Data Visualization Design Strategies for Promoting Exercise Motivation in Self-Tracking Applications

Xing Huang
North Carolina State University, College of Design
ncsuxing@gmail.com

ABSTRACT

In self-tracking applications, data visualizations play a fundamental role in delivering efficient information and creating personalized user experiences. Literature consistently indicates that data visualization is a powerful tool to make data persuasive and improve motivation. However, how to leverage different data visualizations to boost motivation remains largely unknown. In this study, the researcher explores the effects of different data visualizations on user motivation within self-tracking mobile applications. Through design space analysis and semi-structured interviews, the researcher defines a set of design factors that impact users' exercise motivation at different levels of exercise adoption. Based on these factors, the researcher delivers a set of practical design suggestions for design practitioners and people who create visualizations for large data sets.

CCS CONCEPTS

• **Human-centered computing** → Visualization; Human computer interaction (HCI); • **Social and professional topics** → User characteristics.

KEYWORDS

Data visualization, Exercise motivation, Self-tracking, Information design, Digital health

ACM Reference Format:

Xing Huang. 2022. Data Visualization Design Strategies for Promoting Exercise Motivation in Self-Tracking Applications. In *The 40th ACM International Conference on Design of Communication (SIGDOC '22), October 06–08, 2022, Boston, MA, USA.* ACM, New York, NY, USA, 12 pages. https://doi.org/10.1145/3513130.3558981

1 INTRODUCTION

Physical activities and exercises can bring short-term and long-term physical and mental health [1]. Studies have shown that self-tracking applications play a critical role in helping people actively engage in exercise [2–5]. As we are going through the current global health crisis – the COVID-19 pandemic work-from-home has become a new norm, with many people relying on home exercise routines. This change accelerates the growing interest in a healthy and fit lifestyle. Self-tracking applications reduce the barriers to establishing a healthy lifestyle, making it easier for users to obtain their health and fitness data, such as steps, calories, and sleep quality using mobile applications.

In self-tracking applications, data visualizations play a fundamental role in delivering effective information and creating personalized user experiences. Visualizations are a crucial tool that make data accessible, intelligible, engaging, and impactful [6, 7]. Research in the field of persuasive design has shown the opportunity of using data visualization to improve motivation [8, 9]. Related literature showed several common visualization strategies that have the potential to impact users' motivation, including framing theory [10], narrative visualization [6], and gamification [11]. However, how to visualize the self-tracking data for the motivation purpose is not fully understood with regards to: (1) how to use different data visualization design strategies to motivate users to exercise; and (2) in particular, how these strategies vary depending on the user's stage of exercise adoption.

In this work, the researcher focused on data visualization design strategies that are believed to bridge the gap between self-tracking exercise data and motivation to do exercise (see the conceptual framework in Figure 1). The researcher performed semi-structured interviews with college students to uncover why certain design strategies can motivate them to exercise. From these results, the researcher generated a set of design features, called Motivational Design Factors (MDFs), that have the psychological function of promoting exercise motivation. With these MDFs, the researcher derived practical data visualization design suggestions for motivating users at various exercise adoption levels to exercise. With the rapidly expanding market in self-tracking, these design suggestions and emergent MDFs benefit design practitioners and a large group of users while designing visualizations for large data sets.

2 BACKGROUND

This study builds on the intersection between data visualization design, human motivation, and exercise adoption. Each of these fields has extensive literature that supports the construction of the theoretical framework for this research. In the following sections, the researcher will provide a brief introduction of the related work in each field.

2.1 Data Visualization and Persuasion

Data visualizations are visual representations of data and information to amplify human cognition [12]. Traditionally, data visualizations have been used primarily in research and business settings for exploring datasets and generating insights to answer specific questions [13]. In recent decades, data visualizations have been used to engage everyday users [13].

SIGDOC '22, October 06–08, 2022, Boston, MA, USA

ACM ISBN 978-1-4503-9246-4/22/10…$15.00
https://doi.org/10.1145/3513130.3558981

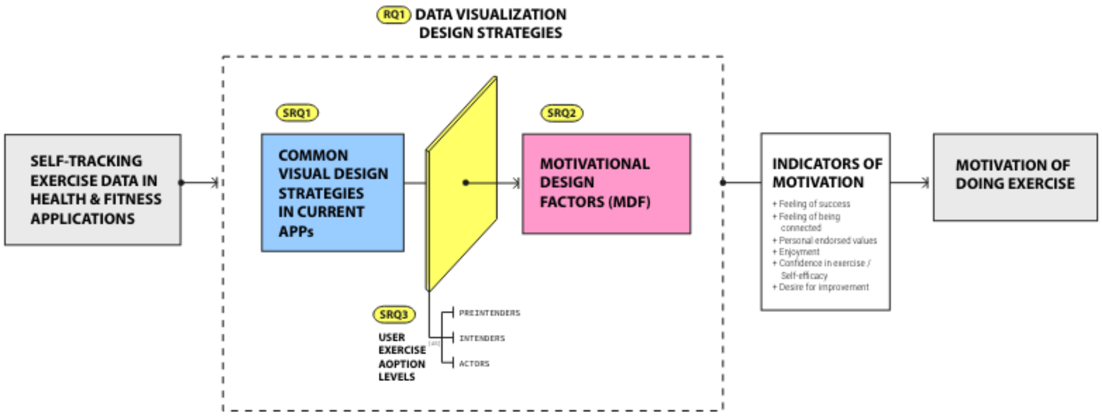

Figure 1: ***The conceptual framework of this study.***

Extensive research shows that visualizations are powerful tools that make data accessible [14], engaging [7], memorable [15], intelligible [16], and impactful [6]. For example, it has been shown that the visualization of information is associated with more active cognitive processes and more rapid assimilation of complex information [17].

Notably, data visualizations can be both analytical and persuasive [18]. Data visualizations can present a particular angle of reality [19]. For example, the way news is framed in certain data visualization formats determines how the news will be interpreted [20]. In the field of visual rhetoric, the impacts of data visualization on persuasion have been explored in various applications, for instance social justice [21], deception [22], and risk communication [23, 24]. In the field of persuasive design, studies have shown that data visualization has a significant opportunity to improve motivation [9, 25]. Experimental studies provide evidence-based analysis of data visualization's impacts on attitude, perception, and decision making [9, 26]. For instance, in an experimental study, Pandey et al. found visual treatments of data presented in graphical form have a stronger and more positive impact on persuasion attitude change than data presented through tables [9]. However, empirical studies are seldom conducted in understanding the powers and limitations of data visualizations on motivation [27].

To promote motivation through data visualization, related literature shows several common visualization strategies, including framing theory [10, 28], narrative visualization [6], and gamification [11]. However, how to visualize the self-tracking data for this motivational process remains largely unknown.

2.2 Self-Determination Theory (SDT)

There are a variety of motivation theories that offer frameworks and approaches to studying human motivation, for example, the Self-Determination Theory [29], the Theory of Reasoned Action [30], and the Theory of Planned Behavior [31], etc. In this article, the researcher focuses on reviewing the Self-Determination Theory (SDT) since it informs the conceptual framework of this study.

SDT is an empirically based motivation theory that primarily focuses on universal psychological needs and types of motivation [29, 32]. It has been applied to a wide range of life domains, including physical activities and healthcare [29, 33]. According to SDT, all human beings have a set of basic psychological needs, including competence (feeling confident and effective about what they are doing), relatedness (feeling cared for by others, caring for others, and a feeling of belonging to groups that are important to the individual), and autonomy (a sense of volition that the behavior is self-determined) [32].

SDT studies and differentiates types of motivation along a spectrum, from *autonomous motivation* to *controlled motivation* [29]. When people feel confident about what they are doing (fulfills the need for *competence*), when people feel related to others (fulfills the need for *relatedness*), and when people get a sense of volition (fulfills the need for *autonomy*), then they are autonomously motivated [32]. On the other hand, when one's behavior is the function of external contingencies (e.g., reward or punishment) and is energized by ego-driven factors such as approval or avoidance of shame, the person has the controlled motivation [29]. For this study, SDT offers a theoretical framework to understand motivation factors that can enhance or reduce exercise motivation. The researcher adopts the SDT framework to analyze Motivational Design Factors (MDFs) in health & fitness self-tracking applications.

2.3 The Health Action Process Approach (HAPA)

Health Action Process Approach (HAPA) is a social-cognition model of health behavior [34]. Although this study does not directly focus on behavioral change, HAPA contains motivation as a part of its framework. Research suggests that there is great potential for using HAPA as a motivational model for the self-management of physical activities [35].

The HAPA model suggests that health behavior change (including the adoption, initiation, and maintenance of health behaviors) is a process that consists of a motivation phase and a volition phase [34]. The motivation phase, which describes what people choose to do, leads to behavioral intention/motivation. The volition phase, which describes how hard people try and how long they persist, leads to actual health behaviors and actions [36]. In the motivation phase, self-efficacy and outcome expectancies are major predictors of motivation, whereas risk perception is seen as an indirect factor [34]. From the first phase to the second, when people develop success scenarios and prepare strategies for facing difficult tasks or situations, it is more likely to translate good intentions into action [36].

The HAPA model yields three groups of people as they go through different mindsets on the way to health behavior change: Preintenders, Intenders, and Actors [36, 37]. This study adopts the concept of exercise adoption stages and applies the definitions described as follows:

- **Preintenders**: people who are unmotivated, having no intention to do exercise or to be more physically active.
- **Intenders:** people who have an intention to exercise but have not started or have short-lived persistence in exercise behaviors.
- **Actors:** people who perform actual exercise and have a certain degree of autonomy to exercise. These people have long-lived persistence in exercise.

For this study, the researcher uses the HAPA model to identify homogeneous target groups of participants based on their exercise adoption stages. The researcher also uses this model to guide the screening survey questions (i.e., sorting participants according to their stages of exercise adoption) and interview questions.

2.4 Research Questions

To guide this study, the researcher asked the following research (RQ) and sub-research (SRQ) questions.

- ***RQ***: *What are effective visual design strategies for self-tracking data in health & fitness applications that can motivate users (i.e., college students) at different stages of exercise adoption to exercise?*
- ***SRQ1***: *What are the commonly used visual design strategies for self-tracking data visualization in current health & fitness mobile applications?*
- ***SRQ2***: *From participants' perspectives, what are the Motivational Design Factors (MDFs) in self-tracking health & fitness mobile applications?*
- ***SRQ3:*** *What are the differences among Motivational Design Factors (MDFs) for users at different exercise adoption levels?*

(Note: Definition of Motivational Design Factors (MDFs): MDFs are motivational factors in visual design and data visualization that can have an impact on users' exercise motivation.)

3 METHODS

3.1 Methods Overview

Driven by the research questions, this study is conducted in two phases. Table 1 shows how the research question and sub-research questions are addressed by a multi-strategy approach. In the first phase, to answer the first sub-research question, the researcher collected data visualizations (in the form of screenshots) from selected health & fitness mobile applications and categorized them into data visualization design strategies with design researchers (n=3) through an affinity clustering workshop. With these results, the researcher randomly selected screenshots from each category and

Table 1: Outline of methods used to address research questions

		RESEARCH QUESTION	HOW I ADDRESS IT
PHASE 1	SRQ1	What are the commonly used visual design strategies for self-tracking data visualization in current health & fitness mobile applications?	**DESIGN SPACE ANALYSIS - AFFINITY CLUSTERING** •Screening health & fitness apps •Collecting screenshots from health & fitness apps that include data visualization •Categorizing screenshots with design researchers to generate commonly used design strategies
PHASE 2	SRQ2	From participants' perspectives, what are the motivational design factors (MDFs) in self-tracking health & fitness mobile applications?	**SCREENING + BACKGROUND SURVEY** •Sorting participants according to their stages of exercise adoptions o Preintender o Intender o Actor **SEMI-STRUCTURED INTERVIEW** •Learn from participants' perspectives - what are the real factors that motivate them in the visual design from the selected screenshots.
	SRQ3	For the purpose of promoting exercise motivation, what are the differences among motivational design factors (MDFs) for users at different exercise adoption levels?	•Participants were asked to arrange selected screenshots based on their perceived motivation. **MEMBER-CHECK** •Send out emails to check with participants about the interpretation on the interview data

Table 2: Self-tracking applications examples

WORKOUT TRACKER	TRAINING/PERSONAL STUDIO	WEIGHT CONTROL	HEALTHY DIET
•Fitbit •Pacer Pedometer & Step Tracker •Strava •Map My Run by Under Armour •Samsung Health	•Home Workout – No Equipment •JustFit!: Home Workout •Workout by Muscle Booster •Workout: Gym Workout Planner •7 Minute Workout	•Lost It! •MyFitnessPal: Calorie Counter •FatSecret •Cronometer •MyNetDiary	•Fooducate •Carb Manager •YAZIO •My Diet Coach •Lifesum: Healthy Eating

used them as research materials for the semi-structured interviews in the next stage.

In the second phase, the researcher conducted semi-structured interviews to identify Motivational Design Factors (MDFs) and to understand how users at different exercise adoption levels would prioritize those MDFs. Specifically, interview participants were grouped based on their exercise adoption level using a background survey. This was followed by a mini-interview to better understand participants' backgrounds and attitudes towards exercise and self-tracking. The researcher then conducted semi-structured interviews to explore what and why certain data visualization designs can motivate participants to exercise. The researcher also asked participants to arrange the selected screenshots (collected from phase one) based on their perceived exercise motivation. The researcher conducted both qualitative and quantitative analyses of the phase two data.

3.2 Phase One – Design Space Analysis

The first phase of this study aims to summarize common visual design strategies used in current health and fitness self-tracking mobile applications. The researcher selected mobile applications using the selection frame outlined below. Only mobile applications that met the following criteria were selected:

1. Applications are from the "Health & Fitness" category in both iTunes App Store and Google Play App Store.
2. Applications are selected from "Popular Apps" in the iTunes App Store and from "Recommended for You" in the Google Play App Store.
3. According to the rating distribution of each category in the App Store, the average rating for the "Health & Fitness" category is around four [38]. To obtain "quality" applications for analysis, only applications with a rating higher than four and with reviews totaling more than 1,000 are considered.
4. Target applications are downloadable for free (for the consideration of accessibility/affordability).
5. Target applications do not rely on devices other than mobile phones to process their core functions.
6. Applications must be in English.

Initially selected applications were classified into different categories according to their objectives (e.g., workout tracker, training/personal studio, weight control, healthy diet) and were arranged in each category based on the user ratings. The researcher selected the top five applications from each category (since some categories only have five qualified applications) and captured screenshots that exemplified different types of data visualizations from those applications. Four of the categories and the associated top five applications are shown in Table 2. This process yielded a total of 110 screenshots from 95 health and fitness mobile applications, which were then used in the affinity clustering analysis.

The researcher used affinity clustering to: (1) categorize the screenshots; and (2) give each category an appropriate name according to the design strategy. This step was conducted via a virtual affinity clustering workshop with three design researchers. Specifically, in the first round, the researchers worked simultaneously on sorting the screenshots into different groups based on the data visualization design strategy. In the second round, the researchers discussed sorting decisions and assigned names for each category. By the end of the session, the researchers checked through all screenshots to ensure they were all sorted appropriately. All researchers agreed on the names of the visual design strategy categories.

3.3 Phase Two

In the second phase, the researcher conducted semi-structured interviews with college students to: (1) uncover Motivational Design Factors (MDFs) that can affect users' (i.e., college students) exercise motivation; and (2) compare group differences and understand how users at different exercise adoption levels may need different MDFs to promote their exercise motivation.

3.3.1 *Participants.*

Participants from different grades and various departments were recruited from three undergraduate classes and a Ph.D. program at a university during the fall semester of 2019. Students were involved in this study only after permission was granted through the Institutional Review Board (IRB).

To obtain reliable interview entries and groupings by exercise adoption levels, participants were recruited through a background survey. Survey questions collected demographic data (e.g., age, gender, grade, major), experience using self-tracking applications, attitudes towards exercise and self-tracking technologies, and exercise routines. Based on the Health Action Process Approach (HAPA) framework, the researcher grouped participants into three groups:

- ***Preintenders****: people who are unmotivated, having no intention to do exercise or to be more physically active.*
- ***Intenders****: people who have an intention to exercise but have not started or have short-lived persistence in exercise behaviors.*
- ***Actors****: people who perform actual exercise and have a certain degree of autonomy to exercise. Those people have long-lived persistence in exercise.*

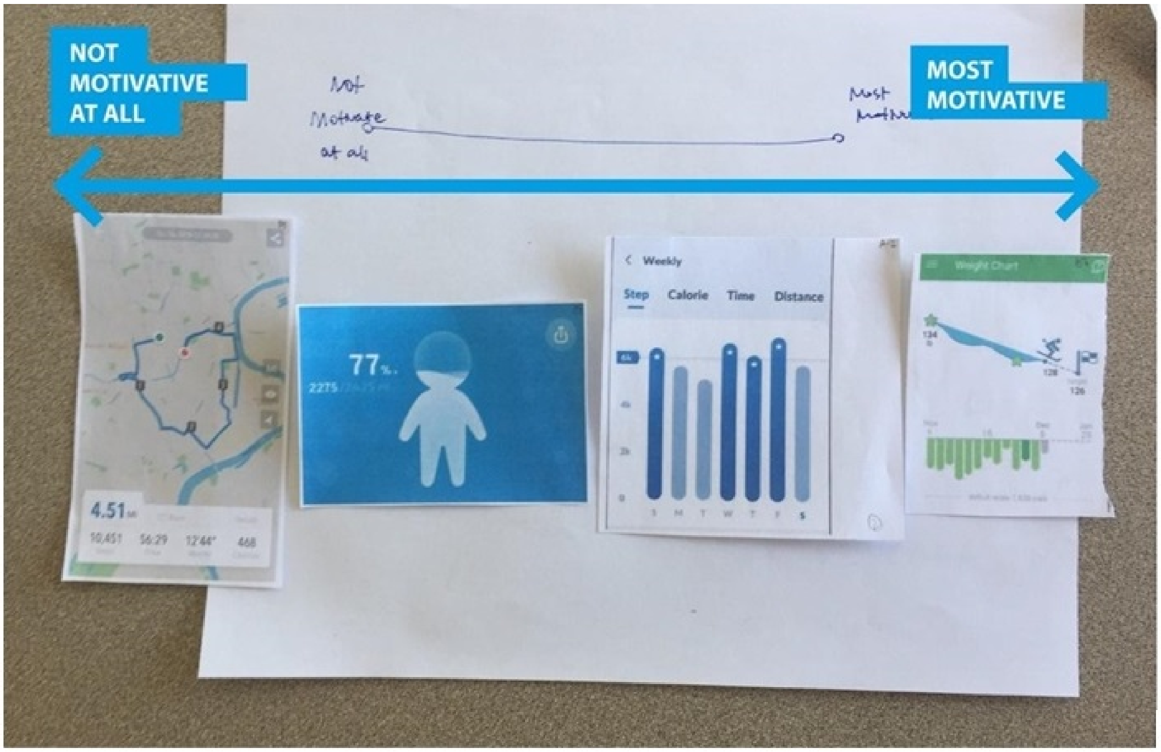

Figure 2: An example of participants arranging screenshots based on their perceived motivation to exercise.

As an extra step to consolidate the groupings and ask clarification questions for the survey responses, the researcher conducted mini-interviews to learn participants' attitudes towards and experiences doing exercise and using self-tracking technologies. From these mini-interviews, 33 students were chosen, all of which were sorted into three groups: Preintenders (n=8), Intenders (n=12), and Actors (n=13).

3.3.2 Data Collection. Semi-structured interviews were then performed to provide in-depth insights into what and why certain visual elements (MDFs) from self-tracking data visualization in health & fitness mobile applications can affect exercise motivation. The researcher included screenshots from phase one as research materials for discussion. Specifically, the researcher randomly selected one screenshot from each subcategory of the common design strategies that had been identified in the first phase. In doing so, the interview materials (and screenshots) covered all the different types of common data visualization design strategies.

The interview was devised in two parts. In the first part, each participant was asked to describe the screenshots one-by-one and identify which part of the data visualization can motivate them to exercise (if any). This process helped participants read through the entire set of screenshots. The researcher took notes on what participants highlighted in their responses. To avoid order bias, the researcher presented the screenshots in random orders.

In the second part, participants were asked to arrange screenshots based on their perceived motivation to exercise. Participants arranged screenshots on a spectrum that ranged from "most motivating" to "not motivating at all" (see Figure 2 as an example). The researcher used this strategy to get participants proactively to think through those screenshots. The researcher asked participants to 'think-aloud' and explain their arrangement decisions while working on the screenshots. The researcher adopted the speech-communication protocol for the think-aloud activities [39]. The researcher took notes on their explanations and specifically focused on their preferred, desired, and concerned design features in related screenshots.

The interviews were documented with a video camera and an audio recording on the researcher's computer. The video recorded close-up views of the materials discussed, so that when analyzing the data, the researcher knew which visualizations the participants were discussing.

3.3.3 Data Analysis. The researcher conducted both qualitative and quantitative analyses of the interview data. After data collection, the researcher transcribed all audio recordings into text transcripts for quickly scanning, searching, and coding. For the qualitative analysis, the researcher went through three main steps (see Figure 3). The first step included reading through the transcripts end-to-end, organizing the data into segments by tagging texts with appropriate codes, and generalizing significant themes (conceptualized patterns). In particular, the researcher focused on identifying MDFs and understanding how those MDFs impacted exercise motivation. In the second step, the researcher conducted a

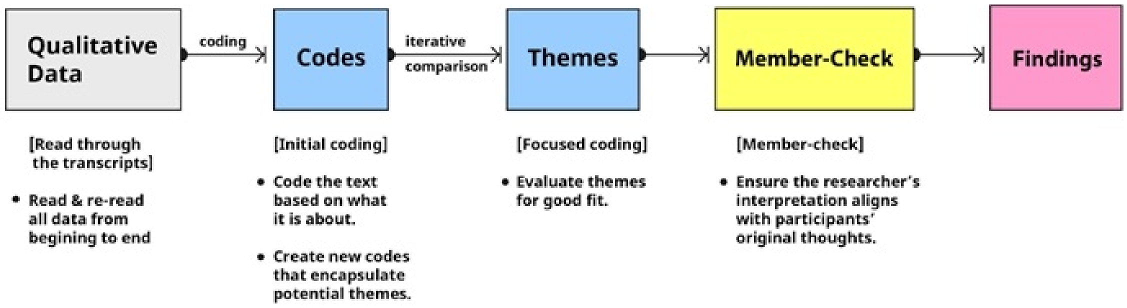

Figure 3: Main steps of the qualitative analysis for the interview data.

member-check to ensure the interpretation aligned with the participants' original thoughts. In particular, each participant received an email with a summary of his/her interview session. Participants replied to the emails to confirm or clarify the interpretation details. In the last step, the researcher reflected on the data to ground findings (MDFs) in the conceptual framework.

The goal of the quantitative analysis was to understand how different exercise adoption groups prioritize the MDFs. There were two main steps in this quantitative analysis: (1) reading through the transcripts and counting the frequency of each MDF mentioned by each participant, and (2) normalizing the frequencies for between-group comparison. For the first step, the rule for counting the frequency was when a participant mentioned a MDF while discussing a screenshot, the researcher would count one for that specific MDF. If the participant mentioned an MDF several times while making the same point and looking at the same screenshot, the researcher would not count the duplicate mentions. In the second step, the researcher calculated the average importance of each MDF to different groups of participants, using the algorithm below (in the following equations, Σ denotes summation). Specifically, for each group, Preintenders, Intenders, and Actors:

1. The researcher started with the number of mentions of each MDF mentioned by each participant, a_{ij} where j denotes the MDF and i denotes the participant.
2. For each participant, the researcher divided a_{ij} by the total number of MDFs mentioned by that participant. The result from this step provided an estimation of the relative importance S_{ij} of each MDF to this specific participant.

$$S_{ij} = RELATIVE\,IMPORTANCE\,OF\,MDF\ \ j\,FOR\,USER\ \ i = \frac{a_{ij}}{\sum_j a_{ij}}$$

3. Last, the researcher computed for each MDF the average importance over the participants in each group. This provided a relative importance of each MDF for this group.

$$AVG\ IMPORTANCE\ FOR\ EACH\ MDF\ \ j \ = \ \frac{\sum_i S_{ij}}{\sum_i 1}$$

4 FINDINGS

4.1 Phase One Findings

In phase one, the design space analysis resulted in twelve data visualization design strategies (listed below) that have been used in current health & fitness mobile applications. Examples are captured in Figure 4 with a screenshot from the affinity clustering result.

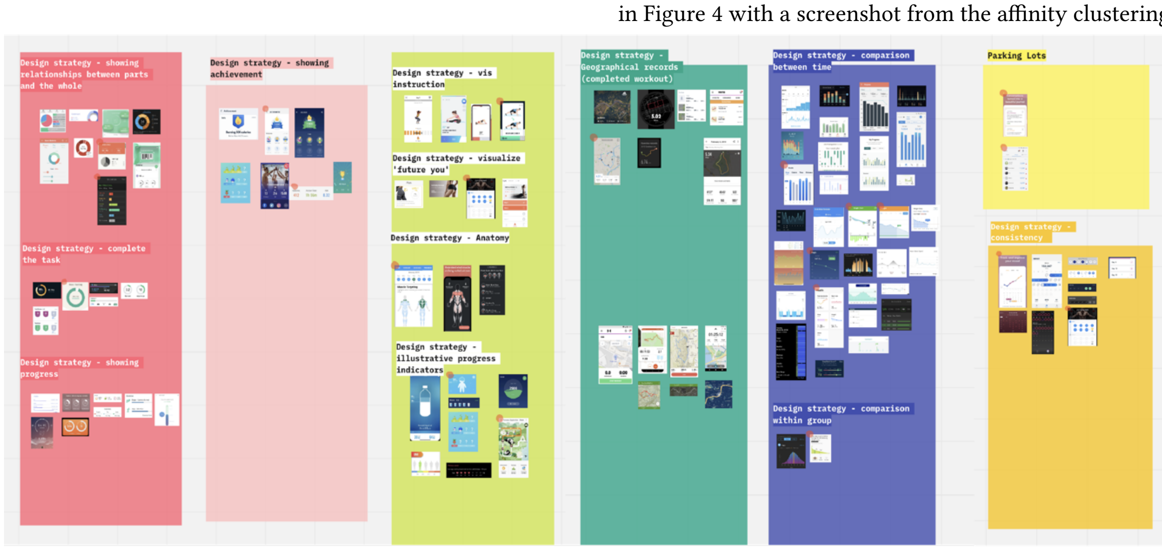

Figure 4: Examples of design strategies from affinity clustering workshop.

(1) **Seeing the big picture**: The visualization highlights how each small part plays a role on a bigger scale.
(2) **Showing accomplishments**: The visualization highlights accomplished exercises. Users can complete the graph by achieving the goal.
(3) **Showing status**: The visualization shows the user's real-time status in a workout (either in a long-term or short-term process).
(4) **Illustrative progress indicators**: The visualization indicates exercise progress using illustrations.
(5) **Visual rewards**: The visualization is used to celebrate users' exercise achievements.
(6) **Visual instruction:** The visualization illustrates how to do a specific exercise.
(7) **The 'future you'**: The visualization depicts what a user can achieve in the future after finishing the workout plan or through a long time of consistency.
(8) **Anatomy**: The visualization shows body parts to highlight muscle groups.
(9) **Geographical records**: The visualization pictures a user's accomplishment on a geographical map.
(10) **Comparison between times**: The visualization shows a retrospective view of how the performance has changed through time.
(11) **Comparison within a group**: The visualization compares the workout between people.
(12) **Consistency**: The visualization indicates workout consistency, usually on a calendar. The purpose is to track long-term consistency.

4.2 Phase Two Findings

4.2.1 Motivational Design Factors (MDFs). In the second phase, as the interview data analysis was processed, there were several emergent data visualization design concepts, known as Motivational Design Factors (MDFs) generated.

MDF-1: **'Data/graph reliability'**

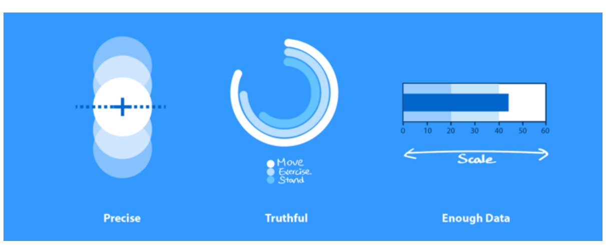

Figure 5: An illustration of MDF 'Data/graph reliability'.

MDF-1: 'Data/graph reliability' refers to the data visualizations that are truthful (the data is honestly reflecting what is going on with the workout) and precise (using clear annotation). Data visualizations deliver a sense of truth when they match the corresponding data and reflect true-to-life workout status (as illustrated in Figure 5). In the interview, data visualizations that missed this MDF caused confusion. As a result, participants would not take the information seriously. Data visualizations that give users a sense of preciseness show accurate measurements and annotations. Those visualizations enabled participants to see the exact numbers and quantify their exercise. Based on the interviews, *extreme values* (e.g., the maximum and minimum data points), information that can *represent exercise levels* (e.g., average pace), and *reflections of accomplishments* (e.g., calories burned, distance, etc.) need to be precise to motivate users.

MDF-2: **'Visualized goals'**

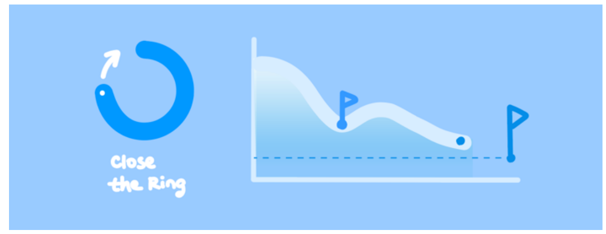

Figure 6: An illustration of MDF 'Visualized goals'.

MDF-2: 'Visualized goals' in self-tracking includes visualizing short-term goals, long-term goals, goals set up by users, or goals set up through the application's suggestions (as illustrated in Figure 6). Goals drove participants' motivation since they reminded people what they want to achieve. Goals also helped participants evaluate their workout, which motivated them to get where they planned to. For example, one said, "I can see the daily goal and if I hit it or not. If not, I will work harder" (PPT10).

MDF-3: **'Visualized progress'**

Figure 7: An illustration of MDF 'Visualized progress'.

MDF-3: 'Visualized progress' refers to visualizing changes in users' exercise performances over time. This MDF helped participants notice that they have been making changes (as illustrated in Figure 7). As one participant said, "It's like a self-journey" (PPT08). Visualized progress motivated participants in several ways. First, participants were able to see how they came to where they were. Second, seeing the progress made participants feel good.

MDF-4: **'Visualized completion and consistency'**

MDF-4: 'Visualized completion and consistency' refers to visualizing how much exercise a user has completed and how consistent it has been (as illustrated in Figure 8). This MDF motivated participants for several reasons. First, participants felt good after knowing how much they have accomplished. As one mentioned, "I can look at how long I have done, and be like - oh, I can do that!" (PPT5). Second, seeing completion made participants more positive and motivated to challenge themselves. For instance, one participant expressed his feeling, "Oh yes! I did it in 56 minutes! Next time, I will

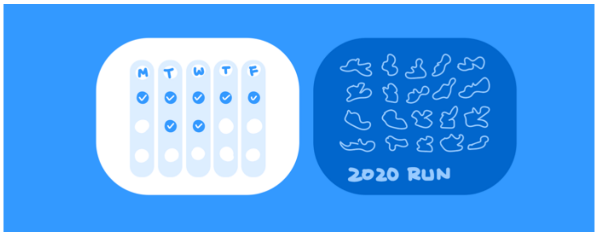

Figure 8: An illustration of MDF 'Visualized completion and consistency'.

do the same route but in 50 minutes" (PPT16). Third, participants did not want to break the consistency of their exercise considering all the efforts contributed.

MDF-5: **'A holistic view of connections and relationships'**

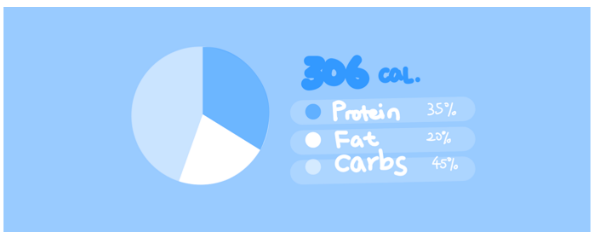

Figure 9: An illustration of MDF 'A holistic view of connections and relationships'.

MDF-5: 'A holistic view of connections and relationships' refers to visualizing the connection and relationships between different types of tracking data (as illustrated in Figure 9). This MDF helped participants (1) understand the importance of exercise to their overall health, (2) know where their results came from, and (3) see the connections and relationships between different data. As a participant mentioned, "It motivates me because it reminds me of the importance of doing it. It makes exercise a part of my overall health" (PPT22).

MDF-6: **'Knowing ongoing status'**

Figure 10: An illustration of MDF 'Knowing ongoing status'.

MDF-6: 'Knowing ongoing status' refers to visualizing real-time data to help users learn their current workout status (as illustrated in Figure 10). For instance - Has the user reached a particular heart rate range to meet the exercise goal? Which part of muscle has the user been exercising? This MDF helped participants to know themselves better throughout the exercise. For example, one participant mentioned, "it is like knowledge-driven, the more you use, the more you know about yourself" (PPT27). Moreover, participants expressed that they would work harder because it was a rewarding experience when they could see the real-time feedback of their exercise.

MDF-7: **'Instructions and suggestions'**

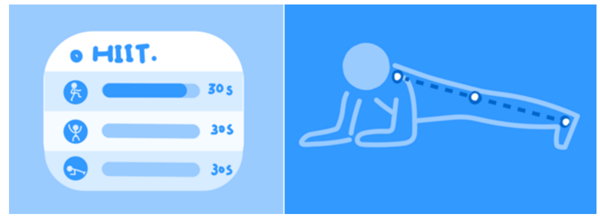

Figure 11: An illustration of MDF 'Instructions and suggestions'.

MDF-7: 'Instructions and suggestions' refers to visual instructions on how to exercise correctly and what to do to achieve a particular fitness goal (as illustrated in Figure 11). This MDF made participants feel confident about exercise. For instance, as participants said, "Having the knowledge of the exercise and feeling confident in what I am doing are the best motivators. Because I feel I can do it" (PPT2). "It makes me feel easy and the ease motivates me" (PPT14). "If I can be instructed on what to do, I will complete it" (PPT30).

MDF-8: **'Competitive social elements'**

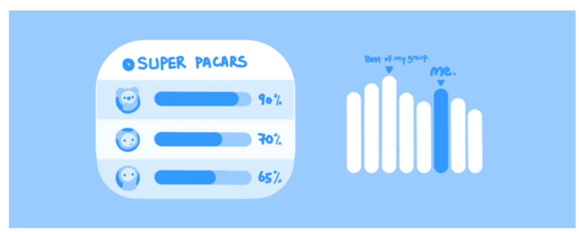

Figure 12: An illustration of MDF 'Competitive social elements'.

MDF-8: 'Competitive social elements' refers to data visualizations that compare a user's data with other users (as illustrated in Figure 12). Participants mentioned that seeing how other people are doing made them want to work harder. However, with some less competitive participants, they believed that workout data was personal. They are neither willing to share their exercise data nor care about other users.

MDF-9: **'Supportive social elements'**

MDF-9: 'Supportive social elements' refer to data visualizations that help connect people and create social support (as illustrated in Figure 13). Participants believed that seeing other people doing the exercise made them feel supported. Moreover, being in social connections pushed participants to be accountable for their health and exercise. For instance, one participant said, "once I connect

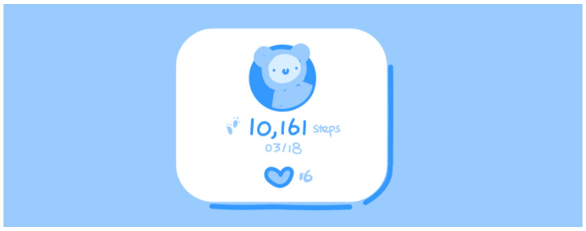

Figure 13: An illustration of MDF 'Supportive social elements'.

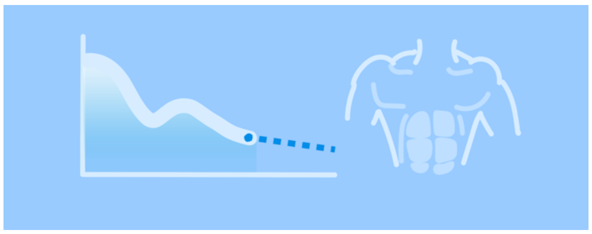

Figure 14: An illustration of MDF 'Framing the future'.

with people, my friends and everyone else can see it. I tell people my goals so they can hold me accountable" (PPT8).

MDF-10: 'Framing the future'

MDF-10: 'Framing the future' refers to data visualizations that represent users' future states of their exercise and health (as illustrated in Figure 14). In particular, users see a trend or prediction indicating what could happen if they would keep doing what they are doing. In the interview, especially when the trend was positive, participants saw themselves doing well and feeling more motivated.

4.2.2 Group Differences. This section reports findings regarding group differences. Specifically, how users at different exercise adoption levels (Preintenders, Intenders, Actors) prioritized the MDFs. Figure 15 shows the average importance of each MDF for each group of participants, as computed in section 3.3.3.

Preintenders

According to phase two data, the main barriers to motivating Preintenders to exercise are (1) Preintenders believe that exercise, in general, is not fun (e.g., "Just not fun and painful. I like to play easily." (PPT22)), and (2) they do not know how exercise benefits them (e.g., "I physically look well. I eat well. I already have a healthy lifestyle and I could not see how exercise benefits me more." (PPT02)). Interview results showed that the top four MDFs prioritized by Preintenders are: 'A holistic view of connections and relationships', 'data/graph reliability', 'visualized instructions and suggestions', and 'competitive social elements'. The researcher also noticed that only Preintenders brought up the MDF 'supportive social elements'. Although it is not ranked among the top, supportive social elements gave Preintenders a feeling of being connected and related.

Intenders

Intenders are at the stage of exploring exercise. Unlike Preintenders, Intenders have thoughts about starting exercise. According to the interview data, the main barriers to motivating Intenders to exercise are (1) not knowing their exercise goals, and (2) not being confident in exercising. Interview results showed that the top four MDFs prioritized by Intenders are: 'Data/graph reliability', 'visualized goals', 'visualized progress', and 'visualized completion and consistency'.

Actors

Actors have ideas about what they want to achieve through exercise. They are capable of interpreting their workout data. Additionally, they can adjust their workout plans according to their performances. The researcher found that actors use data visualizations and tracking data as their tools instead of depending on them. Interview results showed that the top four MDFs prioritized by Actors are: 'Data/graph reliability', 'visualized goals', 'a holistic view of connections and relationships', and 'visualized progress'.

5 DESIGN RECOMMENDATIONS

After developing the MDFs and studying how people from different exercise adoption groups prioritize them, the researcher generated a set of design strategies for promoting exercise motivation through data visualizations in self-tracking applications.

5.1 Design Strategies for Motivating Preintenders

(1) Showing every small step is to achieve big goals - Interestingly, when Preintenders use self-tracking applications, they are not driven by the intention to exercise. To trigger their exercise motivation, they need to understand why they want to exercise. Data visualization can present the connection of how each data input contributes to a healthy and happy life, Figure 16 as an example. Connecting the data with their life improvements can help Preintenders build a mental connection between exercise and what they want to achieve.
(2) Reducing barriers for interpretation - The researcher learned from the interviews that Preintenders perceived exercise as not fun partly because they could not interpret the technical terms used in the data visualizations. Creating data visualizations with appropriate labels and annotations can help people understand the data without extra cognitive effort. An example of this would be to explain whether a result is positive or negative.
(3) Straightforward visual instructions - According to the Self Determination Theory, to be intrinsically motivated, people need to feel confident in what they are doing. Visualized instructions on what the user needs to do and how to do a particular exercise correctly can help Preintenders gain knowledge on doing exercises and build up confidence while exercising.

5.2 Design Strategies for Motivating Intenders

(1) Visualized goals - From the interviews, the researcher learned that Intenders have a vague idea about what they want to achieve through exercise. Visualizing short-term goals, milestones, and long-term goals help Intenders to break down the vague intention and consolidate them into achievable goals. Seeing goals visually also helps Intenders

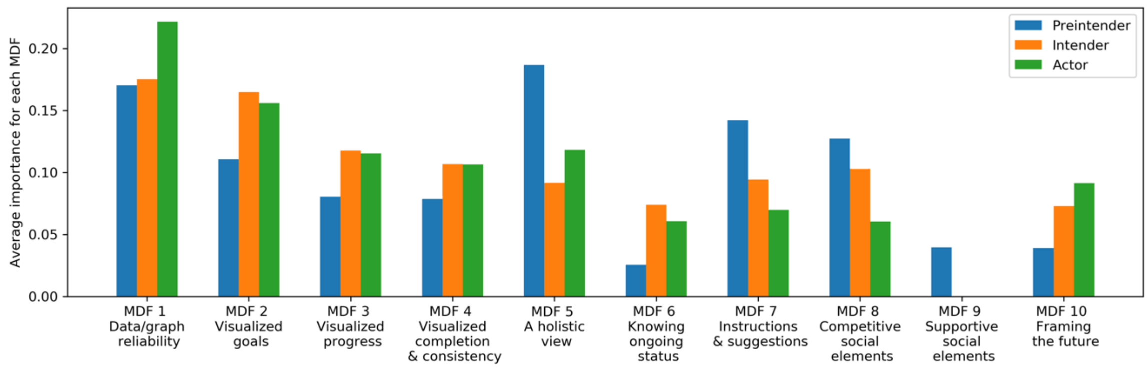

Figure 15: ***Average importance of each MDF for each group of participants.***

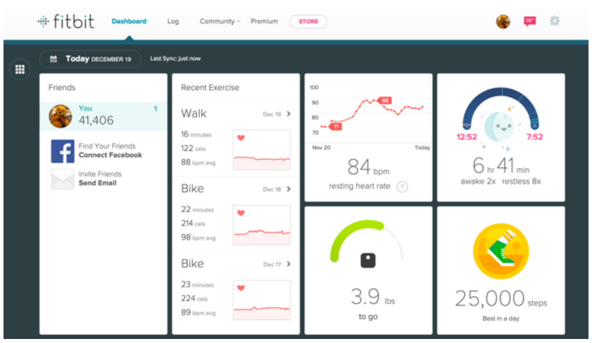

Figure 16: A dashboard from a self-tracking application shows the big picture that exercise is a part of a person's overall health. From the dashboard visualization, users build a mental connection between exercise and health. From https://zapier.com/blog/best-fitness-tracking-apps/.

internalize their goals and set their mind ready to take actions.

(2) 'A spirit lifter' - Intenders struggled to start exercise also because they were unsure if they could be successful. The visualizations can positively frame the result to help Intenders gain self-efficacy. The Framing Effect theory from the literature provides theoretical support for this design strategy. Briefly, when two logically equivalent alternative options were shown, the choice between the alternatives depends on whether people focus their attention on the gain or the loss [10, 40]. For example, suppose there was a cup of water. Someone could say the cup is 70% full or alternatively say it is 30% empty. Studies have shown that a subtle change of the frame can significantly influence users' interpretations, opinions, and responses to a piece of data visualization [10, 41, 42]. In self-tracking applications, practitioners can frame data visualizations to highlight progress, accomplishments, and consistencies to motivate Intenders.

5.3 Design Strategies for Motivating Actors

(1) Opportunities for checking details - In the interviews, the researcher found Actors had substantial knowledge of exercise. They were very used to looking at precise data and exact numbers. Seeing details from the data visualization made them trust the data more and make realistic plans to avoid frustration.

(2) Creating a self-journey - Data visualization is a powerful tool to synthesize, rearrange, and present data. A self-journey is a way to show Actors their journeys to the point where they are and where they want to be. Actors are consistent exercisers. In this journey, they can track progress and visually see themselves getting closer to a target. And even explore the story generated by the user's own exercise data, as what Cairo demonstrated in the book 'The Function Art' [43].

6 CONCLUSION AND FUTURE WORK

In this work, the researcher studied visual design strategies for self-tracking data and their impacts on users' exercise motivation. Through a multi-strategy approach, the researcher introduced Motivational Design Factors (MDFs) (motivational factors in visual design and data visualization that can have an impact on user's exercise motivation) and generated a set of practical design strategies for promoting college students' exercise motivation at different exercise adoption stages. Findings from this study have contributed to knowledge regarding data visualization for improving health and well-being in the digital age. This study contributes to design research by alleviating gaps in the crosscutting areas of information visualization and exercise motivation. This work brings attention to the value and power of data visualization design in self-tracking technologies and the broader social impacts.

Although this study primarily focuses on the data visualization strategies for exercise, there is great potential to apply these methods to other fields. For example, in education, emotion plays a critical role in problem-solving [44]. One exciting direction would be to explore how data visualizations can impact learners' emotions and motivations.

Additionally, it would be interesting to explore the data visualizations in the applications that target different types of exercise.

For instance, data visualizations in yoga, cycling, and weightlifting may require different MDFs. The actionability framework can be considered as an approach to studying the topic.

Furthermore, this work specifically looks into mobile applications in which the user experience is limited to interactions with 2D interfaces. Other technologies, such as exercise equipment (e.g., Peloton), wearable devices, and even Virtual Reality/Augmented Reality, provide more dynamic experiences in which a wider range of interactions are possible. It would be interesting to investigate information visualization and its applications in such a dynamic interactive environment.

ACKNOWLEDGMENTS

The researcher is grateful for all the invaluable discussions with Dr. Deborah Littlejohn, Dr. Matthew Peterson, Dr. Sharon Joines, and Dr. Anne McLaughlin. The researcher thanks Dr. Deborah Littlejohn and Dr. Russell Flinchum for their help in recruiting interview participants. The researcher thanks Anantaya Wonaphotimuke, Rachael Paine, and Payod Panda for their participation in the phase one workshop. The researcher thanks Dr. Seth Hirsh for his feedback on the data analysis. Finally, the researcher appreciates all the participants for their time and effort throughout the interview process.

REFERENCES

[1] Sharma, A., Madaan, V., and Petty, F. D. 2006. Exercise for mental health. Primary care companion to the Journal of clinical psychiatry, 8(2), 106. https://doi.org/10.4088/pcc.v08n0208a.
[2] Parker, K., Uddin, R., Ridgers, N. D., Brown, H., Veitch, J., Salmon, J., Timperio, A., Sahlqvist, S., Cassar, S., Toffoletti, K., Maddison, R., and Arundell, L. 2021. The Use of Digital Platforms for Adults' and Adolescents' Physical Activity During the COVID-19 Pandemic (Our Life at Home): Survey Study. Journal of medical Internet research, 23(2), e23389. https://doi.org/10.2196/23389.
[3] Feng, S., Mañtymaki, M., Dhir, A., and Salmela, H. 2021. How Self-tracking and the Quantified Self Promote Health and Well-being: Systematic Review. J Med Internet Res. 2021;23(9): e25171. doi: 10.2196/25171
[4] Budd, J., Miller, B.S., Manning, E.M. *et al.* 2020. Digital technologies in the public-health response to COVID-19. Nat Med 26, 1183–1192. https://doi.org/10.1038/s41591-020-1011-4
[5] Sullivan, A. N., and Lachman, M. E. 2017. Behavior Change with Fitness Technology in Sedentary Adults: A Review of the Evidence for Increasing Physical Activity. Frontiers in public health, 4, 289. https://doi.org/10.3389/fpubh.2016.00289.
[6] Kosara, R., Cohen, S., Cukier, J., and Wattenberg, M. 2009. Panel: Changing the world with visualization. In *IEEE Visualization Conference Compendium.*
[7] Mason, S., and Azzam, T. 2019. In Need of an Attitude Adjustment? The Role of Data Visualization in Attitude Change and Evaluation Influence. American Journal of Evaluation, 40(2), 249–267. https://doi.org/10.1177/1098214018778808
[8] Kostelnick, C., 2008. "The Visual Rhetoric of Data Displays: The Conundrum of Clarity*," in IEEE Transactions on Professional Communication, vol. 51, no. 1, pp. 116-130, doi: 10.1109/TPC.2007.914869
[9] Pandey, A. V., Manivannan, A., Nov, O., Satterthwaite, M., and Bertini, E. 2014. The persuasive power of data visualization. IEEE transactions on visualization and computer graphics, 20(12), 2211-2220. 31 Dec. 2014. doi: 10.1109/TVCG.2014.2346419
[10] Tversky, A., and Kahneman, D. 1981. The framing of decisions and the psychology of choice. science, 211(4481), 453-458.
[11] King, D., Greaves, F., Exeter, C., and Darzi, A. 2013. 'Gamification': influencing health behaviours with games. Journal of the Royal Society of Medicine, 106(3), 76-8.
[12] Card, Stuart K., Mackinlay, Jock., and Shneiderman, Ben., 1999. Readings in Information Visualization: Using Vision to Think. Morgan Kaufmann, San Francisco.
[13] Sorapure, Madeleine., 2019. Text, Image, Data, Interaction: Understanding Information Visualization. Computers and Composition, Volume 54. ISSN 8755-4615. https://doi.org/10.1016/j.compcom.2019.102519.
[14] Ware, C. 2012. Information Visualization: Perception for Design. Journal of Software Engineering and Applications, Vol.9 No.7. Elsevier.
[15] Few, S. 2009. Now You See It: Simple Visualization Techniques for Quantitative Analysis (1st. ed.). Analytics Press, Oakland, CA, USA.
[16] Clark, R. C., and Mayer, R. E. 2003. e-learning and the science of instruction. San Francisco: Jossey-Bass.
[17] Bilbokaite, R. 2015. Effects of computer based visualization on students' cognitive processes in education process. Society Integration Proceedings of the International Scientific Conference, doi: 10.17770/sie2015vol4.417
[18] Viegas, F. B., Wattenberg, M., Van Ham, F., Kriss, J., and McKeon, M., 2007. "ManyEyes: a Site for Visualization at Internet Scale," in IEEE Transactions on Visualization and Computer Graphics, vol. 13, no. 6, pp. 1121-1128, Nov.-Dec. 2007, doi: 10.1109/TVCG.2007.70577
[19] Dörk, M., Feng, P., Collins, C., and Carpendale, S. 2013. Critical InfoVis: exploring the politics of visualization. In *CHI'13 Extended Abstracts on Human Factors in Computing Systems* (pp. 2189-2198).
[20] Dick, M. 2013. Interactive Infographics and News Values. Digital Journalism. (Ahead-of-print), pp.1-17.
[21] C. A. Welhausen. 2002. "Precarious Data: Crack, Opioids, and Enacting a Social Justice Ethic in Data Visualization Practice," in *IEEE Transactions on Professional Communication*, vol. 65, no. 1, pp. 50-69, March 2022, doi: 10.1109/TPC.2022.3144826.
[22] C. Lauer and S. O'Brien. 2020. "How People Are Influenced by Deceptive Tactics in Everyday Charts and Graphs," in IEEE Transactions on Professional Communication, vol. 63, no. 4, pp. 327-340, Dec. 2020, doi: 10.1109/TPC.2020.3032053.
[23] Lambrecht, K. 2021. Tracking the Differentiation of Risk: The Impact of Subject Framing in CDC Communication Regarding COVID-19. Journal of Business & Technical Communication, 35(1), 94-100.
[24] Richards, D. 2016. Helping Local Residents Make Informed Decisions with Interactive Risk Visualization Tools. *SIGDOC '16: The 34th ACM International Conference on the Design of Communication Proceedings.* New York: ACM.
[25] Velázquez-Iturbide, J. Á., Hernán-Losada, I., and Paredes-Velasco, M. 2017. Evaluating the effect of program visualization on student motivation. IEEE Transactions on Education, 60(3), 238-245.
[26] Park, S., Bakemeier, B., Flaxman, A., and Schultz, M. 2014. Impact of data visualization on decision-making and its implications for public health practice: a systematic literature review. Informatics for Health and Social Care, https://doi.org/10.1080/17538157.2021.1982949
[27] Eberhard, K. 2021. The effects of visualization on judgment and decision-making: a systematic literature review. Manag Rev Q. https://doi.org/10.1007/s11301-021-00235-8
[28] Hullman, J., and Diakopoulos, N. 2011. Visualization rhetoric: Framing effects in narrative visualization. IEEE Transactions on Visualization and Computer Graphics, 17(12), 2231-2240.
[29] Deci, E. L., and Ryan, R. M. 2008. Self-Determination Theory: A Macrotheory of Human Motivation, Development, and Health. Canadian Psychology, Vol. 49, No. 3, p. 182-185.
[30] Fishbein, M., and Ajzen, I. 1975. Belief, Attitude, Intention, and Behavior: An Introduction to Theory and Research. Reading, MA: Addison-Wesley.
[31] Ajzen, I. 1985. From intentions to actions: A theory of planned behavior. In J. Kuhi & J. Beckmann (Eds.), Action-control: From cognition to behavior (pp. 11ó39). Heidelberg: Springer.
[32] Ryan, R. M., and Deci, E. L. 2017. Self-determination theory: Basic psychological needs in motivation, development, and wellness. The Guilford Press. https://doi.org/10.1521/978.14625/28806.
[33] Teixeira PJ, Carraça EV, Markland D, Silva MN, Ryan RM. 2012. Exercise, physical activity, and self-determination theory: a systematic review. Int J Behav Nutr Phys Act. 2012 Jun 22; 9:78. doi: 10.1186/1479-5868-9-78. PMID: 22726453; PMCID: PMC3441783.
[34] Schwarzer, Ralf. *et al.* 2003. On the Assessment and Analysis of Variables in the Health Action Process Approach: Conducting an Investigation. http://userpage.fu-berlin.de/gesund/hapa_web.pdf
[35] Chiu, C.Y. *et al.* 2011. The health action process approach as a motivational model for physical activity self-management for people with multiple sclerosis: a path analysis. Rehabilitation Psychology. Vol.56., p.171-181.
[36] Schwarzer, R. 2008. Modeling health behavior change: How to predict and modify the adoption and maintenance of health behaviors. Applied Psychology: An International Review, 57(1), 1-29.
[37] Schwarzer, R., Lippke, S., and Luszczynska, A. 2011. Mechanisms of health behavior change in persons with chronic illness or disability: The health action process approach (HAPA). Rehabilitation Psychology, 56, 161-170. doi: 10.1037/a0024509
[38] Eberhart, C. 2014. A statistical analysis of the apple app store. http://blog.scottlogic.com/2014/03/20/app-store-analysis.html
[39] Erica L. Olmsted-Hawala, Elizabeth D. Murphy, Sam Hawala, and Kathleen T. Ashenfelter. 2010. Think-aloud protocols: a comparison of three think-aloud protocols for use in testing data-dissemination web sites for usability. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '10). Association for Computing Machinery, New York, NY, USA, 2381–2390. https://doi.org/10.1145/1753326.1753685
[40] Levin, I. P., and Gaeth, G. J. 1988. How consumers are affected by the framing of attribute information before and after consuming the product. Journal of Consumer Research, 15(3), 374–378. https://doi.org/10.1086/209174

[41] Neff, G., and Nafus, D. 2016. Title of work: Making sense of data. The Self-Tracking. The MIT Press. 70-93.
[42] Choe, E. K., Lee, B., and Schraefel, M. C. 2015. Characterizing visualization insights from quantified selfers' personal data presentations. IEEE Computer Graphics and Applications. P.28-37.
[43] Cairo, A. 2013. The functional art: An introduction to information graphics and visualization. New Riders Publishing, CA.
[44] Azevedo, R., Millar, G. C., Taub, M., Mudrick, N., Bradbury, A. E., and Price, M. J. 2017. Using data visualizations to foster emotion regulation during self-regulated learning with advanced learning technologies: a conceptual framework. In Proceedings of the Seventh International Learning Analytics & Knowledge Conference (LAK '17). Association for Computing Machinery, New York, NY, USA, 444–448. https://doi.org/10.1145/3027385.3027440