Take a Walk: Evaluating Movement Types for Data Visualization in Immersive Virtual Reality

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ABSTRACT

3D virtual reality (VR) technology has long promised to provide new ways to view and interact with abstract data, but it has been held back by technological limitations and the difficulty of moving through 3D environments. Recent innovations in VR technology overcome previous constraints, but existing research has had mixed insights into the optimal types of virtual movement for task performance. We conducted a two-factor between subjects (N = 20) pilot experiment testing two types of viewpoint interaction for exploring a 3D scatterplot in a virtual environment developed using consumer-grade VR hardware and software tools. In one condition users changed their viewpoint by physically walking around the 3D scatterplot, the system matching their physical location to their virtual one. In the other users stood still and rotated the scatterplot with a controller. An exploratory analysis of plot-specific memory tasks revealed that individual differences played a strong role depending on the condition. In particular, low spatial ability users were better supported by walking interaction rather than interaction using a controller. The pilot experiment revealed potentials for improvements in the chosen measures, and the findings will inform the design of future larger-scale evaluations.

Keywords: Virtual reality, visualization, immersive analytics, 3d navigation, evaluation

Index Terms: • Human-centered computing~Laboratory experiments • Human-centered computing~Virtual reality

1 INTRODUCTION

Representing information graphically has long helped people understand data, but as we generate increasingly large, complex datasets our visualization toolset struggles to keep pace. Recent advances in immersive virtual reality (IVR) promise to make implementation of highly intuitive interactions with full 3D environments relatively straightforward for the first time [1]. Many researchers have looked to IVR to help users unlock meaning latent in large datasets, speaking of the potential power of immersing users in their data [2, 3]. For example, Nagel et al. [4], proposed that interacting through embodied movement would aid in understanding data representations.

Currently, 3D representations are often eschewed within information visualization and visual analytics [2, 5]. A major obstacle has been that 3D visualizations necessitate movement, or *viewpoint transition*, which requires more complexity than an equivalent 2D visualization. The difficulty of navigating in a 3D environment itself has long held back 3D visualization [6, 7], and moving through 3D environments is a high cognitive load task [8]. Shovman et al. [9] even found that restricting degrees of freedom of movement can increase performance for some tasks in 3D.

Studies regarding viewpoint transitions have had mixed results regarding task performance differences between rotating or moving stimuli and moving/rotating users. For example, Wraga et al. [10] found support for bodily rotation being superior to pure virtual rotation in a search task in a virtual environment. Similarly, Riecke et al. [11] found that walking was superior compared to joystick-driven viewpoint changes, also using a virtual environment search task. In contrast, Holmes et al. [12] did not find a difference in performance in a memory task between participants who rotated a model on a table and those who instead walked around it. They did find, however, that both types of rotations were superior to a series of static views, indicating the importance of the transitions themselves.

Given that VR studies have found advantages for coupling physical and virtual movement (i.e., embodied movement), as well as pointing to the difficulty of 3D navigation using hand-held input devices, we hypothesized that walking around a 3D data representation would result in better comprehension of the data than simply rotating the representation using an input device (remaining static themselves). In order to begin evaluating this hypothesis, we created an IVR platform to display 3D scatterplots in a room-scale virtual environment that allowed users to either walk around the scatterplot object, or rotate and move it using a controller. We use scatterplots as a departing point for evaluating 3D IVR visualization techniques as they are comparatively simple representations that are readily adaptable to an added dimension, and have been used in previous 3D visualization studies [5, 13].

2 METHODS

2.1 Participants

20 participants (11 female, 9 male) in total took part in the study. The average age was 24.9 years and all were students in the Department of Geography, Pennsylvania State University. Each participant was paid 5 dollars for completing a session.

2.2 Materials

We selected the HTC Vive room-scale VR system running a SteamVR-based virtual environment developed in Unity game engine as the IVR platform. See Figure 1 for the physical setup and

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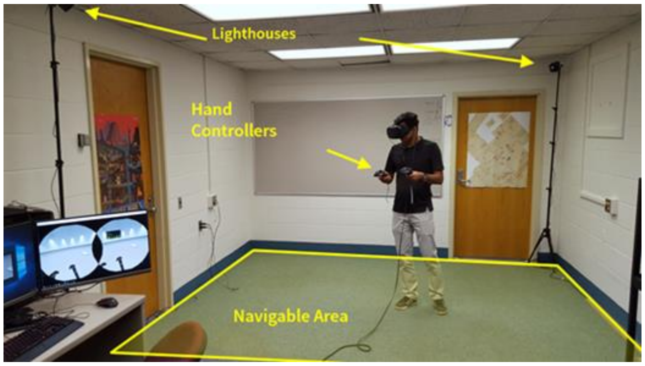

Figure 1: The IVR hardware (HTC Vive), which allows a user to move around a limited physical area, in which their physical position is matched to their virtual position.

experiment location. The virtual environment provided a consistent reference frame while lacking distinguishing features that would detract from the plot itself (Figure 2). The scatterplots could be rotated around the vertical axis using a controller. The scatterplots were generated using a set 3D model for the axes and tick marks, with the labels and points being generated using five datasets exported from base R [14]: *airquality, mtcars, iris, state* (renamed "Countries" within the experiment), and *seatbelts*.

Three performance measures were created for this experiment to ascertain participants' comprehension, or more accurately, their ability to *memorize* of each of the scatterplots encountered. First, participants were asked to estimate the number of points of the last scatterplot presented as a basic memory task. Estimates were scored as the error from the true value, as a percent of the true value (lower is better). Second, users were asked which pairs of graphed variables in the presented scatterplot were positively correlated, if any, and which pairs were negatively correlated, if any.

Third, participants were given two matching questions, where they were presented with images of four similar graphs, and tasked with selecting the one correct image of the last scatterplot they viewed. For the correlation and matching tasks, scores are percentage of correct selections (higher is better).

Two measures of individual differences were administered, one as a measure of graph reading ability, and another as a proxy for spatial abilities (mental rotation). The mental rotation questionnaire was made up of six items from the original 24-item scale (Cronbach's alpha: $\alpha = .81$) from Peters et al. [15]. We selected nine items from Galesic's [16]) 13-item graph literacy questionnaire, removing questions that appeared to duplicate one another (e.g., multiple questions about bar charts). The Cronbach's alpha was low ($\alpha = .32$), and no spurious items were apparent, so caution must be used in interpreting results.

Several additional features were implemented to facilitate the experiment. Graphic user interface (GUI) elements included a timer that counted down until the end of an exposure for the participant, and a virtual laser pointer-like visual attached to the HTC Vive controller. The height of the scatterplot was adjusted automatically according to the height of the user.

2.3 Design and Procedure

To evaluate our hypothesis that walking/embodied interaction increases user memory of a 3D graph object compared to rotating the object using an input device, we designed a between-subjects experiment. Participants encountered a series of five 3D scatterplots within an IVR system. They answered performance-based questions regarding the scatterplots in one of two conditions, which represented two different types of viewpoint interaction

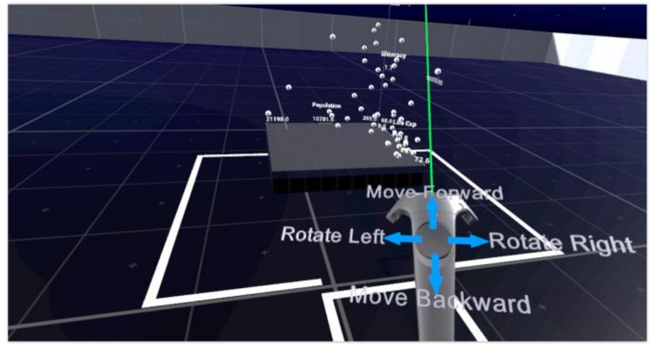

Figure 2: Interacting with a 3D scatterplot in rotating condition within the virtual environment. The virtual controller functions are labeled.

(Figure 3). The first is walking, where the user is able to walk around the 3D scatterplot embedded in an IVR environment, their virtual viewpoint being matched to their physical location and look direction by the system. The second condition is rotation, where users are immersed in the same IVR environment, but do not move. Instead, they must use a controller to rotate and move the scatterplot in order to view it from different sides (Fig. 3).

Experiments were conducted in 225 Walker building on Pennsylvania State University's main campus (Figure 1). At the beginning of a session, participants were informed of the nature of the experiment, and briefed on their rights as a participant in accordance with the approval obtained by the Pennsylvania State University Institutional Review Board (IRB). Condition assignment was randomized, with 10 participants per condition. Once verbal consent was obtained, participants were then given the demographics questionnaire, the mental rotation test, and the graph reading test, before moving to the training phase.

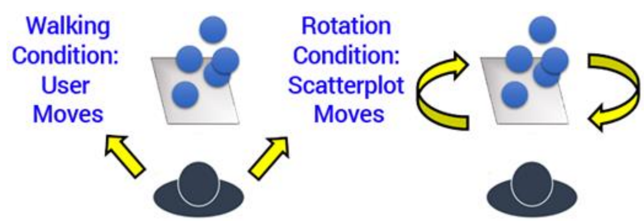

Figure 3: The two experimental conditions.

In the training and encoding phases, participants were assigned to one of the two conditions (i.e., walking or rotating). Participants alternated between viewing five scatterplots and completing the accompanying task questionnaire on a desktop computer, which required removing the headset. The first scatterplot was used for training and the participant viewed it for three minutes as the experimenter verbally instructed the participant, but the viewing time was restricted for two minutes for the remaining four scatterplots. In the Walking condition, participants were instructed to walk one full loop around the scatterplot, while in the Rotation condition participants were instructed to rotate the scatterplot completely around one time. Afterwards, participants in both conditions were allowed to view the scatterplot for the remaining amount of time using the assigned interaction technique. After the viewing time was complete, they completed the accompanying set of task questionnaires. Once all task sets were complete, the participants filled out a demographics questionnaire and two other data collection instruments (regarding cognitive absorption and presence), which we do not analyze here.

3 Results

For analysis, we considered the mean of the results of the training task and the four graph tasks as our performance measures, on a per-task basis (see Table 1 for a summary). We tested each task using independent-sample T-tests with Welch's correction for unequal variance (all reported statistics are so adjusted) to evaluate our hypothesis that performance in the walking condition would be superior. In measured point estimation performance, Walking (M = 0.28) did not differ significantly from Rotation (M = 0.38), t (17.83) = -2.04, p = 0.97. Similarly, in measured correlation performance, walking (M = 0.55) did not differ significantly from Rotation (M = 0.5), t (17.40) = 0.68, p = 0.25. For matching performance, walking (M = 0.64) also did not differ significantly from Rotation (M = 0.64), t (17.44) = 0.00, p = 0.50. Therefore, we surprisingly found no evidence that walking results in superior comprehension of a data object in terms of our measures. We review potential reasons for these non-significant results in the Discussion section.

Table 1: Summary statistics for dependent variables.

		Correlation (proportion correct)	Matching (proportion correct)	Estimation (error as proportion of true value)
Walking	Mean	0.55	0.64	0.28
	SD	0.16	0.17	0.11
Rotation	Mean	0.50	0.64	0.38
	SD	0.13	0.14	0.12

3.1 Exploratory ANCOVAS

For a more detailed analysis, we conducted a series of exploratory factorial (three-way) ANCOVAs using the per-graph performance measures as the dependent variables and the condition, mental rotation score, and graph reading score as the independent variables. This was intended to identify potential interactions between those factors and tasks which were not apparent in the aggregate scores. In total, 15 ANCOVAs were conducted (five datasets with three tasks each), and three had significant interactions. These significant interactions are detailed in the following subsections. Please note that while within the ANCOVA mental rotation scores were treated as continuous variables, for the purposes of tables and graphing we performed a median split on mental rotation score.

The matching task of the Iris dataset scatterplot was the first significant interaction found. There was an interaction between condition and mental rotation, F(1, 12) = 35.53, p < .01., and a main effect for both condition, F(1, 12) = 13.14, p < .01, and mental rotation, F(1, 12) = 23.21, p < .01. As can be seen in Figure 4, Rotation condition users who had lower mental rotation scores also had lower scores on the matching task, wherein the walking condition there was little difference between low- and

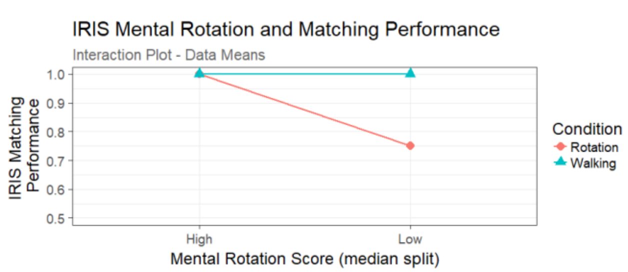

Figure 4: Interaction plot for the IRIS dataset, matching task.

high-scoring mental rotation participants and performance. Essentially, participants in the walking condition did well at the task regardless of their mental rotation score, while the performance of participants in the Rotation condition was correlated with their mental rotation scores.

For the correlation task of the Countries dataset scatterplot, there was an interaction between condition and mental rotation, F(1, 12) = 6.59, p = .03. Similar to the results of the Iris dataset and matching task, in the Rotation condition users who had lower mental rotation scores also had lower scores on the task (Figure 5).

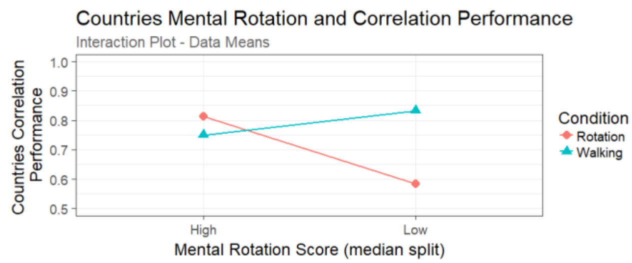

Figure 5: Interaction plot for the Countries dataset, correlation task.

For the matching task of the Countries dataset scatterplot, there was a significant three-way interaction between condition, mental rotation score, and graph reading score, F(1, 12) = 8.37, p = .01. As can be seen in Figure 6, low-spatial ability participants do better in the walking condition, but interestingly they do better even than high spatial ability users. This interaction is partly due to participants with high graph reading scores *and* high spatial ability scores having done poorly on the task in the walking condition, compared to participants with similar graph reading scores in the rotation condition.

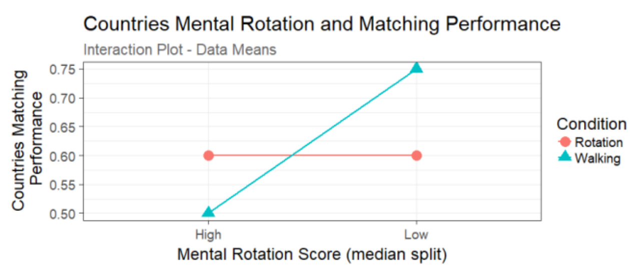

Figure 6: Interaction plot for the Countries dataset, correlation task.

4 Discussion

In terms of our collected data, we did not find significant differences between conditions in terms of performance, but this may be due to the small sample size, rather than a lack of effect. However, in our exploratory ANCOVAs we found a relationship between condition and mental rotation in three sets of tasks and datasets, one of which also interacted with graph reading performance.

Spatial abilities are known to have an impact in virtual tasks; for example, participants with low spatial abilities take longer and make more errors [17]. In our study, low spatial ability participants have more difficulty in the Rotation condition. This may because they are forced to adopt a response-based (egocentric) spatial learning strategy rather than an place-based (allocentric) strategy [12], as the 3D scatterplot environment lacks suitable points of reference. The Walking condition may support a response-based strategy much better than the Rotation condition because of participant self-locomotion. We speculate high spatial ability participants are not affected by that limitation in the Rotation condition to the same degree, explaining the interactions found. High spatial ability participants then may have been able to exploit the superior rotation speed in the Rotation condition, explaining the better performance in that condition for some tasks.

Overall, our the data points towards physical walking being a useful interaction approach to help low-spatial ability users in virtual environments, but either not making a strong difference or having a negative influence on high-spatial ability users. Notably, the combination of virtual and physical spaces appears to be important even in the context of abstract virtual environments that are not meant to simulate a real place. If this finding holds true in higher-power follow up studies, it has implications for the design of future VR systems for all users. For example, data visualizations intended for the broadest possible audience might be more effective using walking-type navigation despite the added space requirements.

5 Future Work

This pilot study was intended as a prelude to future experimental evaluations of different aspects of IVR, and provided valuable insights into the overall validity of our methods, procedures, and materials, particularly our custom IVR system. This study will lead to more rigorous evaluations of visualization and interactive techniques for the creation of IVR workbenches, such as those for environmental planning as discussed in Simpson et al. [18]. Naturally, as a pilot study, there were numerous discoveries that will augment future work.

The measures of comprehension of representations will be further refined, to increase our construct validity, reflect more real-world tasks, and further exploit the multidimensional aspects of representations. Notably, we will work towards an approach that will measure comprehension rather than simple memorization. As for other tasks, Amar et al. [19] provide a useful generalized list of potential data retrieval tasks: *retrieve value, filter compute, derived value, find extremum, sort, determine range, characterize distribution, find anomalies, cluster, and correlate*. There was a notable issue with the correlation task, in that the optimal solution (which nearly all participants adopted) was to rotate the graph in order to have a direct side-view of pairs of variables, essentially aligning their view until the 3D representation was functionally 2D. 3D specific tasks from previous scatterplot studies will be integrated, such as the trivariate pattern detection task in Shovman et al. [9].

The specific measures of individual difference used here, graph reading and mental rotation ability, will also be revised in future studies. The graph reading pre-test did not produce reliable results, and another questionnaire will be used in follow-up studies. For the mental rotation test, half the participants had a perfect score, indicating a problematic ceiling effect which can be addressed by adding more questions and adding a time limit. Other spatial abilities measures will be explored, such as working spatial memory [20].

While we focus in this work on graph reading skill and spatial abilities, how individual differences of all types affect technology use more broadly of are of great research interest. These differences are important since they can drastically affect perception and operation of new technology in particular, but which traits are the most salient for particular tools or tasks in immersive environments has not been fully investigated. Some visualization research has established strong correlations between task strategy and personality traits, such as work by Ottely et al. [21] on the *locus of control* trait. Research on technology acceptance (e.g., [22]) has also examined all personality traits identified in the field of psychology such as the five-factor model on technology adoption and use. We believe individual differences research should inform future immersive studies and software design in order to maximize our understanding of how to create usable immersive analytics systems.

For future iterations of the navigation conditions evaluated in this study, there are particular aspects that could be updated to increase the validity of the comparison. For example, the effective rotation speeds in the two conditions should be more similar in order to compare the types of interaction. In the rotation interaction, it took approximately 3 seconds to rotate the graph 360 degrees, which is much faster than users in the Walking condition could reasonably walk around the graph. Therefore, while available viewpoints of the scatterplot were constant, users in the Rotation condition could navigate between those views more quickly. This was particularly pertinent in the correlation task, where users in the Rotation condition could more easily “double-back” and review the scatterplot from the direction that revealed the given bivariate relationship. On the other hand, this also reveals practical implications: virtual rotation is not limited by the physical mobility of users, and can therefore be much faster.

In the future, a greater variety of scatterplots will be used in order to increase the generalizability of the findings. In the current study, the Iris graph was the only one with very apparent clustering (clustering itself being an important property examined by other work [13]), while the other graphs had points spread across a wider range of values. While we did attempt to have a range of graphs in terms of the number of data points (32 to 192), three of the plots had 150 points or more, which may very well be beyond the point where most users can easily identify trends. More datasets with more varied patterns should be examined.

The experimental software was intentionally simple, but several features would assist in running evaluations. For instance, ideally all tasks would be completed within an IVR environment. The requirement for the participant to remove the headset to fill out the task questionnaire was distracting, and may have affected performance. It also does not reflect likely future use-cases, where users will be performing many tasks entirely within in an IVR environment.

6 Conclusions

This study successfully demonstrated the feasibility of running human participants data visualization experiments using commercial consumer-grade virtual reality technologies. Users had no apparent difficulty with learning and operating the IVR system. While there does not appear to be a direct overall difference in memory of scatterplots between users who explored the scatterplots by walking and those who stood still and rotated the scatterplot with a controller, the exploratory analysis revealed individual differences can play a large role depending on the type of navigation. Mental rotation ability seems to largely determine performance in the Rotation conditions, but less so in the Walking condition. If this finding holds in higher-power follow up studies, this implies that despite the lack of overall difference, walking better supports users with low spatial abilities in IVR systems. As a pilot study, it succeeded in identifying weak points in the experimental framework that will be addressed in future work.

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REFERENCES

[1] C. Donalek *et al.*, *Immersive and Collaborative Data Visualization Using Virtual Reality Platforms*, 2014.

[2] T. Chandler *et al.*, *Eds.*, *Immersive Analytics*. Big Data Visual Analytics (BDVA), 2015, 2015.

[3] D. F. Keefe and T. Isenberg, “Reimagining the Scientific Visualization Interaction Paradigm,” *Computer*, vol. 46, no. 5, pp. 51–57, 2013.

[4] H. R. Nagel, E. Granum, S. Bovbjerg, and M. Vittrup, “Immersive Visual Data Mining: The 3DVDM Approach,” in *Lecture notes in computer science, State-of-the-art survey 0302-9743*, vol. 4404, *Visual data mining: Theory, techniques and tools for visual analytics / Simeon J. Simoff, Michael H. Böhlen, Arturas Mazeika (eds.)*, S. J. Simoff, M. H. Böhlen, and A. Mazieka, Eds., Berlin: Springer, 2008, pp. 281–311.

[5] J. Poco *et al.*, “A Framework for Exploring Multidimensional Data with 3D Projections,” *Computer Graphics Forum*, vol. 30, no. 3, pp. 1111–1120, 2011.

[6] F. Amini *et al.*, “The Impact of Interactivity on Comprehending 2D and 3D Visualizations of Movement Data,” (eng), *IEEE transactions on visualization and computer graphics*, vol. 21, no. 1, pp. 122–135, 2015.

[7] P. Klemm *et al.*, “3D Regression Heat Map Analysis of Population Study Data,” (eng), *IEEE transactions on visualization and computer graphics*, vol. 22, no. 1, pp. 81–90, 2016.

[8] N. Elmqvist, P. Dragicevic, and J.-D. Fekete, “Rolling the dice: multidimensional visual exploration using scatterplot matrix navigation,” (eng), *IEEE transactions on visualization and computer graphics*, vol. 14, no. 6, pp. 1141–1148, 2008.

[9] M. Shovman, J. Bown, A. Szymkowiak, and K. C. Scott-Brown, “Twist and Learn,” in *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, Seoul, Republic of Korea, 2015, pp. 313–316.

[10] M. Wraga, S. H. Creem-Regehr, and D. R. Proffitt, “Spatial updating of virtual displays,” *Memory & Cognition*, vol. 32, no. 3, pp. 399–415, 2004.

[11] B. E. Riecke *et al.*, “Do We Need to Walk for Effective Virtual Reality Navigation? Physical Rotations Alone May Suffice,” in *Lecture Notes in Computer Science*, Vol. 5248 : Lecture notes in artificial intelligence, *Spatial cognition*, C. Freksa, Ed., Berlin, Heidelberg, New York, NY: Springer, 2010, pp. 234–247.

[12] C. A. Holmes, S. A. Marchette, and N. S. Newcombe, “Multiple Views of Space: Continuous Visual Flow Enhances Small-Scale Spatial Learning,” (eng), *Journal of experimental psychology. Learning, memory, and cognition*, 2017.

[13] M. Sedlmair, T. Munzner, and M. Tory, “Empirical guidance on scatterplot and dimension reduction technique choices,” (eng), *IEEE transactions on visualization and computer graphics*, vol. 19, no. 12, pp. 2634–2643, 2013.

[14] R. Core Team, *R: A Language and Environment for Statistical Computing*. Vienna, Austria. Available: https://www.R-project.org/.

[15] M. Peters *et al.*, “A redrawn Vandenberg and Kuse mental rotations test: different versions and factors that affect performance,” (eng), *Brain and cognition*, vol. 28, no. 1, pp. 39–58, 1995.

[16] M. Galesic and R. Garcia-Retamero, “Graph literacy: a cross-cultural comparison,” (eng), *Medical decision making : an international journal of the Society for Medical Decision Making*, vol. 31, no. 3, pp. 444–457, 2011.

[17] J. L. Gabbard and D. Hix, *A Taxonomy of Usability Characteristics in Virtual Environments*.

[18] M. Simpson *et al.*, “Immersive Analytics for Multi-objective Dynamic Integrated Climate-Economy (DICE) Models,” in *Nature meets interactive surfaces: Companion proceedings of the 2016 ACM International Conference on Interactive Surfaces and Spaces : ISS 2016 : November 6-9, 2016, Niagara Falls, Canada*, Niagara Falls, Ontario, Canada, 2017, pp. 99–105.

[19] R. Amar, J. Eagan, and J. Stasko, “Low-level components of analytic activity in information visualization,” in *Proceedings of the 11th IEEE Symposium on Information Visualization 2005: INFOVIS 2005 ; October 23- 25, 2005, Minneapolis, Minnesota*, Minneapolis, MN, USA, 2005, pp. 111–117.

[20] H. D. Zimmer, S. Münzer, and K. Umla-Runge, “Visuo-spatialWorking Memory as a Limited Resource of Cognitive Processing,” in *Cognitive technologies, Resource-adaptive cognitive processes*, M. W. Crocker and J. H. Siekmann, Eds., Berlin, London: Springer, 2010, pp. 13–34.

[21] A. Ottley, H. Yang, and R. Chang, “Personality as a Predictor of User Strategy,” in *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, Seoul, Republic of Korea, 2015, pp. 3251–3254.

[22] S. Devaraj, R. F. Easley, and J. M. Crant, “Research Note —How Does Personality Matter?: Relating the Five-Factor Model to Technology Acceptance and Use,” *Information Systems Research*, vol. 19, no. 1, pp. 93–105, 2008.