Towards a Taxonomy for Evaluating User Engagement in Information Visualization

Narges Mahyar*
University of British Columbia

Sung-Hee Kim†
University of British Columbia

Bum Chul Kwon‡
University of Konstanz

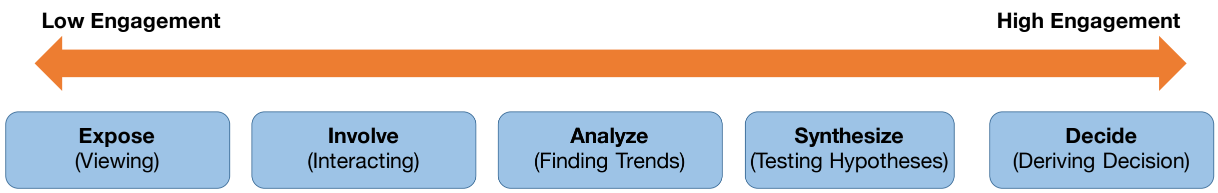

Figure 1: The degree of user engagement with visualizations (adopted from Bloom's digital taxonomy [1]). The degree of engagement increases from left to right as user performs higher-level cognitive tasks such as synthesizing information, and making finial decisions.

Abstract

Nowadays, with the availability of massive amounts of personal data, the role of Information Visualization is getting more and more important. There are a lot of visualization and visual analytics tools to help people to make sense of their personal data in their everyday lives. There is a consensus in the visualization community about the importance of user engagement for personal visual analytics. However, there are many challenges associated with this topic. As of yet, there is no clear and widely accepted definition for user engagement. Consequently and despite some recent efforts, there are no systematic and unified methods for evaluating different aspects of user engagement. In this paper, we bring attention to some fundamental open issues in the context of Information Visualization: What is the definition of engagement? What are the levels of engagement? How to measure engagement? How to improve user engagement level? This research is an initial attempt towards addressing some of these issues. Our main goal is to enable visualization researchers to more accurately measure and evaluate user engagement with visualizations. To this end, we reviewed definitions, measures, and frameworks from various other disciplines and specified the gap in the visualization community. We propose a five level taxonomy for engagement which is deeply inspired by Boloom's Taxonomy. In addition, we address some important open questions that require further exploration. This paper establishes a groundwork for future research in user engagement with visualizations.

1 Introduction

The importance of engaging new audiences for visualization becomes more and more prominent in the Information Visualization (InfoVis) community [8]. While user engagement with visualization is important in general, it is even more critical when dealing with non-visualization and non-domain experts. These users' information-seeking motivations and objectives are usually different from those of expert users. While data visualization and visual analytics can empower non-expert users to make sense of their data [5, 9], many challenges remain in designing visualization for such a diverse audience. Prior research on personal data visualizations aims to visually present the data so that users quickly gain insights by deeply engaging with visualizations (e.g. [3, 9–11]). Though the concept of engagement appears important, we do not have a unified definition of the engagement and understanding on how to systematically measure it.

Commonly, engagement is measured and evaluated using metrics such as "count of user interactions with view", "how much they remember from visualization" and "time spent on view". Yet, these measures fall short in evaluating deeper levels of engagement. According to Pirolli and Card model [17] sensemaking consists of two iterative loops: information foraging and sensemaking. The information foraging loop involves searching, reading, filtering and extracting information, whereas the sensemaking loop involves iterative development of a mental model that leads to formation and reevaluation of hypotheses, and publishing the results. Pirolli and Card [17] describe the sensemaking loop as a high cognitive load process, people may fail to go to deeper levels of sensemkaing such as generating new hypotheses. This is especially true for novice users who can be easily overloaded by the large amount of data.

Few research have tried to address engagement in deeper levels. For instance, Wood et al. [21] used "willingness to annotate a visualization" as an indirect measure of engagement with the visualization. While annotation could only address simple findings, they could also report some insights derived from data which is a product of a deeper level of the sensemaking loop.

In this paper, we argue that engagement has multiple levels, and in each level users may perform different levels of cognitive tasks with visualizations. However, it is not clear how to measure these deeper levels of engagement with visualization. In other words, the deepest engagement with visualizations may not mean that users frequently perform actions on visualizations, but it could mean that users perform more creative tasks using visualizations. Thus, the degree of engagement should also be captured and measured by diverse activities that are related to such degrees. To address this issue, we suggest metrics such as measuring people's ability to remember, understand, analyze, and derive insights from data. We emphasize that while deriving insight is one of the main purposes of InfoVis [16], measuring how much people gained insight/s from visualization is still a challenge.

In the following sections, we address how prior research in different domains have defined and measured engagement. Then we discuss existing frameworks for engagement from other related

*e-mail: nmahyar@cs.ubc.ca
†e-mail:kim731@cs.ubc.ca
‡e-mail:bumchul.kwon@uni-konstanz.de

fields. Finally, we propose a taxonomy which we adopted based on previous frameworks for information visualization. This work is an initial step towards answering the question of "How to measure engagement with an Information Visualization system? and there are many other open questions that need to be explored in more depth.

2 BACKGROUND

In this section, we address how engagement has been defined, measured and categorized in information visualization and other related domains.

2.1 Engagement in Information Visualization

2.1.1 Definition

There is no clear definition of what engagement means in the Information Visualization domain. From a behavioral perspective, Boy et al. and Haroz et al. refer to engagement as users' willingness to invest effort to explore further and gain more information from the visualization [2, 6]. Moere et al. [12] used the term engagement as the (perceived) effectiveness of visualizations, measured by higher participation/use of visualizations. We think that these definitions, along with behavior-specific measurements of them, do not highlight the granularity of engagement.

2.1.2 Methods for User Engagement

Previous research mainly addressed three dimensions for engagement: **aesthetic**, **narrative**, and **interactive** [13]. Recently, researchers have reported empirical results of what triggers engagement with visualizations. Different aspects of visualizations have been evaluated to see whether the participants were engaged with the visualizations. Wood el al. suggested that using a **sketchy style** InfoVis may increase engagement. They observed participants had more positive attitudes while annotating sketchy style visualizations. Moere et al. tested **different styles of visualization** such as analytical style, magazine style, and artistic style [12] and found that users could find more fact-based and deeper insights with analytical style visualizations. Haroz et al. showed that **ISOTYPE** that uses simple pictographic elements helps users to inspect visualizations more closely [6]. At last, **Storytelling** was used to trigger user-interaction and exploration. However, the results indicated that augmenting stories with visualizations did not increase user-engagement [2].

Prior research categorize methods to engage people with InfoVis with respect to following aspects of visualizations: **Visual Encoding**, **Aesthetic**, and **Interaction Techniques**. We believe that an engagement taxonomy should not only reflect all of these methods but also include users' goals, familiarity, interest, and background knowledge of the data. These factors can affect the willingness to explore the visualizations and eventually determine the insights that users gain [22]. In addition, we think that there are other factors that could affect user engagement particularly in the context of personal visualization. Factors such as **Display Type, Size and Input** and, **Accessibility and Device Compatibility**.

While designing methods for engagement, we also need to consider the users' context while using Personal Visualization and Personal Visual Analytics applications. Huang et al. [9] categorized current applications on Personal Visualization and Personal Visual Analytics and distinguished the designs based on the different levels of attentional demands, explorability, and actionability. For example, a sleep-related activity reminder app would require low attentional demand, low explorability, and high actionability. These different levels of design could require different levels of engagement to fulfill the goal of the application.

2.1.3 Measures

Prior research provide measures of engagement. Boy et al. [2] measured low-level interactions such as hovering and clicking that were mapped to certain activities such as retrieving values, filtering, or exploring with the visualization. The total amount of these type of interactions were considered as the level of engagement. However, we suspect that the metrics used may have been inadequate and insufficient for measuring engagement. Haroz et al. gave a 3x3 grid of thumbnails that include text, plain InfoVis, and ISOTYPE InfoVis, and captured how much users clicked to get more details in 2 minutes [6]. This measure could also be inaccurate as it does not reflect user level of understanding. Wood et al. used "willingness to annotate a visualization" as an indirect measure of engagement with the visualization [21]. Though this type of measure can capture higher-level engagement, it is too intrusive so that users need to explicitly report the willingness.

2.2 Research on Engagement in Other Domains

Sutcliff [20] defines user engagement as "how people are attracted to use interactive products. User engagement is a complex concept that synthesizes several influences to promote a sense of flow and fluid interaction leading to satisfying arousal and pleasurable emotions of curiosity, surprise, and joy". Sutcliff refers to **interaction**, **media** and **presence** as three main components of user engagement. "Interaction describes the content being communicated. Media describes how the user and the means of interaction are represented, ranging from simple cursors to icons and interactive avatars. Presence is determined by the representation of the user and how immersion is afforded by the interface on a 2D interactive surface or in a more elaborate 3D interactive world" [20].

In the context of scientific visualization, Edelsona and Gordinb proposed a design framework for the creation of scientific investigation tools based on differences between scientists and science students [4]. Although the context is different, we believe their framework can be adopted for designing visualizations in more general terms. One common attribute is that they address the differences between experts and learners. Their goal is to "Take resources that enable experts to extend their knowledge and turn them into resources that enable learners to develop some of the knowledge possessed by experts by performing personally meaningful tasks".

Hart and Angeli [7] refer to **positive affect** and **high arousal** as measures for engagement. According to them "interaction design may promote positive affect and arousal through serendipitous effects, variable pace, use of avatars and virtual environments". They address the influence of task, context and user characteristics on perceptions of engagement as important factors.

2.3 Frameworks for Engagement

There are different frameworks that have been suggested for user engagement in different domains. Naps et al. framework [15] focuses on the educational impact of algorithm visualization. This framework has been used and extended for a variety of contexts (e.g. software education and collaboration [14]). Although this framework has been mostly used for pedagogy purposes, we believe there are a lot of common concepts that can be adopted for personal visualization. They argue that no matter how well visualization technology is designed, there is little educational value unless it engages learners in an active learning activity. There is a commonality between our audience and learners. Learners do not have expertise as scientist, same as novice users who are non-visualization experts who are trying to make sense of their own data.

Naps et al. [15] engagement taxonomy defines six different forms of learner engagement with visualization technology: *1) no viewing, 2) viewing, 3) responding, 4) changing, 5) constructing, and 6) presenting*. We can adopt some of these levels, except no viewing, which means that there is no visualization technology in use, and changing, which means that the system asks students for input to affect the execution of a program. Myller et al. [14] extended this taxonomy for software visualization and collaborative learning. One of their added items is: reviewing (i.e., viewing the visualization for the purpose of providing comments, suggestions, and feedback on the visualization itself or the program.) It is notable that they do not consider this taxonomy to be an ordinal scale and they mention that " The relationships among these six forms of engagement do not form a simple hierarchical relationship."

Another relevant taxonomy in the context of learning visualization is Bloom's taxonomy [1]. They look at the depth of understanding and define levels while interacting with visualizations. This taxonomy has six levels as, the knowledge level, the comprehension level, the application level, the analysis level, the synthesis level, and the evaluation level. We elaborate on definitions of each level as we believe it relates to the field of InfoVis.

1. **The knowledge level**: refers to mere factual recall with no real understanding of the deeper meaning behind facts.

2. **The comprehension level**: learner is able to discern the meaning behind the facts.

3. **The application level**: learner can apply the learned material in specifically described new situations.

4. **The analysis level**: learner can identify the components of a complex problem and break the problem down into smaller parts.

5. **The synthesis level**: learner is able to generalize and draw new conclusions from the facts learned at prior levels.

6. **The evaluation level**: learner is able to compare and discriminate among different ideas and methods. By assessing the value of these ideas and methods, the learner is able to make choices based on reasoned arguments.

This taxonomy has been revised and listed as six levels of remembering, understanding, applying, analyzing, evaluating, and creating which provides a better means to evaluate visualization tools. In the following section we introduce which is very similar to this one, but has been adopted for measuring users engagement in InfoVis.

3 Discussion and Future Work

In this section, we conclude by addressing our proposed taxonomy and how it can capture the granularity of engagement. Then we address some of the open research issues in this field that requires further exploration. We hope that our effort will motivate other researchers to further investigate this problem and to establish a better foundation for engagement.

3.1 Defining Engagement with its Degrees

As mentioned before, in order to be able to measure engagement, we first need to have a framework that encompasses different levels of engagement. Based on our survey of engagement literature in related domains, we propose the following taxonomy that defines engagement based on the level of user involvement (See Figure 1). Our taxonomy includes five levels: Expose, Involve, Analyze, Synthesize, and Decide. Each level includes former levels, but it refers to a deeper level of engagement which also correspond to deeper level of sensemaking. We adopted our taxonomy from Bloom's digital taxonomy [1]. Similar to Bloom's taxonomy, the degree of engagement increases from left to right as user performs higher-level cognitive tasks such as synthesizing information, and making finial decisions. This classification provide a working definition of degrees of engagement and a systematic approach to capture the individual degrees of user engagement.

1. **Expose** (Viewing): the user knows how to read data points.

2. **Involve** (Interacting): the user interacts with the visualization and manipulate the data.

3. **Analyze** (Finding Trends): the user analyze the data, finds trends, and outliers, etc.

4. **Synthesize** (Testing Hypotheses): the user is able to form and evaluate hypotheses.

5. **Decide** (Deriving Decisions): the user is able to draw final decisions based on evaluations of different hypotheses.

To better enable visualization researchers to evaluate user engagement, we capture what can be generated about the data at each level. We speculate that each level re-acquires different metrics. While, addressing metrics for each level needs further research and exploration, we believe that many of Bloom's taxonomy concepts can be adopted here. For instance, Expose level can be measured by people's ability to **remember**. Whereas **understand**, **apply**, **derive insights** from data are addressing deeper level of engagement. To address deeper level of engagement, there are other possible metrics such as users' new questions and hypotheses which can address Synthesize level. This shows the users' ability to go beyond initial questions to gain some insights [16].

3.2 Open Research Questions

In this section, we bring attention to some open research questions in the context of Information Visualization. These questions can be used for future researchers to discuss the future direction of engagement research in the visualization community.

- What is the definition of engagement? This is the most critical question to be answered. Addressing other issues are determined by this definition.

- What are the levels of engagement? It is necessary to identify and distinguish between different levels of engagement.

- How to measure engagement? The inherent complexity of engagement makes measuring a challenge. What should be measured and what the appropriate metrics are, are still unclear.

- What are the differences between short-term vs long-term engagement? Do they require different metrics for measurement? There are situations (e.g. monitoring health indicators) where a user needs to interact with a visualization for longer periods of time. This issue should be reflected in any future evaluation framework because short and long term engagement may require different evaluation methods.

- How to increase the engagement level by visualization design? Although designing engaging visualizations is beyond the focus of this paper, we believe that a clear definition of engagement along with a taxonomy of different levels of engagement would be useful for visualisation researcher and designers.

- Do certain personal traits correlate with the degree of engagement with a visualization? There is also the issue of personal differences and preferences. What are the type and magnitude of personal traits on engagement? Would factors such as gender, age, background and education affect engagement?

- How can we incorporate the user engagement level into visualization models, such as knowledge generation [19] and trust building under uncertainty [18]?

References

[1] B. S. Bloom. *Taxonomy of Educational Objectives: The Classification of Educational Goals. Handbook 1-2*. Longmans: McKay, 1974.

[2] J. Boy, F. Detienne, and J.-D. Fekete. Storytelling in information visualizations: Does it engage users to explore data? In *Proceedings of the 33rd ACM Conference on Human Factors in Computing Systems (CHI 2015)*, pages 1449–1458. ACM, 2015.

[3] S. Consolvo, P. Klasnja, D. W. McDonald, D. Avrahami, J. Froehlich, L. LeGrand, R. Libby, K. Mosher, and J. A. Landay. Flowers or a robot army?: encouraging awareness & activity with personal, mobile displays. In *Proceedings of the 10th international conference on Ubiquitous computing*, pages 54–63. ACM, 2008.

[4] D. C. Edelson and D. Gordin. Visualization for learners: A framework for adapting scientists' tools. *Computers & Geosciences*, 24(7):607–616, 1998.

[5] C. Fan. The future of data visualization in personal informatics tools. In *Personal Informatics in the Wild: Hacking Habits for Health & Happiness CHI 2013 Workshops*, 2013.

[6] S. Haroz, R. Kosara, and S. L. Franconeri. Isotype visualization–working memory, performance, and engagement with pictographs. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, pages 1191–1200. ACM, 2015.

[7] J. Hart, A. Sutcliffe, and A. De Angeli. Using affect to evaluate user engagement. In *CHI'12 Extended Abstracts on Human Factors in Computing Systems*, pages 1811–1834. ACM, 2012.

[8] J. Heer, F. Van Ham, S. Carpendale, C. Weaver, and P. Isenberg. Creation and collaboration: Engaging new audiences for information visualization. In *Information Visualization*, pages 92–133. Springer, 2008.

[9] D. Huang, M. Tory, B. A. Aseniero, L. Bartram, S. Bateman, S. Carpendale, A. Tang, and R. Woodbury. Personal visualization and personal visual analytics. *Visualization and Computer Graphics, IEEE Transactions on*, 21(3):420–433, 2015.

[10] I. Li, A. Dey, and J. Forlizzi. A stage-based model of personal informatics systems. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pages 557–566. ACM, 2010.

[11] J. J. Lin, L. Mamykina, S. Lindtner, G. Delajoux, and H. B. Strub. Fishnsteps: Encouraging physical activity with an interactive computer game. In *UbiComp 2006: Ubiquitous Computing*, pages 261–278. Springer, 2006.

[12] A. V. Moere, M. Tomitsch, C. Wimmer, B. Christoph, and T. Grechenig. Evaluating the effect of style in information visualization. *Visualization and Computer Graphics, IEEE Transactions on*, 18(12):2739–2748, 2012.

[13] S. Murray. Engaging audiences with data visualization: Communicating your research, data, and findings to people outside your field [audio podcast], Feb. 2013.

[14] N. Myller, R. Bednarik, E. Sutinen, and M. Ben-Ari. Extending the engagement taxonomy: Software visualization and collaborative learning. *ACM Transactions on Computing Education (TOCE)*, 9(1):7, 2009.

[15] T. L. Naps, G. Rößling, V. Almstrum, W. Dann, R. Fleischer, C. Hundhausen, A. Korhonen, L. Malmi, M. McNally, S. Rodger, et al. Exploring the role of visualization and engagement in computer science education. In *ACM SIGCSE Bulletin*, volume 35, pages 131–152. ACM, 2002.

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

[17] P. Pirolli and S. Card. The sensemaking process and leverage points for analyst technology as identified through cognitive task analysis. In *Proc. Int. Conf. on Intelligence Analysis*, volume 5, pages 2–4, 2005.

[18] D. Sacha, H. Senaratne, B. Kwon, G. Ellis, and D. Keim. The Role of Uncertainty, Awareness, and Trust in Visual Analytics. *IEEE Transactions on Visualization and Computer Graphics*, PP(99):1–1, 2015.

[19] D. Sacha, A. Stoffel, F. Stoffel, B. C. Kwon, G. Ellis, and D. Keim. Knowledge Generation Model for Visual Analytics. *IEEE Transactions on Visualization and Computer Graphics*, 20(12), Dec. 2014.

[20] A. Sutcliffe. Designing for user engagement: Aesthetic and attractive user interfaces. *Synthesis lectures on human-centered informatics*, 2(1):1–55, 2009.

[21] J. Wood, P. Isenberg, T. Isenberg, J. Dykes, N. Boukhelifa, and A. Slingsby. Sketchy rendering for information visualization. *Visualization and Computer Graphics, IEEE Transactions on*, 18(12):2749–2758, 2012.

[22] J. S. Yi, Y.-a. Kang, J. T. Stasko, and J. A. Jacko. Understanding and characterizing insights: how do people gain insights using information visualization? In *Proceedings of the 2008 Workshop on BEyond time and errors: novel evaLuation methods for Information Visualization*, page 4. ACM, 2008.