Personalized Visualization: Making Data Meaningful to a Person in the Context of Daily Life

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Overview

Aging demographics in the US and beyond emphasize the importance of extending healthspans to meet individuals' lengthening life spans. Studying older adults in vivo brings insight to individuals' health behaviors, psychological, and physiological processes within the context of their daily lives. In these studies, participants are queried daily, or multiple times within the day, about aspects of their day such as emotion, who they're with, and what they're currently doing. The increase in computing power and use of internet and mobile devices among older adults has digitized this information. The result is a wealth of data, that if properly visualized, could be applied to engage participants in the research, encourage specific behaviors [1, 2], and also serve as a tool for researchers. In this project we build on previous work in context-sensitive adjustments of data visualization's level of detail [3] by integrating knowledge about the person and their day so that the resulting display provides contextually relevant information to the participant.

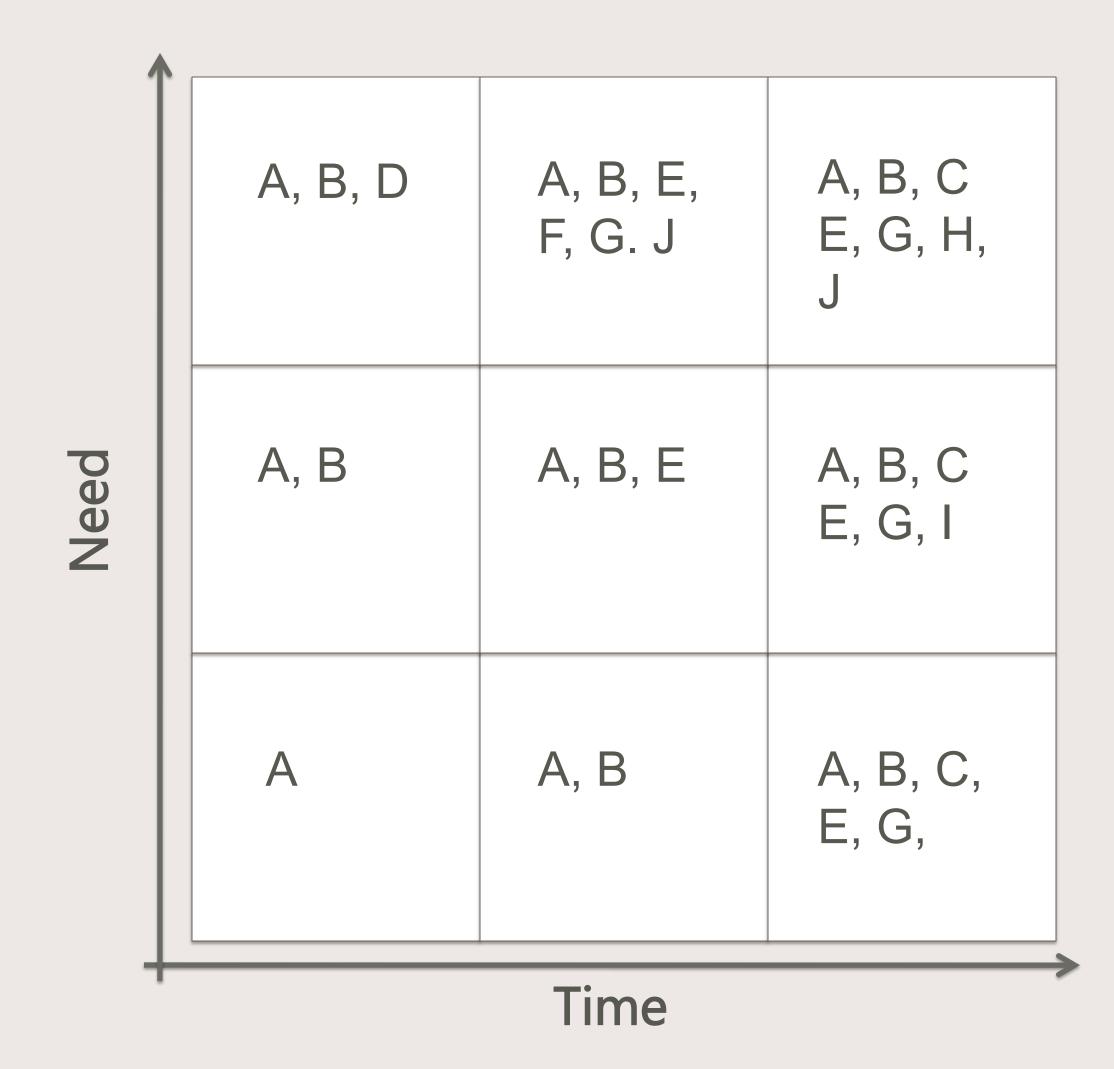


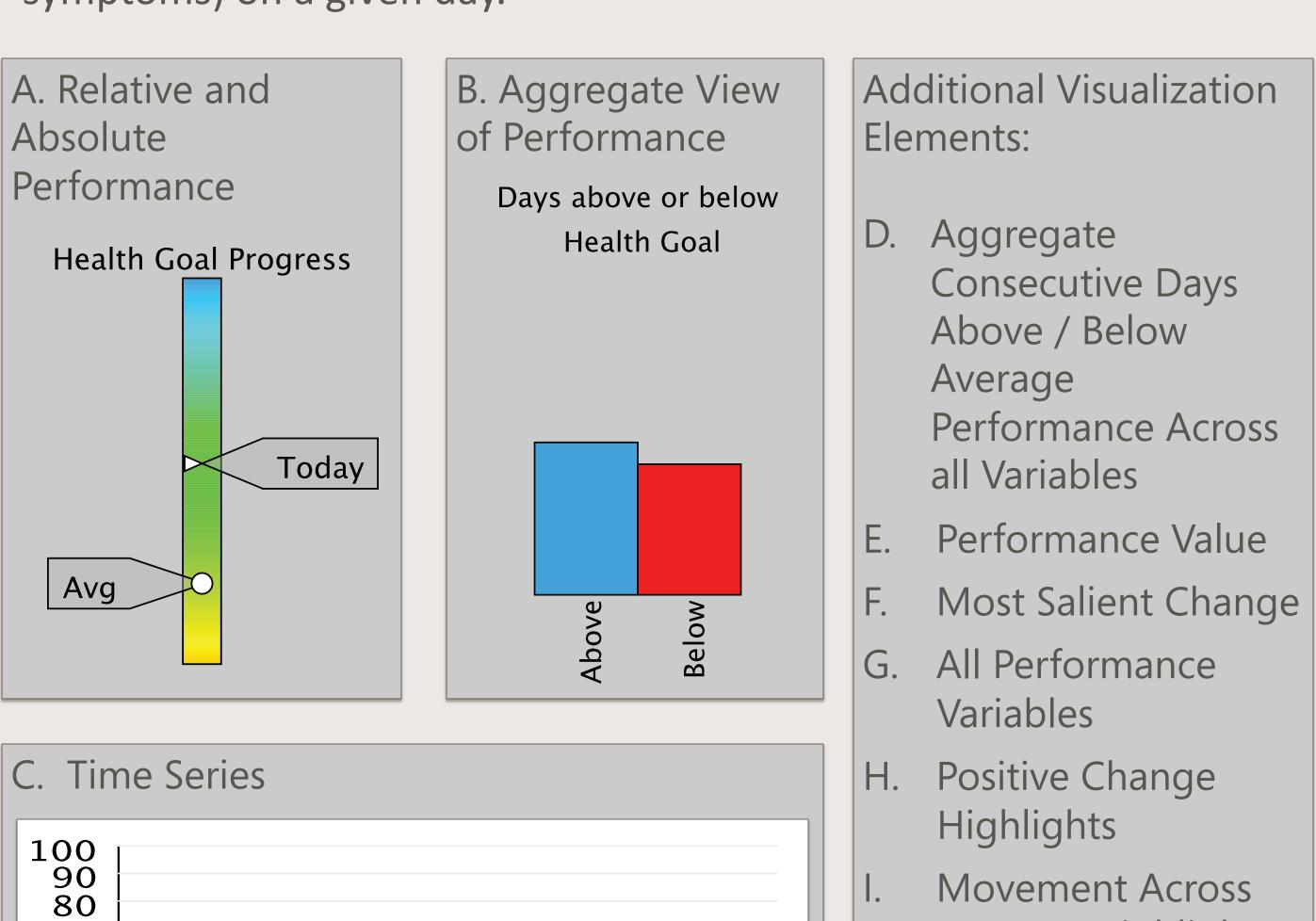
Fig. 1: Examining the variation in the level of detail in the visualization space across the axes of need and time.

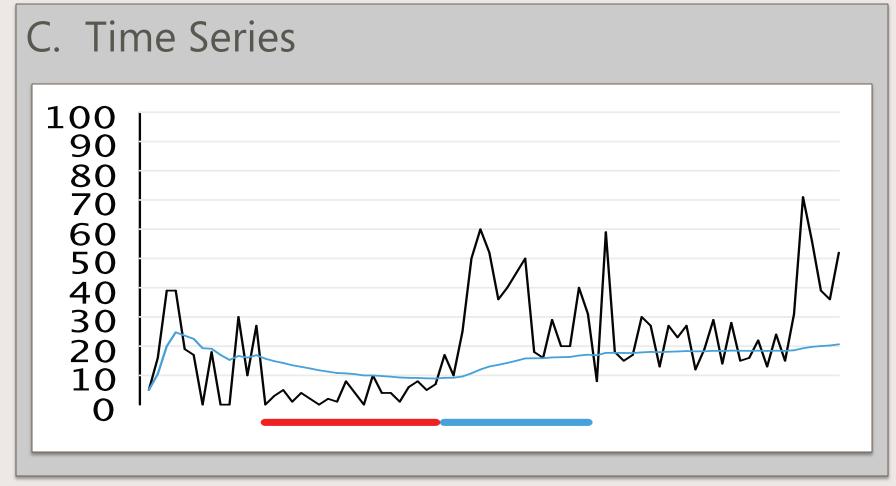
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Method and Analysis

To identify characteristics of the person and day that predicted visualization use on that day, we analyzed data from the Personal Understanding of Life and Social Experiences (PULSE) project, a 100day internet-based study of self-regulatory processes and health behaviors of 100 older adults (Age_m = 63.29, Range = 52 - 88). Multilevel analysis showed that higher negative affect (NA), lower positive affect (PA), lower stress, longer duration of survey use, and reporting more physical symptoms than usual were associated with longer use of the data visualization on that day. From these findings, we constructed a conceptual model [See Fig. 1] that characterizes visualization use as a function of an individual's available time (low stress, high duration of survey use) and need (low PA, high NA, more symptoms) on a given day.





Additional Visualization

- Performance Across
- Average Highlights
- **Current Consecutive** Days Above Average

Fig. 2: Examples of data visualization at varying levels of detail applied depending on individuals' time and need

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Personalized Visualization

From the conceptual model [Fig. 1] we constructed visualizations that varied by levels of detail and relevant content [Fig. 2]. Our guiding hypothesis is that a broad overview of the most salient information is appropriate when need is high and time is low, whereas data exploration is appropriate when time is high and need is low. Each element was chosen on the basis of accessibility, the most accessible of which is the display of relative and absolute performance [Fig 2.A]. The bar-graph [Fig. 2.B] displays the aggregate of recorded days above and below the individual's Following reports from PULSE participants that average. visualizations can be superfluous [2], the time-series visualization [Fig 2.C] is only visible on days where individuals' data indicate have available time and thus more potential interest in data exploration. The visualization is dynamic and interactive. The initial view presented to users on a given day provides an overview of their performance at a level of detail that we have predicted will be most useful based on their need and time measures. They can then explore that data, and extract details following Schneiderman's [4] taxonomy: overview first, zoom, and filter, and details on demand.

Future Work

The next steps for our research are to a) customize visualization based on characteristics of the person, such as their approach and avoidance motivations, and other personality characteristics; b) dynamically customize the visualization based on user interactions and response to specific questions; and c) develop automated methods for constructing the visualization algorithmically.

References

[1] Sherman, D. K., Mann, T., & Updegraff, J. a. (2006). Approach/avoidance motivation, message framing, and health behavior: Understanding the congruency effect. Motivation and emotion, 30(2), 165–169. doi:10.1007/s11031-006-9001-5

[2] Pham, T., Mejía, S., Metoyer, R., & Hooker, K. (2012). The effects of visualization feedback on promoting health goal progress in older adults. In M. Meyer & T. Weinkauf (Eds.), Eurovis- Short Papers (pp. 91–95). Vienna, Austria. doi:10.2312/PE/EuroVisShort/EuroVisShort2012/091-095

[3] Bade, R., Schlechtweg, S., & Miksch, S. (2004). Connecting time-oriented data and information to a coherent interactive visualization. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (pp. 105–112). New York, NY, USA: ACM. doi:10.1145/985692.985706

[4]Shneiderman, B. (1996). The eyes have it: a task by data type taxonomy for information visualizations. In IEEE Symposium on Visual Languages, 1996. Proceedings (pp. 336–343). Presented at the IEEE Symposium on Visual Languages, 1996. Proceedings. doi:10.1109/VL.1996.545307



