

# Evaluating User Engagement in Information Visualization Using Mixed Methods

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## ABSTRACT

Engagement is an important aspect of user experience, yet its evaluation has not received much attention in the InfoVis literature. For visualization design and evaluation, it is useful to understand both the characteristics of user engagement and how engagement develops and changes over time. We describe a study that used a mixed-methods approach to evaluate user engagement with two different types of visualizations. Multiple qualitative and quantitative methods—including think aloud, eye-tracking, questionnaires, and interviews—were employed. We report initial results involving verbal protocols and eye-tracking data. We reflect on the findings and discuss plans for further data analysis and future research.

**Index Terms:** H.5.m [Information interfaces and presentation (e.g., HCI)]: Miscellaneous—

## 1 INTRODUCTION

As InfoVis research and practice expands increasingly beyond performance-related concerns, issues related to the broader user experience need to be addressed. One such issue is *user engagement*. Increasing a user’s level of engagement can enhance experience—making users feel more involved, motivated, and empowered. While engagement is generally understood as positive cognitive, emotional, and behavioral involvement, there is currently no clear and comprehensive understanding of user engagement in InfoVis scholarship [3], and no well-established instruments exist for measuring and assessing user engagement with interactive visualizations [5].

In a previous study [1], we proposed an initial scope of user engagement for InfoVis along with a preliminary assessment instrument. However, we found several limitations from the on-line pilot study of the proposed instrument—e.g., the unauthentic task setting which violates our scope-related factors of intention, autonomy, and purpose. Also, the sophistication of the visualizations was necessarily low, due to the limitations of conducting studies on crowd-sourcing platforms. Finally, because the study was conducted on-line, we could not observe participants’ physical behaviors such as eye movements and facial expressions, nor could we collect rich qualitative data via verbal protocols. Previous research shows that such behaviors and verbalizations provide insight into inner subjective activity, thus being relevant in assessing user engagement.

As a followup study, we used a mixed-methods (i.e., quantitative and qualitative) approach to evaluate user engagement in a laboratory setting.<sup>1</sup> We had two primary research questions for the study:

1 – What factors contribute to the development and fluctuation of engagement over time as users interact with visualizations?

2 – How do users understand their own engagement levels when interacting with visualizations?

Our goal was to assess and characterize participants’ engagement levels via verbal protocols, eye tracking, behavioral indicators, and

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Figure 1: Two visualizations (L: Explanatory; R: Exploratory) with heatmap overlays showing gaze fixation for one participant during the think-aloud session.

self-assessments. The results of this research can contribute to the development of descriptive and explanatory models and frameworks of engagement and its development over time, and can suggest guidelines on how to design and evaluate interactive visualizations with user engagement in mind.

### 1.1 Mixed Methods

Although a mixed-methods approach typically requires extra time and effort, it can provide rich data about non-quantifiable aspects of user experience in addition to quantifiable performance-related aspects. Our approach relies on various self-reporting methods, eye tracking, and mouse tracking.

**Self-reporting** is one of the most popular approaches to assessing psychological constructs. Popular methods include *interviews*, *think-alouds* and *think-afters*, and *questionnaires*. Many self-reporting instruments exist for assessing psychological constructs such as flow, immersion, playfulness, and enjoyment. **Eye tracking** is used to identify and analyze patterns of visual attention as users perform specific tasks. Measures such as pupil dilation, gaze fixation, and visit count can be used as indicators of task difficulty, fatigue, mental activity, and intense emotion. Pupil dilation can suggest cognitive load and emotional arousal. Eye-tracking approaches for evaluating visualizations have been receiving considerable interest in recent years [2]. **Mouse tracking** can capture users’ interaction behavior and can be used to cross-reference such behaviors with eye-tracking measures and verbal protocols.

## 2 EXPERIMENT

We recruited 13 participants (ages 21 to 47; 8 females, 5 males; all native English speakers). Participants were recruited at Purdue University and their participation was completely voluntary.

### 2.1 Procedure

Participants were introduced to two interactive visualizations (see Fig. 1). Due to the impracticality of studying all visualization techniques, we chose two different types of visualizations: (a) explanatory—those with pre-defined messages that designers intend to communicate to users (e.g., some journalistic visualizations);

<sup>1</sup>For more details visit: <https://yahsin.github.io/MixEngage/>

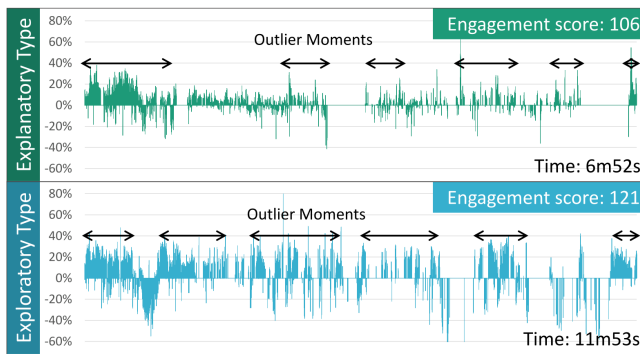


Figure 2: Pupil size change over time for one participant's think-aloud session. Baseline is calculated from 0ms-500ms before the session. Engagement score calculated from questionnaire in [1].

and (b) exploratory—those with no pre-defined message that need to be investigated to derive meaning (e.g., visual analytics tools). Although there is not always a clear distinction between the two types, we believe it is a useful starting point for studying engagement in different contexts.

Participants were asked to **think aloud** while exploring and making sense of the two visualizations. During the session, an eye tracker and a microphone recorded participants' voice, eye movements, and mouse movements. The **eye-tracker** used in this study was the Tobii X3-120. At the end of each think-aloud session, participants filled in our previously developed **questionnaire** [1] that provides a self-reported assessment of engagement levels using various measures. Finally, **semi-structured interviews** were conducted to determine participants' prior experience with visualizations and to elicit their thoughts and opinions regarding their own engagement and how and why it developed over time.

### 3 RESULTS

We share our initial analysis and elaborate on pupil size changes and preliminary observations in user engagement. The visualizations in Fig. 1 have heatmap overlays showing gaze fixation for one of the participants during the think-aloud session.

#### 3.1 Outlier Moments

We plotted pupil size changes over time to identify patterns (see Fig. 2). From the plots, we can identify points in time in which a participant's pupil size increased significantly—we refer to those moments as outlier moments.

We conducted a preliminary transcription of verbal protocols and correlated participants' verbalizations to outlier moments. We found that, in general, the first outlier moment appears right after participants first encounter a visualization. This is to be expected, as cognitive resources are expended when first making sense of a new phenomenon. Subsequent outlier moments occur while participants are exploring and making sense of the visualizations. One interesting finding at this point is that all participants have clearly identifiable outlier moments, independent of their level of frustration or satisfaction. Our future work will carefully analyze these outliers and correlate them with the transcribed verbal protocols in an attempt to generalize our findings to higher-level patterns.

#### 3.2 Preliminary Observations

Based on our analysis, we speculate here on some factors that contribute to user engagement.

**Interest and Prior Knowledge**—The underlying content (i.e., data) of visualizations plays a significant role in the initial point of engagement [4] and influences engagement levels throughout

a user's interaction with the visualization. This factor is strongly dependent on users' interests and prior knowledge.

**Visual Embellishments**—In our interview session, several participants mentioned that pictures in the visualizations—e.g., presidents' photos or movie posters—increased their levels of engagement. Although controversial, this is in line with recent findings on potential benefits of visual embellishments in InfoVis.

**Disengagement**—Participants' state of engagement was easily disrupted by a single frustrating or confusing moment. This phenomenon is in line with the *disengagement* stage of engagement noted by O'Brien et al. [4], where engagement is a process comprising distinct stages.

**Positive Feedback Loop**—While interacting with the visualizations, we observed positive feedback loops that would keep users engaged—similar to Csikszentmihalyi's notion of feedback in a flow experience. For example, participants would explore the visualization, discover something interesting, and probe further while making interpretations and testing their assumptions. Here positive feedback serves to maintain or increase engagement, and can possibly lead to reengagement after disengagement.

### 4 DISCUSSION AND FUTURE WORK

While we reported an initial analysis of some of our collected data, and speculated on its implications, more in-depth analysis will yield stronger insights into engagement in InfoVis. We have a number of steps planned. **First**, we plan to take a grounded theory approach to analyze the think-aloud data. The results can contribute to a model of how users' sense of engagement develops and fluctuates over time. **Second**, by identifying gaze fixation from the eye-tracker data and cross-referencing with the verbal protocol data, we can identify key visual, cognitive, and emotional characteristics of engagement. **Third**, by cross-referencing the patterns in pupil size changes with the verbal protocol data, we can identify factors that contribute to high or low engagement levels. **Fourth**, we plan to cross-reference the questionnaire responses with the other collected data to develop a richer understanding of participants' engagement levels based on their self-assessments. A comprehensive analysis of the collected data will lead to a better understanding of different states and stages of engagement and their contributing factors. The results will enable us to refine the preliminary VisEngage questionnaire and contribute to the theoretical basis of engagement in InfoVis. Finally, we will be able to identify particular features of visualizations (e.g., visual encodings, embellishments, interactions) that influence engagement. Operationalizing these models will provide actionable insights for visualization designers and researchers.

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