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THE ROLE OF DATA VISUALIZATION IN SELF-GENERATED HEALTH DATA

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Abstract. *Smartphones and wearable devices have allowed individuals to easily collect their personal health data. Patients who are consumers of healthcare services are playing an increasing role in their own personal healthcare alongside trained professionals. Individual self-management of health, and eventual behavioral changes, requires an understanding about various health conditions and self-awareness. Personal data are often provided through mobile apps, and it can be challenging to design an effective interface. Data visualization is common in such apps and seeks to appease multiple stakeholders, including patients, caregivers, and clinicians. Although research exists regarding effective visualization designs, the area of self-generated data has scarcely been explored. In the current study, we conducted a qualitative systematic review on related data visualization studies for self-generated data in the healthcare domain. In this paper, we suggest a framework that includes the impacts of data visualization, form factors of visualization, and individual differences that affect its effectiveness for self-generated health data. We believe that this work can be used as a guideline for designing visualizations in the domain of healthcare for the general public.*
Keywords: Data visualization, Self-generated data, Healthcare services, mHealth

1. **Introduction.** Individuals can easily collect longitudinal health data easily outside of the clinical setting using mobile technology such as smartphones and wearable devices. On such devices, users can easily enter personal data, and sensors collect ongoing activity data to assess the wearer's physiology. Measured data can include the wearer's step counts and heart rate. Without such a device, these types of data are usually only assessed by trained professionals in a clinical setting. Patient self-management of health conditions can empower individuals to take charge of their behavioral changes.

However, designing an effective interface and fulfilling the diverse needs of users is challenging. Among many factors, providing users with easy and frequent access to data that is organized and presented in a meaningful way is the key [1]. In this case, data visualization is commonly used to provide users with a simple understanding of data [2]. Effective visualization accurately represents data, displays trends, and enables easy comparisons that allow for further engagement [3]. The development of data visualization for health management requires addressing the needs of several stakeholders such as patients, caregivers, and clinicians [4]. However, only when implemented effectively, it can facilitate positive behavioral changes.

Although research exists regarding effective visualization designs, research on self-generated data is scarce. We seek to investigate how visualizations have been used; if

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so, in what areas; and which factors should be considered for proper visualization design. In our research, we introduce factors that should be considered for effective data visualization design to fill the gaps among these research areas. As such, we conducted a qualitative systematic review on related studies on data visualization for self-generated data in the health care domain and suggested a framework for self-generated data visualization design so that providers can present effective applications.

The research will be described in the following order. We introduce the methodology of the research and the results regarding the type of studies, type of data, impact of visualizations, and framework for visualization design on self-generated data. We summarize that how this can be used for further research regarding visualization for applications using these types of data.

2. **Methods.** We identified relevant studies by searching PubMed, IEEE Xplore, Proceedings from the Association for Computing Machinery Conference on Human Factors in Computing Systems, and Google Scholar articles published between 2017 and 2022. Searches included a combination of terms such as "self-generated data", "mHealth", "data visualization", and "activity tracker" along with other terms related to health care services and data visualization. We first screened manuscripts by reading their abstracts of 93 papers. We included studies that introduced applications of data visualization, qualitative or quantitative experiments, or suggestions for service design. We excluded research that did not include specific data visualizations, leaving us with 12 papers. We then analyzed this final list of studies and identified common themes.

3. **Results.** We organized the results by type of studies, impact of data visualization as shown in Table 1, form factors, and moderators that come from users that may affect the usefulness of the visualization.

Type of studies. We focused on studies related to mental illness such as depression [5], bipolar disorder [6], diabetes [7,8], sleep management [9], and increase of activity [10]. Regarding evaluation methods, we examined both one-time and "in-the-wild" studies that could be field studies, experiments that try to preserve realistic environments, or online crowdsourcing studies. One-time experiments were conducted to introduce a study approach in which surveys and semi-structured interviews were conducted. The "in-the-wild" studies were largely longitudinal and conducted over a period of 4 weeks to 3 months [11], and also in clinical settings [10].

Type of data. The type of collected data can be divided into two types: self-reported data and data collected automatically by tracking devices. Self-reported data includes personal mood [5,6] and blood test results [7,8]. Data collected automatically via tracking devices include step counts [12,13] and sleep waves [9]. The type of data analyzed can determine the most effective types of visualization and how it impacts user behavior.

Impact of data visualizations. Participants report that data visualizations provide an additional value to their data collection experience. We categorized research in the theme of how visualizations have impact on the users: facilitate understanding personal data, enhance self-awareness, increase engagement, impact on behavioral changes, and help effective communication with other stakeholders. We have added quotes or behaviors that were mentioned in the literature. Visualizations help users understand and interpret their data, enabling them to identify and observe temporal patterns. Visualizations are particularly effective in illustrating historical data, which is a large part of health care data. And due to the nature, the volume is large and also can be easily forgotten as time passes by. Data visualizations allow users to easily recall their experience or past symptoms. As a result, they gain insight into their behaviors and possible reasons behind them.

Table 1. Impact of data visualization

Theme	Explanation	Quotes or actions
Facilitate understanding	Objectively see progress or identify patterns	"Hypnogram was useful to see last night's sleep phases" [9]
Self-awareness	Improve users' recall of their experience or accurately reflect past symptoms	"[The self-monitoring component] made me realize about all the happy small moments that I was having so I notice that I was happier I guess and that my anxieties weren't as big of a deal" [11] "it is revealed that passive activities (e.g., 'cinema' or 'watching TV') all have low mastery scores, whereas more active activities (e.g., 'homework' and 'meeting new people') have higher mastery scores" [4]
Increase engagement	Gain insight or think about why certain patterns appear	"know that they slept longer on weekend days than weekdays" [9] "Yes! It [the bubble chart] gave me an insight into when – during the day – I enjoyed training the most" [11]
Behavioral change	Promote proactive self-management or give reminders to maintain health behaviors	"they increased their step counts" [4] "had a significantly higher average daily step count, greater perceived quality of recovery and less difficulty in being mobile" [3]
Effective communication	Help communicate with professionals and caregivers	"Visual aids help patients make the most out of short and infrequent appointments, especially when the current health status was not representative of the patient's experience over previous weeks" [15]

The primary purpose of understanding and engaging with personal health care data is to get the momentum to move toward a healthier lifestyle. Visualizations are also effective in promoting communication with care givers and other medical professionals. Practices that use these self-generated data systems may gain a better understanding of their patients' everyday lives, as their use has been demonstrated to be effective in these areas [14]. Visualizations helped to recall past symptoms and also helped to describe certain patterns. It also helped when the appointment was scheduled weeks or even months after the symptom appeared [15]. Visualizations are also often used with gamification apps to display the user's performance in comparison to that of other users, which provides additional motivation to increase healthy behaviors [4].

Form factors of data visualizations. Data visualization is "the use of computer-supported, interactive, visual representations of abstract data to amplify cognition" [2]. It includes simple graphs as bar chart or line chart to new types of visualizations that are not taught in k-12 education, such as area charts or data streams. As visualizations can be shown in the web or mobile devices, it varies its form compared to printed static visualizations shown on paper. It can have mouse interactions or can be zoomed in by finger interactions. In this section, we analyze the form factors that can be considered when selecting an effective visualization. The first step is to select what **type of visualization** will be used to represent the data. This can be also determined by the query type

FIGURE 1. Comparison on different types of visualizations for certain tasks [2]

requested to the data. In other words it can depend if we are fetching a single value, multiple values, a certain time phase, or comparing two points of data. For example, a single value could be total step counts today or how much I reached the goal. Comparing could be requesting step counts for this week and last week. It has been shown that different visualizations are effective in different scenarios, such as showing "*last night (bar chart), weekly overview (area chart), social comparison (horizontal bar)*" as shown in Figure 1 [2]. The overall visualizations that were used in the literature were bar chart, line chart, pie chart, radial chart, multi-bar charts, horizontal bars, data streams, calendar view and area chart.

Although the visual representation is the most important component, other factors can also have impact. **Interaction techniques** are becoming more important as it is the key that differentiates static and interactive visualizations [16]. For example, changing dates, hovering, zooming, filtering interactions provide engaging moments while navigating through the data. However, compared to desktop visualization applications, mobile devices have the limitation of knowing if interaction is possible as there is no mouse cursor. Careful design is needed and other modalities such as speech are also being used recently. **Degree to offer customization** is also an important factor as these visualizations are showing personal data. Apps can offer different types of views for the same data and let the users select or offer to change the layouts. At last, as mobile phones have a limited display space, apps tend to have simpler visualizations. However, there is a tradeoff between simplicity and the richness to analyze. We can have **single or multiple views**. Single views can easily offer information to make sense in a simple glance which is important while using mobile devices. However, there are cases when users have the time to explore through data. Deeper engagement with data also can enhance when one has deeper understanding by analyzing personal data that is easily offered by multiple views [17].

Factors from users. Although visualizations are known to be effective to help understand data, there are individual differences from users that can have impact of the experience. Some users describe themselves as data people in which they would like to have control over visualizations, and some people just want simple visualizations. Data visualization literacy is the ability to read and construct data visualizations [18]. To make sure that the patients or users are properly understanding the visualization, app designers should take this factor into consideration. Literacy tests might have to be taken before the apps are deployed to certain patients [19]. Another individual difference can come from technology affordance, such as familiarity with technology devices and how much they trust about data collection as it is directly related to privacy issues. At last, individual health status that come from types of diseases, activity levels, management strategies, and certain disorders can have impact on the use of the visualization.

Framework for visualization design on self-generated data. First we need to understand what type of data is collected. Based on that, to design data visualization to be a valuable component, it is important to understand the role of visualization on self-health management. The findings we found through literature could be considered as values that should be provided after using certain functions. Based on the needs of

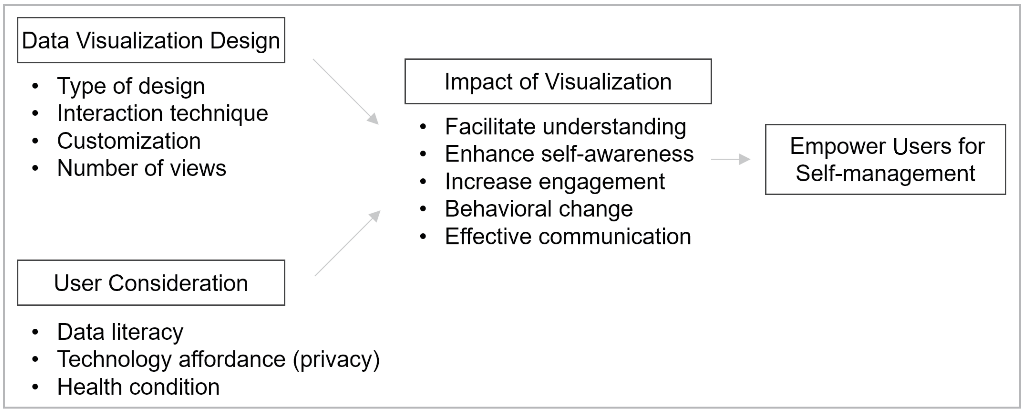

Figure 2. Framework for visualization design on self-generated data

users, we need to know the design space of visualizations so that we can decide on proper components. Users should include the patients but also caregivers and clinicians. Figure 2 describes the themes we found and relationship with other design factors identified in this research.

4. **Conclusions.** In this study we found that data visualizations can have valuable impact on self-health management. For proper design, we need to understand the characteristics of data visualizations, decide on components that fit the task on mobile devices, and also understand the individual differences of the users. We introduce a preliminary framework to consider when designing a visual interface so that one can ensure that visualization would fulfill users' needs. However, the research has limitations in terms of analyzing the applications as a whole. For further research, we need to analyze the literature based on diseases, and compare between non-clinical setting and clinical setting, age ranges of users, and frequent use of apps. These all can have impact on more specific design.

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