Journal of the American Medical Informatics Association, 2024, **31(2)**, 465–471
https://doi.org/10.1093/jamia/ocad117
Advance access publication 20 July 2023
Brief Communications

Brief Communications

Improving the design of patient-generated health data visualizations: design considerations from a Fitbit sleep study

Ching-Tzu Tsai [1,2], Gargi Rajput [1,3], Andy Gao [1,3], Yue Wu [1,2], and Danny T.Y. Wu [1,2,3,*]

[1]Department of Biomedical Informatics, College of Medicine, University of Cincinnati, Cincinnati, Ohio, USA
[2]School of Design, College of Design, Architecture, Art, and Planning, University of Cincinnati, Cincinnati, Ohio, USA
[3]Medical Science Baccalaureate Program, College of Medicine, University of Cincinnati, Cincinnati, Ohio, USA

*Corresponding Author: Associate Professor Danny T.Y. Wu, PhD, MSI, Department of Biomedical Informatics, Medical Science Building, Room 6465, 231 Albert Sabin Way, Cincinnati, OH 45229, USA; wutz@ucmail.uc.edu

ABSTRACT

Interactive data visualization can be a viable way to discover patterns in patient-generated health data and enable health behavior changes. However, very few studies have investigated the design and usability of such data visualization. The present study aimed to (1) explore user experiences with sleep data visualizations in the Fitbit app, and (2) focus on end users' perspectives to identify areas of improvement and potential solutions. The study recruited eighteen pre-medicine college students, who wore Fitbit watches for a two-week sleep data collection period and participated in an exit semi-structured interview to share their experience. A focus group was conducted subsequently to ideate potential solutions. The qualitative analysis identified six pain points (PPs) from the interview data using affinity mapping. Four design solutions were proposed by the focus group to address these PPs and illustrated by a set of mock-ups. The study findings informed four design considerations: (1) usability, (2) transparency and explainability, (3) understandability and actionability, and (4) individualized benchmarking. Further research is needed to examine the design guidelines and best practices of sleep data visualization, to create well-designed visualizations for the general population that enables health behavior changes.

Key words: patient-generated health data, sleep quality, user-centered design

BACKGROUND AND SIGNIFICANCE

The collection of patient-generated health data (PGHD) has been on the rise due to wide adoption of smartphone apps and wearable devices, allowing patients to access traditionally unobtainable information and improve the patient-clinician decision-making process.[1–3] Wearable devices enable continuous tracking and measurement of disease and health biomarkers through biosensors.[4] Among PGHD, sleep patterns and quality have been of great interest because improved sleep quality correlates to improved mental health, decreased stress,[5,6] blood pressure dipping, and lower biological risks.[7,8] Sleep tracking apps, by extension, can increase users' awareness on sleep quality and provide tailored and minimally invasive interventions to support sleep self-management.[9,10]

Despite the potential benefits, sleep tracking apps may require improvement in terms of quality and content and more validation studies to improve their clinical value.[11,12] It is recommended to apply user-centered design and mixed-method approaches to determine the user requirements when developing sleep tracking apps.[13] On the other hand, a systematic review pointed out that more scales for assessing the usability and quality of mobile health apps should be developed for end users, especially patients or caregivers.[14] While studies have explored end-user needs and engagement as well as usability of mobile health apps and wearables in sleep monitoring,[15,16] very few studies focused on the usability of sleep data visualization.

Our study sought to address this gap by exploring overall user experiences and collecting user feedback on the design of sleep data visualization provided in the Fitbit app. Fitbit wearables have been shown to have good sleep-tracking performance when compared to the gold standard of polysomnography (PSG).[17,18] A specific focus was maintained on end users' perspectives to identify areas of improvement and potential solutions and further draw design considerations. With the Fitbit application programming interfaces (APIs), the design considerations of the present study can be implemented as a separate web-based or mobile health application to address specific user needs and make unique impact.

MATERIALS AND METHODS

Participant recruitment

The study recruited participants from a medical sciences baccalaureate program (MSBP) at a research one (R1) university in the Midwest United States. The MSBP consists of premedicine (premed) college students, who are generally interested in

Received: 22 January 2023. **Revised:** 11 May 2023. **Editorial Decision:** 7 June 2023. **Accepted:** 28 June 2023

medicine and public health. It is worth noting that premed students are not medical students, as they have not yet received a college degree or professional qualification. While this population may possess more medical knowledge than the general population, they are not experts. Their opinions are valuable in the present study because the general population is likely to experience difficulties if the MSBP students already have issues in using wearables and interpreting the sleep data.

Study design

Figure 1 shows the study design. Eighteen participants were recruited from our parent study where a survey was given to 103 MSBP students to collect their self-reported sleep patterns. The 18 participants were invited to a 2-week study to wear a Fitbit Inspire 2 watch and provide feedback on Fitbit visualizations via an exit semistructured interview. The details of the 2-week Fitbit study are described in Supplementary Material. The feedback was analyzed qualitatively to generate sweet and pain points of user experience. A focus group was conducted subsequently to ideate solutions to the pain points (PPs). Not all 18 participants were invited to the focus group. Those who were not invited ($N = 16$) received a summary email and were asked to provide feedback (member check-in). The study was reviewed and approved by our instructional review board (IRB No. 2021-1119).

Semistructured interview

The guide of the semistructured interviews was developed following the framework proposed by Kallio et al.[19] The interview questions are listed in Supplementary Material. The interview guide was piloted with 2 research team members who were MSBP students. During the interviews, key information was extracted and recorded on virtual sticky notes using an online platform called "Miro" (www.miro.com). Affinity mapping was then applied on these notes to group similar ideas together and forms categories.[20] This process identified the sweet and pain points (PPs) of user experience. Additionally, a user-journey map[21] was generated to outline the participants' actions, touchpoints, emotions, goals, and PPs throughout their experience with the app.

Focus group

A focus group[22] was conducted to generate ideas and potential solutions specifically for the PPs identified through the semistructured interviews. A focus group usually includes 6–8 people.[23] In the present study, a diverse group of 6 individuals with various backgrounds were invited, including: 2 participants from the 2-week Fitbit data collection, and 4 domain experts (1 biomedical informatics doctoral student, 1 doctoral-level statistician, 1 master-level application developer, and 1 master of design student). The 4 domain experts were recruited via convenience sampling in the research team's professional network. The experts were purposely not involved as part of the affinity mapping so that they can provide fresh input on the design solutions. This focus group was conducted virtually on Miro for 2 h, with an overseeing facilitator (CT) providing an overview of the identified PPs and guiding the participants throughout the ideation process. An assistant (YW) was present to facilitate the discussion and take notes.

The focus group consisted of several ideation sessions. In each session, the participants were asked to comment on each PP for 3 min, followed by a 10-min group discussion. Throughout the sessions, participants were asked to record their ideas on sticky notes. Audio and screen recordings were made to support detailed analysis. Affinity mapping was also employed to analyze the data.[20] The solutions and recommendations were generated, excluding those related to technical issues or visual features (eg, color and shape). Mock-ups were created accordingly to demonstrate the final solutions.

RESULTS

Interview analysis results

Table 1 summarizes the 6 identified PPs through affinity mapping. The PPs emerged through 2 rounds of analysis: the first 5 interviews generated 4 PPs. These PPs were refined and enhanced the analysis of the remaining 13 interviews, resulting in 6 PPs. Specifically, 2 new PPs were identified (PP#4 and #5) and 1 was reorganized and expanded (PP#3). PP#4 highlighted a need for enhancement of the bar chart of weekly sleep scores, while PP#5 revealed the participants' confusion regarding the deep and REM sleep charts. On the other hand, PP#3 was originally described as trouble in finding explanations of the information shown on the user interface, which was expanded to reflect the fact that users expressed a desire for an overall improved instruction to access their sleep data.

Figure 2 presents details of the user journey map constructed based on the interview analysis results. The journey was divided into 7 stages; each stage (column) of the user

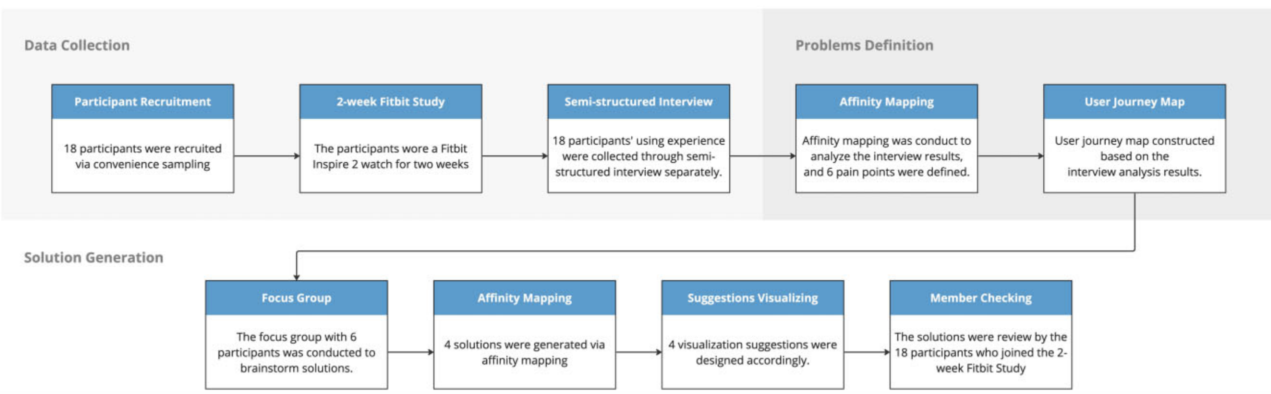

Figure 1. Study design workflow.

Table 1. List of pain points with descriptions and representative quotes

Pain point #	Description	Representative quote(s)
1. Undefined calculation of sleep score	Users were aware that the final sleep score was determined by factors such as time asleep, sleep cycle, and restoration. However, detailed calculations for each component were missing causing confusion, particularly when the scores did not match perceived sleep quality.	"I think it did not elucidate how the scores were calculated, which added some skepticism of whether it really was indicative of sleep. I also think there were times when I felt I was awake (but the app showed a different status)." (P11)
2. Lack of practical suggestions to improve sleep scores	Users were unsure how to improve their sleep score and desired personalized guidance. The tips provided on the app were not tailored to their needs and were also difficult to locate.	"In addition to sleep more, I did not know what I could do to change my score." (P9)
3. In need of better ways/instructions to access sleep data	Users stated that due to the abundance of information, they needed better guidance to help them access the details and description of the data.	"I wasn't aware that there were more features on the app that delved deeper into my sleep. I had only been aware of the screen and data that was on the main screen when you first open the app." (P18)
4. Unclear representation of weekly sleep scores in a bar graph	Users found the bar graph of weekly sleep score to be inadequate as it was difficult to comprehend and provided limited information.	"I also disliked the bar graph chart of the weekly sleep score as it just doesn't offer me any information past what I already know as the week goes on." (P17)
5. Difficult to understand the deep and REM graph	Users had trouble understanding the deep and REM sleep graph due to lack of relevant knowledge and confusing visual representation.	"I did not feel like I understood the sleep stages well at all. It seemed like they were presented with no explanation, and I did not know how that was impacting my sleep score." (P9)
6. Unsure about "Normal" sleep patterns for an individual	Users relayed a preference for personalized standards to evaluate their sleep quality more accurately, since differences in age, gender, physical fitness, and lifestyle may result in varying sleep patterns.	"I just wish there was a description of what one should aim for in each sleep stage, like what percent of sleep should you have or how much time should you be spending in each stage." (P13)

journey map illustrates the actions, emotions, goals, and PPs of the users at each stage. The user-journey map was utilized to aid the 6 members of the focus group in understanding the PPs.

Focus group analysis results

Table 2 displays suggestions to improve the Fitbit visualizations synthesized through affinity mapping. A thorough examination and discussion by the research members led to a selection of 4 key solutions to effectively address the identified PPs. The first solution addresses PP#1, #3, and #5 by introducing a tutorial to present users with a comprehensive overview of the dashboard to review at any time. The second solution addresses PP#1 by utilizing pie charts to visually exhibit the calculation of 3 subscores that feed into the composition of the final sleep score. The third solution addresses PP#2 by offering personalized recommendations. This solution generates recommended actions based on individual data to make the dashboard more helpful and convincing. To address PP#4, #5, and #6, the fourth solution allows selection of multiple graphical views (ex: bar/line graph) and utilizes benchmarks to enhance data comprehension. Figure 3 displays 4 mock-ups to illustrate the proposed solutions.

DISCUSSION

Key findings

This study addresses the gap in PGHD literature regarding the design and usability of sleep data visualization from end users' perspectives. Through the 2-week Fitbit study and the subsequent focus group, the study identified 6 PPs and ideated 4 design solutions, which were illustrated through a set of mock-ups. While the study is limited in its scope, it offers potentially useful considerations for designing sleep data visualization.

Design considerations

The study identified 4 design considerations. The first design consideration is Usability. Applying Nielsen's usability heuristics[24] can be an efficient way to improve the usability of sleep data visualization through a set of 10 general principles that optimize user interactions to facilitate the visualization design process. In our study, PP#3 and #5 match the heuristic of Help and Documentation in a way that the dashboard should guide the users to access their data and provide tooltips when users are confused in interacting with the sleep data visualization. PP#4 matches the heuristic of Flexibility and Efficiency of Use, indicating that the visualization should allow users to select multiple chart types with visual clues to facilitate the use.

The second consideration is Transparency and Explainability. The Fitbit app did not define the calculation (scoring algorithm) of the sleep scores (PP#1), which puzzled the users especially when the scores did not match their daily experiences. In other words, the scoring algorithm was neither transparent nor explainable. This issue can be exacerbated when applying artificial intelligence (AI)-based models to predict sleep patterns. A recent study indicated that transparency can facilitate an appropriate level of trust in human-AI interaction.[25] However, appropriate trust, rather than maximizing trust, would be a better goal in the healthcare domain.[26] Therefore, algorithms behind sleep data visualizations should be highly transparent and explainable and provide users with appropriate level of trust.

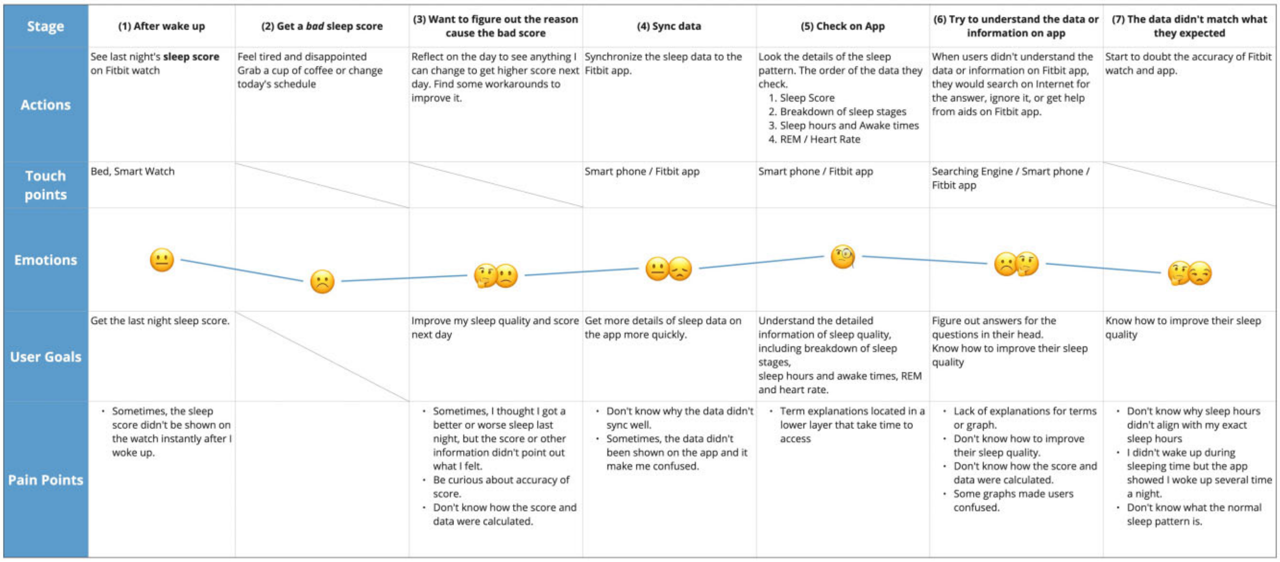

Figure 2. User-journey map.

Table 2. Synthesized suggestions and potential solutions based on focus group

Pain point #	Synthesized suggestions and potential solutions
1. Undefined calculation of sleep score	• *Display the breakdown of the user's sleep score using a pie chart* • Incorporate a demonstration of the calculation methodology within *the tutorial* • Implement an *interactive tooltip feature* adjacent to the sleep score, allowing the user to view the composition of the score upon selection • Position the "What is sleep score" feature in a prominent location, linking to a dedicated section for sleep score explanations.
2. Lack of practical suggestions to improve sleep scores	• Implement a "How do I improve my sleep score" button • *Utilize the user's sleep data to generate personalized recommendations for activities and behaviors that can improve their sleep score* • Develop a self-assessment questionnaire to identify potential factors impacting the user's sleep quality.
3. In need of better ways/ instructions to access sleep data	• *Provide a brief tutorial for new users to familiarize themselves with the app's functionality and features.* • Utilize illustrations or images in addition to text to enhance the visual appeal and accessibility of key information. • Implement a tabbed navigation system to facilitate the switching between sections, rather than relying on scrolling through the page. • Incorporate tooltip icons next to terms or titles that may require additional explanation for the user's understanding.
4. Unclear representation of weekly sleep scores in a bar graph	• Allow the user to choose from *multiple chart types*, including line, bar, or a combination of both, to display their weekly sleep score. • Incorporate the user's average sleep score on the chart and use color coding to indicate whether a particular day's score is above or below the average • Implement a feature that displays an explanation of the factors contributing to changes in the user's sleep score when there is an increase or decrease.
5. Difficult to understand the deep and REM graph	• Incorporate *an interactive tutorial* to provide an in-depth understanding of the sleep cycle process. • *Offer the user a choice of graph views*, including bar charts and line charts. • Present the chart with a distinct line to enhance clarity of the chart. • Implement a horizontal bar chart to represent the sleep cycle data • Remove any discontinuous awake events to make the graph clearer and reduce users' confusion.
6. Unsure about "Normal" sleep patterns for an individual	• Implement a color-coding system to distinguish between different sleep metrics and indicate whether they fall above, below, or within the average range. • *Include a benchmark* for each sleep metric to provide a reference point for the user.

The third consideration is Understandability and Actionability. The Fitbit app did not provide any practical suggestions or actionable information to help users improve their sleep scores (PP#2). Understandability and Actionability should also consider 2 heuristics in the visualization design: (1) Match Between the System and the Real World and (2) Use the Language/Concepts that Users Are Familiar With. Moreover, Understandability and Actionability have been heavily studied in designing and evaluating patient education materials and online health information.[27–29] The design of sleep data visualization could adopt the principles from these studies to improve its utility.

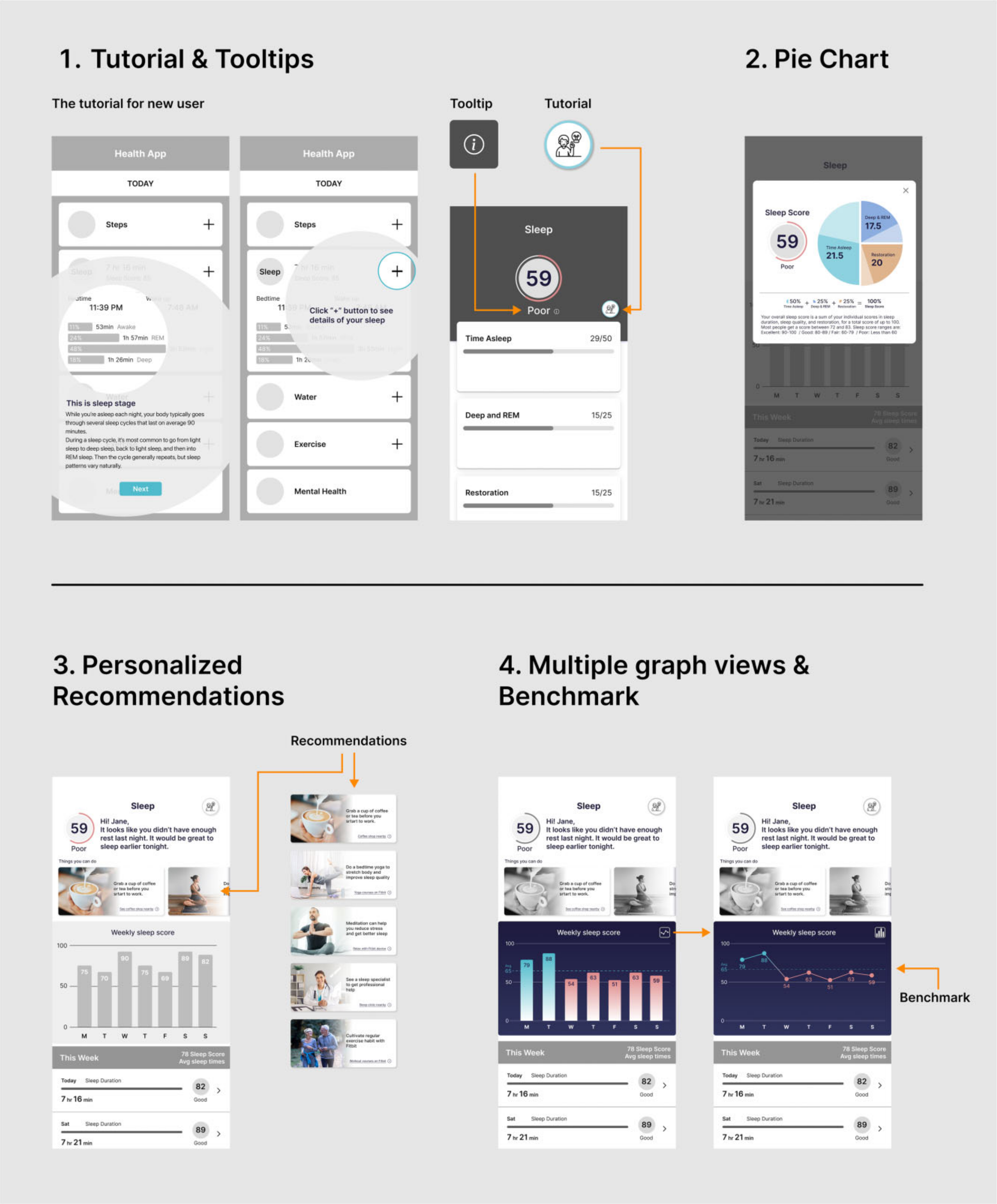

Figure 3. Mock-ups of sleep data visualization based on the solutions. Of note, the mock-ups utilize some elements from the original Fitbit app with modifications and blurred effects.

The fourth consideration is Individualized Benchmarking. The participants in our study were unsure about whether certain sleep patterns were considered normal given a wide range of individual differences (PP#6). PatientsLikeMe, an online community founded in 2004, has been producing graphics and measurements with individualized benchmarks based on users with similar characteristics.[30] Sleep data visualization should include such design to help users make better sense of their data.

Limitations

This study is limited in several ways. First, the study was conducted in a single program at a single institution, which limits the generalizability of the study findings. Second, the participant recruitment was not inclusive, and the study participants (premed college students) may have unique sleep patterns from the general population. Third, the participants may have a higher educational level and health/graph literacy than the general population, which can affect their experience in using sleep data visualization. Next, the usability of the mock-ups was not determined through formal testing. Lastly, this study focused on a particular type of PGHD (sleep data), which limits the applicability of the design considerations to other types of PGHD.

Future work

Our future work involves implementing the mock-up with the 4 design considerations as a web-based application that can collect sleep data through the Fitbit APIs and visualize the sleep patterns. We will conduct formal usability testing on this web-based application, and a large-scale experiment that uses this web-based application as an informatics-based intervention to trigger health behavior changes. Further down the road, we will investigate the best practices to integrate tracked sleep data into electronic health records and use our web-based application to facilitate shared decision-making.[31–36]

CONCLUSION

The present study investigated the user experience of sleep data visualization on the Fitbit app with a group of premed college students and generated 4 design considerations. Further research is needed to improve the generalizability of our findings and explore design considerations, guidelines, and best practices to visualize PGHD for the general population and use those well-designed visualizations to enable health behavior changes and support shared decision-making.

FUNDING

This research was partially supported by the internal funding from the University of Cincinnati (UC)'s Undergraduates Pursuing Research in Science and Engineering (UPRISE) Program and the Summer Undergraduate Research Fellowship (SURF) Program Medical Exploration track (MedEx). This research received no external support from any funding agency in the public, commercial, or not-for-profit sectors.

AUTHOR CONTRIBUTIONS

DTYW designed the study and mentored C-TT (first author) and GR (second author) to conduct the study. GR collected the Fitbit data from the study participants. AG (third author) searched the literature and drafted as well as refined the background and significance section. C-TT and YW (fourth author) conducted the focus group and generated the qualitative analysis results. All authors supported the manuscript writing and discussed the results as well as provided critical feedback on the content of the manuscript. All authors reviewed and approved the final version of the manuscript.

SUPPLEMENTARY MATERIAL

Supplementary material is available at *Journal of the American Medical Informatics Association* online.

ACKNOWLEDGMENTS

We thank the study participants in both the Fitbit data collection and the focus group for their time and effort. We also thank Dr Claudia Rebola for providing Fitbit wearable devices and Mr Abdulla Qureshi for his support in the study data collection.

CONFLICT OF INTEREST STATEMENT

The authors have no competing interests to declare.

DATA AVAILABILITY

The research data of this study (ie, the semistructured interview questions and the affinity diagrams of the semistructured interviews and the focus group) have been submitted as supplement files for download.

REFERENCES

1. Demiris G, Iribarren SJ, Sward K, *et al.* Patient generated health data use in clinical practice: a systematic review. *Nurs Outlook* 2019; 67 (4): 311–30.
2. Alpert JM, Manini T, Roberts M, *et al.* Secondary care provider attitudes towards patient generated health data from smartwatches. *NPJ Digit Med* 2020; 3: 27.
3. Lindroth T, Islind AS, Steineck G, *et al.* From narratives to numbers: data work and patient-generated health data in consultations. *Stud Health Technol Inform* 2018; 247: 491–5.
4. Sharma A, Badea M, Tiwari S, *et al.* Wearable biosensors: an alternative and practical approach in healthcare and disease monitoring. *Molecules* 2021; 26 (3): 748.
5. Grandner MA. Sleep, health, and society. *Sleep Med Clin* 2017; 12 (1): 1–22.
6. Scott AJ, Webb TL, Martyn-St James M, *et al.* Improving sleep quality leads to better mental health: a meta-analysis of randomised controlled trials. *Sleep Med Rev* 2021; 60: 101556.
7. Loredo JS, Nelesen R, Ancoli-Israel S, *et al.* Sleep quality and blood pressure dipping in normal adults. *Sleep* 2004; 27 (6): 1097–103.
8. Carroll JE, Seeman TE, Olmstead R, *et al.* Improved sleep quality in older adults with insomnia reduces biomarkers of disease risk: pilot results from a randomized controlled comparative efficacy trial. *Psychoneuroendocrinology* 2015; 55: 184–92.
9. Torossian M, LeBlanc RG, Jacelon CS. Use of a personal sleep self-monitoring device for sleep self-management: a feasibility study. *J Gerontol Nurs* 2021; 47 (1): 28–34.
10. Jakowski S, Stork M. Effects of sleep self-monitoring via app on subjective sleep markers in student athletes. *Somnologie (Berl)* 2022; 26 (4): 244–51.
11. Karasneh RA, Al-Azzam SI, Alzoubi KH, *et al.* Smartphone applications for sleep tracking: rating and perceptions about behavioral change among users. *Sleep Sci* 2022; 15 (Spec 1): 65–73.
12. Choi YK, Demiris G, Lin S-Y, *et al.* Smartphone applications to support sleep self-management: review and evaluation. *J Clin Sleep Med* 2018; 14 (10): 1783–90.
13. Al Mahmud A, Wu J, Mubin O. A scoping review of mobile apps for sleep management: User needs and design considerations. *Front Psychiatry* 2022; 13: 1037927.
14. Azad-Khaneghah P, Neubauer N, Miguel Cruz A, *et al.* Mobile health app usability and quality rating scales: a systematic review. *Disabil Rehabil Assist Technol* 2021; 16 (7): 712–21.

15. Aji M, Gordon C, Peters D, *et al*. Exploring user needs and preferences for mobile apps for sleep disturbance: mixed methods study. *JMIR Ment Health* 2019; 6 (5): e13895.
16. Yoshizaki A, Mohri I, Yamamoto T, *et al*. An interactive smartphone app, Nenne Navi, for improving children's sleep: pilot usability study. *JMIR Pediatr Parent* 2020; 3 (2): e22102.
17. Chinoy ED, Cuellar JA, Jameson JT, *et al*. Performance of four commercial wearable sleep-tracking devices tested under unrestricted conditions at home in healthy young adults. *Nat Sci Sleep* 2022; 14: 493–516.
18. Haghayegh S, Khoshnevis S, Smolensky MH, *et al*. Accuracy of Wristband Fitbit models in assessing sleep: systematic review and meta-analysis. *J Med Internet Res* 2019; 21 (11): e16273.
19. Kallio H, Pietilä A-M, Johnson M, *et al*. Systematic methodological review: developing a framework for a qualitative semi-structured interview guide. *J Adv Nurs* 2016; 72 (12): 2954–65.
20. Pernice K. Affinity diagramming for collaboratively sorting UX findings and design ideas. 2018. https://www.nngroup.com/articles/affinity-diagram/. Accessed January 22, 2023.
21. Rosala M. Why map in discovery: 3 mapping methods. 2022. https://www.nngroup.com/articles/mapping-in-discovery/. Accessed September 11, 2022.
22. Stewart DW, Shamdasani PN. *Focus Groups: Theory and Practice*. 3rd ed. Los Angeles: SAGE; 2015.
23. Wilkinson S. Focus group methodology: a review. *Int J Soc Res Methodol* 1998; 1 (3): 181–203.
24. Nielsen J, Molich R. Heuristic evaluation of user interfaces. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems Empowering People – CHI '90. Seattle, Washington: ACM Press; 1990: 249–56. doi: 10.1145/97243.97281.
25. Zerilli J, Bhatt U, Weller A. How transparency modulates trust in artificial intelligence. *Patterns* 2022; 3 (4): 100455.
26. Ananny M, Crawford K. Seeing without knowing: limitations of the transparency ideal and its application to algorithmic accountability. *New Media Soc* 2018; 20 (3): 973–89.
27. Skalitzky MK, Gulbrandsen TR, Lorentzen W, *et al*. Health literacy in clubfoot: a quantitative assessment of the readability, understandability and actionability of online patient education material. *Iowa Orthop J* 2021; 41: 61–7.
28. Lang JJ, Giffen Z, Hong S, *et al*. Assessing vasectomy-related information on YouTube: an analysis of the quality, understandability, and actionability of information. *Am J Mens Health* 2022; 16 (2): 15579883221094716.
29. Parker PD, Prabhu AV, Su LJ, *et al*. What's in between the lines: assessing the readability, understandability, and actionability in breast cancer survivorship print materials. *J Cancer Educ* 2022; 37 (5): 1532–9.
30. PatientsLikeMe: Find Your Community. Find your strength. Live better, together! https://www.patientslikeme.com/. Accessed January 22, 2023.
31. Wu DTY, Xin C, Bindhu S, *et al*. Clinician perspectives and design implications in using patient-generated health data to improve mental health practices: mixed methods study. *JMIR Form Res* 2020; 4 (8): e18123.
32. Tiase VL, Wawrzynski SE, Sward KA, *et al*. Provider preferences for patient-generated health data displays in pediatric asthma: a participatory design approach. *Appl Clin Inform* 2021; 12 (3): 664–74.
33. Blondon K, Ehrler F. Design considerations for the use of patient-generated health data in the electronic medical records. *Stud Health Technol Inform* 2022; 294: 229–33.
34. Blondon K, Ehrler F. Integrating patient-generated health data in an electronic medical record: stakeholders' perspectives. *Stud Health Technol Inform* 2020; 275: 12–6.
35. Vaidyam A, Halamka J, Torous J. Enabling research and clinical use of patient-generated health data (the mindLAMP Platform): digital phenotyping study. *JMIR Mhealth Uhealth* 2022; 10 (1): e30557.
36. Ye J, Ma Q. The effects and patterns among mobile health, social determinants, and physical activity: a nationally representative cross-sectional study. *AMIA Jt Summits Transl Sci Proc* 2021; 2021: 653–62.