Personality as a Predictor of User Strategy: How Locus of Control Affects Search Strategies on Tree Visualizations

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ABSTRACT
Individual differences matter. While this has been the theme for many recent works in the Visualization and HCI communities, the mystery of how to develop personalized visualizations remains. This is largely because very little is known about *how* users actually use visualizations to solve problems and even less is known about how individual differences affect these problem-solving strategies. In this paper, we provide evidence that strategies are indeed influenced by individual differences. We demonstrate how the personality trait locus of control impacts strategies on hierarchical visualizations, and we introduce design recommendations for personalized visualizations.

Author Keywords
visualization; individual differences; strategy; personality; locus of control

ACM Classification Keywords
H.5.2 Information Interfaces and Presentation (e.g. HCI): User Interfaces

INTRODUCTION
There is no optimal visualization design. However, research advocating this notion is still in its infancy and has primarily focused on correlating individual differences to users' speed and accuracy [7, 10, 14]. While these results do highlight differences between groups of users, they give us little to no insight into *how* or *why* groups of users differ. Many open questions remain. For instance, *Do user groups adapt different problem-solving strategies? How can we choose between existing tools?* and *How can we design new tools to better facilitate users' needs?*

We hypothesize that the observed differences in users' speed and accuracy are due to differences in their strategies. Furthermore, we believe that users' strategies can be uncovered by analyzing their interaction patterns and that these strategies are mediated by cognitive traits. By better understanding how individuals use visualizations, the community can begin to design tools that target users' specific cognitive needs.

In this paper, we focus on the personality trait locus of control (LOC) and how it impacts users' search strategies - their data exploration path as they perform searches using a given visualization. LOC describes the extent to which an individual believes that he is in control of external events. Individuals with internal LOC (*Internals*) tend to believe that events are influenced by their own actions, while individuals with external LOC (*Externals*) are more likely to blame outside factors such as luck. LOC has been shown to consistently correlate with performance when using visualizations [2, 7, 10, 14].

We present results from a user study where we captured participants' mouse interactions as they completed simple search tasks using two popular hierarchical visualizations (Figure 1). Overall, we found a strong correlation between LOC and strategies. An initial analysis found that Externals were almost twice as fast as Internals when using the indented tree visualization and conversely, Internals were almost twice as fast as Externals when using the dendrogram.

Further analysis demonstrated that the search patterns for the two groups of users (Internals and Externals) differed significantly, and even within groups, we found that search patterns differed across visualizations. Altogether, our results provide evidence that Externals are less efficient when a visualization affords open exploration than when a visualization provides a guided/restricted exploration.

We make the following contributions:

- We demonstrate how personality (LOC) affects users' speed and search strategies.
- We introduce recommendations for designing personalized visualizations based on the observed user strategies.

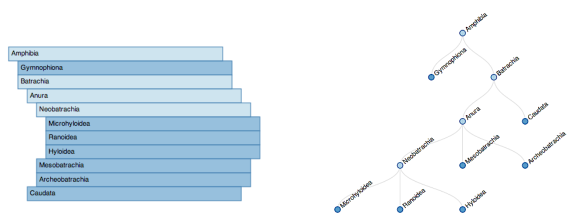
RELATED WORK
The impact of LOC has been explored for many decades beyond the Visualization and HCI communities, and research suggests that the differences between Internals and Externals are quite vast. Internals tend to have a strong sense of self-efficacy allowing them to take control even when faced with difficult problems. Conversely, Externals believe that they have no control over external events, making them far more likely to adapt to situations. However, because of this perceived lack of control, Externals are also more likely to give up when faced with difficulty.

Past research corroborates this. Internality has been shown to correlate with increased effectiveness at work [8], better academic performance [4] and greater ability to cope with stress [1]. LOC also affects learning style. Cassidy and Eachus [3] showed that Internals are more likely to practice deep learning, while Externals are more likely to practice surface learning. In the medical community, LOC has been shown to affect patients' recovery outcomes. Fisher and Johnstion [5] found that users with external LOC were more likely to become discouraged and give in to their disability.

LOC and Visualization

In the visualization community, Green and Fisher [7] and Ziemkiewicz et al. [14] showed a significant correlation between LOC and users' speed and accuracy when using visualizations. More recent work by Ottley et al. [10] demonstrated the solidity of the relationship between LOC and performance on visualization tasks. By using psychological priming to temporarily alter a user's LOC, they showed how changes in LOC can predictably influence a users' performance on visualization tasks.

More recent work by Brown et al. [2] captured click stream data as users performed a visual search task with an interactive visualization system, and successfully used machine learning techniques to classify users based on their LOC. By using mouse interactions as features, this work by Brown et al. [2] suggests that LOC also impacts users' strategies.



(a) Indented Tree (b) Dendrogram

Figure 1: The two visualizations used for our experiment.

EXPERIMENT DESIGN

Grounded by existing work, our experiment examines exactly how LOC impacts strategies. To test participants' LOC, we used the LOC inventory from the International Personality Inventory Pool [6]. We recruited 54 participants over Amazon's Mechanical Turk service (28 males). Participants' age ranged from 20 to 60 with an average age of 33 years. Only 16% of our participants self reported to be familiar with interactive visualizations and 66.7% self reported to have at least a college education.

Each participant was only able to complete the task once and was paid a base pay of $1 plus a bonus for every section successfully completed. A successful participant received a total of $5. This method of renumeration was chosen to dissuade participants from simply clicking through the task to be paid, thus increasing the reliability of our data.

Visualizations

Participants completed search tasks using two hierarchical visualizations: an indented tree (Figure 1a) and a dendrogram (Figure 1b). These particular visualizations were chosen because they are typical representations of hierarchical data [12], are commonly used in real world scenarios and have been extensively studied in the visualization community [7, 10, 14]. The indented tree uses indentation to depict hierarchy while the dendrogram uses a classic node-link structure.

With the exception of the layout, all other the design features were consistent across the two visualizations. Participants were able to explore the datasets by clicking parent nodes to expand their children. Clicking an already expanded node "hides" that subtree. If a user clicks a parent node to expand a "hidden" subtree, the subtree would be restored to its former state.

Datasets

We used two different datasets; both were subsets of a full taxonomic tree retrieved from National Center of Biotechnology Information's Genome database [9]. Each dataset was a phylogeny tree where the leaf nodes were actual species. By hovering over a leaf node, participants were able to access attributes of the species.

Tasks

For the main task, participants performed two simple search tasks (one with each visualization) where they were instructed to find a species under a specified classification with a specified attribute. For example:

> Under the classification "Pelophylax", find the species with the lowest length value.

Procedure

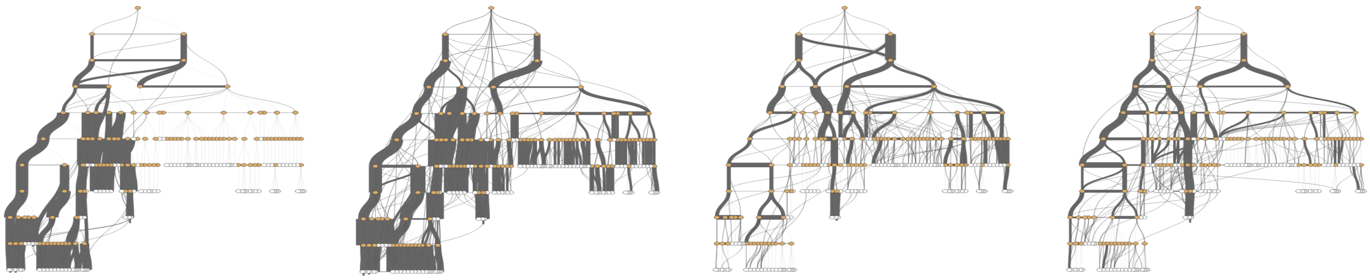
Prior to beginning the experiment, participants completed the LOC survey. The main task was divided into two sessions, one for each visualization. For each session, the participants were first given an opportunity to interact and familiarize themselves with the visualization (a third dataset was used for the trials). They were then instructed to take as long as they needed to interact with the visualization to find the target species.

Once they found the species, they clicked "Ready to Answer" and were then able to enter the species name in the text field provided. At this point, they were no longer able to interact with the visualization and we recorded their search times, mouse clicks, hovering and scroll events. After the main tasks, each participant completed usability and demographic surveys.

RESULTS

Each participant performed 2 search tasks (one with each visualization), resulting in a total of 108 trials. To filter the inherent "noise" in our Mechanical Turk data, our analysis only includes trials where the participant successfully found the target (91 trials).

The average time spent completing the task was 259 seconds (σ = 207.7) with an average of 75 clicks (σ = 11), and the overall accuracy rate was 68% (75.6% with the indented tree and 62% with the dendrogram). While participants were slightly more accurate with the indented tree, the observed difference was not statistically significant ($\chi^2(1, N= 91)= 1.92, p = .166$).



(a) Externals with indented tree (b) Internals with indented tree (c) Externals with dendrogram (d) Internals with dendrogram

Figure 2: The figures above show the aggregated exploration paths for users who were successful in locating the target. We grouped users based on a median split of their LOC scores and the visualization design used. For ease of comparison, we used a dendrogram to visualize the exploration paths of both visual designs used in our experiment. The weight of the links represent the percentage of users from that group who traversed that link during their search.

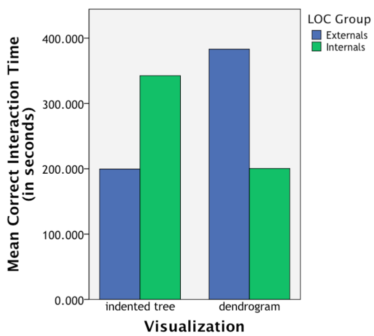


Figure 3: Mean correct response time for the two LOC groups across the two visualization designs.

Interaction Time

We divided participants into two groups based on the median split of their LOC scores. We then ran a 2x2 Univariate Analysis of Variance on the log interaction times to test for differences between the two LOC groups (Externals vs. Internals) across the two visualization designs (indented tree vs. dendrogram). Our overall model was significant ($F(3, N=91) = 3.189$ $p = .03$) and the interaction between LOC group and visualization was also statistically significant ($F(1, N=91) = 9.297$ $p = .003$).

Figure 3 summarizes our interaction time findings. Taking a closer look at interaction times, we found that Externals were almost two times faster with the indented tree visualization (Figure 1a) than the Internals. The Externals were also almost two times faster with the indented tree than they were using the dendrogram (Figure 1b). Interestingly, we observed the exact opposite effect with the Internals.

Strategies

During the experiment, a user explored a non-leaf node by clicking to expand or collapse its children and explored a leaf node by hovering to view its attributes. For our analysis we recorded each participant's mouse click and mouse hover events.

With this data, we were then able to reconstruct each user's exploration path as they searched for the target species. This analysis was performed manually using a visualization tool that we developed specifically for this study, and utilizes animation and juxtaposition to compare different exploration paths. Figure 2 summarizes our findings.

In general, we found that visualization design influences a user's strategies. When using the indented tree visualization, most participants explored the tree in a top-down fashion, resulting in a search strategy that resembles a depth-first search. Search patterns with the dendrogram were usually less structured and were often a combination of depth-first and breadth-first search.

Again, we separated participants into LOC groups. When using the indented tree visualization, Externals tended to be very strategic and explored the tree in top-down fashion, following the search strategy afforded by the visualization design (Figure 2a). While this strategy logically follows the indented tree's top-down design, we found that Internals were far less likely to adopt this strategy (Figure 2b). This resulted in a more exploratory but less effective search strategy.

Conversely, when using the dendrogram visualization, we found that Externals adopted more sporadic search techniques, resulting in much slower interaction times (Figure 2c). On the other hand, Internals performed a combined depth- and breadth- first search that proved quite effective with the dendrogram (Figure 2d).

DISCUSSION

While we seldom think about a user's personality traits when designing interfaces, the current work demonstrates why they must be considered. Between the tested designs, no design was suitable for all users. We found that Externals performed better with the indented tree but the Internals were more effective with the dendrogram. When asked which visualization they preferred using, 78% of Externals reported to prefer the indented tree over the dendrogram and 63% of Internals said they preferred the dendrogram.

These results are consistent with the LOC construct. Internals prefer control and tend to struggle when a visualization does not fit the their mental model of a problem [14]. While both visualizations were fully exploratory, the design of the indented tree best facilitates a top-down exploration and users who adapted this strategy were fastest (see figure 2a). This design property is subtle, still it proved to be a hindrance for the Internals. Conversely, since Externals in general do not believe that they can influence external events, they are more adaptable and were able to adopt the top-down search strategy afforded by the indented tree.

The scenario was reversed for the dendrogram visualization. The dendrogram proved to be more versatile and as a result, the Internals excelled with this visualization. They were able to freely search in a manner that best fit their mental model of the data. Unfortunately, this versatility was incompatible with the Externals. Their perceived lack of control coupled with the lack of guidance may have been too overwhelming.

Our design implication follows directly from this finding. When designing for Internals, designers should ensure that designs are flexible to users' mental models. Internals perform better when a visualization allows them to explore the data freely and doesn't impose a strategy. However, the needs of Externals are quite different. While they are in general more flexible and are likely to adapt to novel designs, our findings suggest that adapting to a flexible system may be overwhelming. Unlike Internals who take control of difficult situations, Externals are more likely to feel hopeless and may give up. Thus, it is essential to provide guidance (implicit or explicit) to Externals.

That said, LOC is a multidimensional construct and there are also many other cognitive traits and states that may impact performance on visualization systems [11]. Thus, it is important for us to better understand how these factors, individually and collectively, impact the usability of our designs. There is also evidence that certain traits can be detected from users' interactions [2, 13]. Future work can expand this existing research by exploring how systems can automatically detect and adapt to an individual's specific needs.

CONCLUSION

Altogether, we have demonstrated that individual differences, specifically the personality trait locus of control, do impact both interaction times and search strategies. We believe that our work is a significant step toward fully understanding *how* individual differences affect visualization use and how we can begin to design visualizations that better facilitate users' cognitive needs.

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