical reasoning through the use of interactive visual interfaces. In the Personal Equation of Interaction, we will provide a new tool in that pursuit.

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