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RESEARCH ARTICLE

Understanding User Perspectives on Data Visualization in mHealth Apps: A Survey Study

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ABSTRACT Mobile health (mHealth) applications rely on personal data visualisations to promote user adoption and engagement. To ensure the success of these applications, it is crucial to understand user requirements when utilising these visualisations. This study investigates the needs and challenges of mHealth app users with a focus on data visualisations. This paper presents the results of a user survey with 56 participants, which found curiosity to be the top motivation behind using health-tracking apps. 51% of the participants had to use more than one mHealth app to achieve their health tracking goals, which usually come with inconsistency and duplication of data entry. Bar and pie charts were the most preferred forms for viewing health data. Users do not want to use complex charts. Furthermore, users preferred a combination of text summaries and charts to make sure they correctly interpret the charts. On the other hand, users face challenges related to improper information presentation, inaccurate touch interface, and an overwhelming amount of data. Customisable and readable charts encouraged frequent app usage. The implications of these findings confirms the gap we identified in existing data visualisation design and development guidelines. We have developed a set of data visualisation guidelines to address these challenges, and currently conducting evaluations on designers and end users.

INDEX TERMS Data visualization, mHealth apps, user requirements and challenges.

I. INTRODUCTION

Mobile health (mHealth) tracking applications have revolutionised the way individuals monitor and manage their health. With the widespread adoption of wearable devices and smartphones, as well as the heightened awareness of the importance of maintaining a healthy lifestyle, particularly in the wake of the COVID-19 pandemic, the popularity of health tracking applications (apps) has seen a surge in recent years. This has resulted in a significant interest from a variety of stakeholders, including app developers, investors, and researchers [1], [2]. The market for mHealth tracking apps has grown significantly, with over 350,000 applications developed to assist users in managing various health conditions, including mental health, diabetes, and cardiovascular diseases [3]. Furthermore, a recent survey involved 20,000 participants revealed that approximately 47% of smart device owners utilised their devices for health tracking purposes, and data from 2022 indicated that the number of health, fitness, and wellness app users in the United States alone reached 86.3 million [4], [5].

Given the wide adoption and utilisation of health tracking apps, it is crucial to understand the needs and requirements of users in this domain. Prior research has explored users' perspectives towards mobile health (mhealth) apps using both qualitative and quantitative methods. For instance, Philip et al. [6] examined the challenges faced by users in mHealth apps, including functional overlaps and unused features, data management, and the need for multiple apps, and made recommendations to developers to address these challenges and enhance user experience. Similarly, Haggag et al. [7] analysed user comments and identified challenges in the registration process, privacy concerns, handling of requests, accessibility and user experience (UX) / user interface (UI) issues.

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A critical feature of successful and widely adopted health tracking apps is data visualisation [2], [8]. Current design practices acknowledge the importance of involving end-users in the initial stages of app design to ensure the development of effective mHealth apps that meet user needs, including data visualisation requirements [9]. For example, previous studies have explored the creativity of older adults in designing mHealth apps [10], developed personal tools to enable users to create accounts of their data [11], and constructed models to allow users to customize their tracking goals [12].

The current state of research on data visualisation in mHealth apps reveals significant gaps in understanding the challenges and needs of users, particularly regarding the content and design of charts targeting multiple users. Additionally, best practices for evaluating mobile data visualisations on small screens and their compatibility with user preferences for chart types, tasks, and interactions have not been studied [13]. To address these gaps, we first investigated mHealth app reviews from Google Play to understand user challenges and concerns related to data visualisations. We found 18 data visualisations related to missing charts (based on data entries), chart interactivity (such as zooming to access more details), and chart layout and style. The poor quality of data visualisations resulted in a negative impact on the user experience and app rating [14]. Although the paper contributed to our understanding of user challenges, gaps in comprehending end users' attitudes and beliefs towards data visualisations in mHealth apps still exist. These gaps could be addressed by implementing a systematic data collection process. Therefore, our focus in this paper is on the UX and identifying the challenges and preferences of end users with respect to visualisations in mHealth apps. This paper extends [15] and provides a detailed version of the collected results focusing on identifying end-users' preferred apps, charts, everyday tasks, and user feedback on data visualisations in mHealth apps. Our paper addresses the following key questions:

- RQ1: What are the top mHealth apps providing good data visualisations?
- RQ2: What are the preferred data visualisation charts for ease of reading and understanding?
- RQ3: What are the most common data visualisation tasks and goals users want to achieve?
- RQ4: What do users like or dislike in the data visualisations provided by their apps?
- RQ5: What are the key user requirements to improve their experience when using data visualisation in these apps?

The rest of the paper is organised as follows: Section II presents the related work, and Section III presents the study design. Section IV presents survey results and addresses the proposed research questions. Section V analyses the identified gaps and presents recommendations for mobile data visualisations. Section VI presents the study limitations. Finally, Section VII presents the conclusion and future work.

II. RELATED WORK

A. MOBILE VISUALISATION

Web visualisation, mobile visualisation and dedicated visualisation environment are the three favourable environments to adopt data visualisation beyond desktop screens [16]. However, mobile data visualisations introduce several limitations around smaller screen size and different interaction methods [17]. Therefore, commendable efforts have been made around mobile device data visualisation, some of which focused on designing data visualisation interfaces. Others focused on the suitability of charts displayed on smartphone screens. For example, Roberts et al. [18] highlighted that a compact data visualisation must be built to fit the screen size and interaction modality (touch and tap). Additionally, in 2018, Brehmer et al. [19] investigated viewing ranges over time on mobile devices by adopting two layouts: linear and radial range charts. Both designs possess a similar number of errors - in radial layouts, the errors were in reading value and locating Max/Min; in linear formats, errors were in discovering Max/ Min value and comparing ranges of values. Despite these errors, participants performed tasks quicker in linear than in the radial chart. In a comprehensive examination, the same authors [20] conducted an additional experiment to find the efficiency of using small multiples and animations in scatter plot graphs for mobile devices. Trend comparisons were performed in the study which indicated that both visualisations suited mobile devices when applied to large data sets.

In contrast, limited studies focused on data visualisation design for smartphones. For example, in 2015, Games and Joshi [16] conducted a user study on Roambi (a commercial visualisation system). The study recruited 24 participants aged (18-50) to evaluate the system and its visualisation. The evaluation involved providing feedback on the level of difficulty in understanding the visualised data and how well they could interact with it. The authors developed a list of recommendations for mobile data visualisations based on participants' responses. However, these guidelines are limited to only simplified data visualisation layout and interface navigation. A further limitation of this study was that it focused on tablet devices with bigger screens making it unclear if these recommendations can also be applied to smartphones. A 2018 study [21] presented a prototype of a data visualisation app for health data using PhoneGap - a hybrid platform that supports the development of cross-platform mobile applications. Based on 20 responses, the authors highlighted three main concerns: colour usage, complex data visualisations, and the lack of ideal data visualisations. Although these works have made some advances in addressing data visualisation challenges for smaller screens, they focus on general use cases and more work needs to be done in the mHealth domain.

These findings underscored the importance of investigating data visualisation literacy and integrating universal design principles into the context of data visualisation. In 2020, Lee et al. emphasised the significance of ensuring accessible mobile data visualisation for non-expert users [17]. Similarly, in 2021, Jena et al. conducted a study that identified characteristics of non-expert users of mobile data visualisation, highlighting the need for further investigation in this area. The study revealed that non-expert users often lacked educational opportunities related to numeracy and graphics, came from diverse cultural backgrounds, had limited exposure to visualisation, and had diverse needs stemming from disabilities. Based on these findings, the study recommended actively identifying opportunities and use cases for underrepresented minorities and non-experts in visualisation research. It stressed the development of universal design principles that catered to diverse user needs and avoided biases. The study also emphasised the importance of asking the right questions and engaging with other academic communities to ensure fairness and inclusivity. It suggested involving a broader constituency in visualisation research and addressing barriers to participation. Their research promoted inclusive visualisation research and advocated for engagement with diverse populations [22].

Furthermore, in 2022, Kim provided a comprehensive set of recommendations for effectively delivering data visualisation in the context of self-generated health data based on an extensive literature review [23]. Kim highlighted the need to consider various aspects of data visualisation design, including selecting suitable data, determining effective visualisation types, and incorporating interactive features to enhance user engagement. These recommendations aim to improve the accessibility and usability of mobile data visualisation for non-expert users. Additionally, Fernandez-Luque et al. discussed the principles of universal design by emphasising the need to incorporate user perspectives and needs into the design of systems, including those driven by data-driven algorithms [24].

B. SELF-TRACKING AND MOBILE HEALTH APPS

The main self tracking activities covered in research studies include sports activities [25], nutrition [26], health conditions [27], memories tracking [28], mood tracking [29] and sleeping habits [30]. However, they have also indicated unsolved challenges related to these mobile tracking apps. For instance, Choe et al. [26] experimented to understand quantified users and their interaction with tracking apps. They posted their experiment in a quantified self forum and asked its members to record videos and answer 3 questions around what they did, how they did it and their learning. Based on the 52 videos they received, the authors noted that while they mostly tracked health conditions, the amount of presented data deterred the respondents from further using the apps. Spreadsheet applications were the most used tools for analysing personal data collected through commercial hardware. However, users desired customisable tools for tracking their goals and visualising their health data. One of the main challenges was the difficulty in understanding the data due to a lack of scientific knowledge, suggesting the need to develop simpler mHealth apps to serve a wider population.

As data visualisation is crucial for tracking data, Lee et al. [13] conducted a workshop to explore the potential of mobile devices for self-tracking. They highlighted the apps Sleep Tight, ConCap, and OmniTrack, which assist in tracking sleep, diabetes, and personal health data. They also emphasised the need for consolidated best practices and evaluation methods for mobile data visualisation. Significant efforts have been made in this area, focusing on providing specific frameworks to develop a well-defined contextual mHealth app [31], and to protect the privacy of personal data analysis and visualisation in mHealth apps [32]. Although these studies focused on user needs related to the privacy and contextual design of mHealth apps, there is a gap in user needs related to mHealth data visualisation.

This motivated us to deeply explore user needs, challenges and factors influencing users' reactions to charts in their mHealth apps. Given the diverse user base, it is essential to consider data visualisation literacy and universal design principles. This paper builds upon previous recommendations by surveying end users to gain insights into their needs and preferences regarding data visualisation.

III. STUDY DESIGN

The main objective of this study is to understand the users' experiences, challenges and needs around data visualisation methods in mHealth apps (following the research questions outlined in the introduction section) using a user survey.

A. SURVEY DEVELOPMENT METHODOLOGY

To address our research questions, we leveraged two established approaches widely used in product development: the design thinking process [33] and the value proposition canvas [34], [35]. These methods have also been applied in prior studies on mHealth app development and evaluation [36], [37], [38].

A visual representation of our design thinking process is depicted in Figure 1, illustrating the process of understanding user needs, ideating survey questions, and refining them through subsequent iterations. The figure outlines the following stages - (1) To gain empathy and insight into users' perspectives, we explored the current state of research on data visualisations in mHealth apps [39]. This exploration allowed us to identify gaps and areas of concern specifically related to the use of data visualisation by non-expert users. Consequently, our focus shifted towards understanding users' experiences, preferences, and challenges in relation to data visualisation in mHealth apps. In order to tap into the direct experiences and perspectives of mHealth app users, we examined user reviews from app comments [14]. These insights shed light on the diverse challenges, needs, and positive experiences of mHealth app users. Drawing from this qualitative information, we developed our survey questions

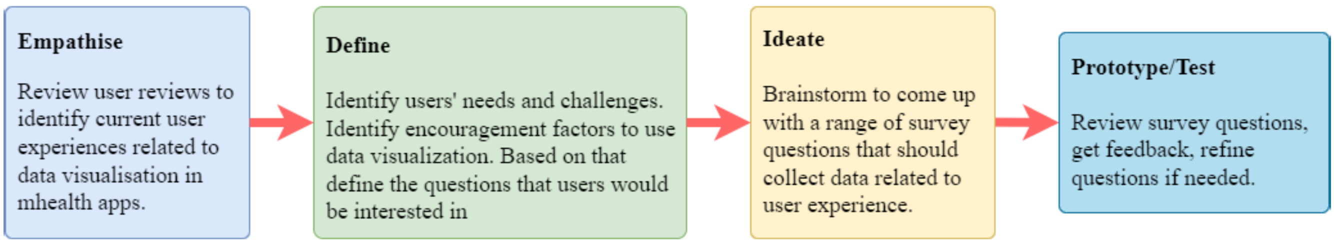

FIGURE 1. Design thinking process.

aligned with the real-world experiences of end users as identified from relevant sources.

(2) In the define stage, we carefully articulated our objectives and focused on comprehending users' experiences, preferences, and challenges related to data visualisation in mHealth apps. Driven by the identified gaps, we structured our questionnaire to address key sections: A, B, C, and D in Figure 2, which were mapped to our research questions RQ1 - RQ5 (see section III-C). These sections are thoughtfully designed to collect demographic information, enabling us to assess participants' levels of experience and ensuring the acquisition of diverse and comprehensive results. Moreover, they allow us to explore users' needs, challenges, and best practices regarding data visualisation methods.

Based on this understanding, the (3) ideation phase commenced, where we generated a comprehensive list of questions for each section in our questionnaire. This phase involved a collaborative process, including multiple meetings with the co-authors, to decide which questions to include. Our goal was to incorporate a diverse range of question types, including both open-ended and closed-ended questions. This approach allowed respondents to provide detailed answers, minimising the potential bias associated with suggesting specific responses while also facilitating straightforward data analysis in the case of closed-ended questions. Although open-ended questions pose challenges in terms of high non-response rates, they offer participants the freedom to express their opinions openly and provide rich insights [40].

Additionally, we carefully structured the questions in a logical order to ensure a seamless flow throughout the questionnaire. During the ideation phase, we embraced an iterative approach, continuously refining and revising the question list to ensure its effectiveness in addressing our defined objectives.

(4) To ensure the relevance and effectiveness of the survey questions, a pilot study was conducted, which involved recruiting a subset of participants from our organisation who tested the survey instrument. Their invaluable feedback, encompassing aspects such as question clarity, relevance, and comprehensibility, contributed to the refinement and enhancement of the survey questions.

To ensure that our survey questions aligned with the values and expectations of end-users, we incorporated insights extracted from the value proposition canvas. This canvas is

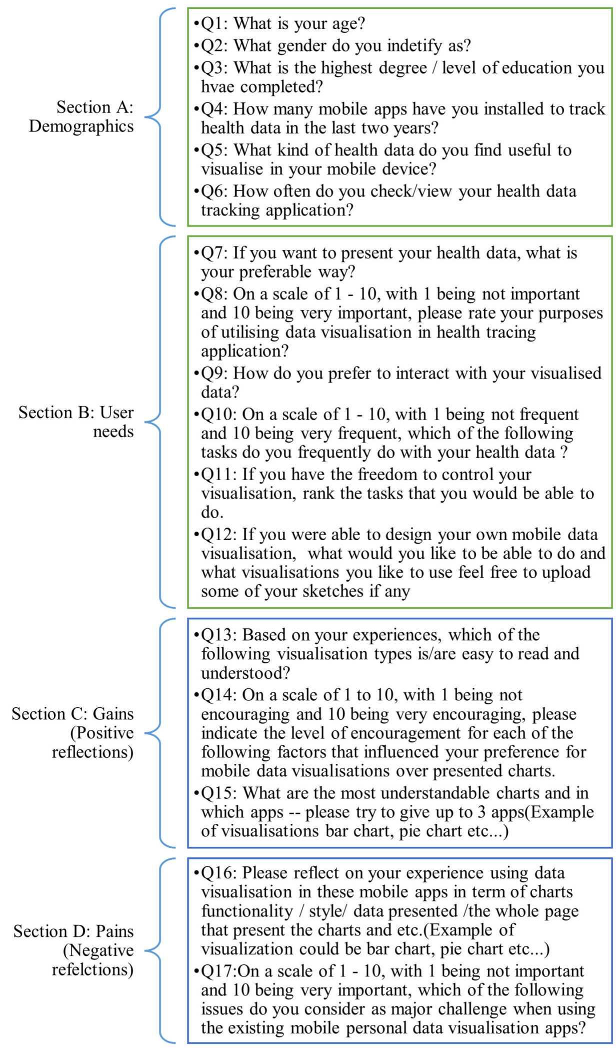

FIGURE 2. Questions distribution based on customer profile aspects.

a commonly used tool for developing user-centred products and services based on their needs. It consists of two parts: the Customer Profile and the Value Proposition [41].

In this study, we focus on the Customer Profile in the context of mHealth apps. We aim to identify the challenges (referred to as "pains") that users face when using mHealth apps, the encouraging factors (referred to as "gains") that support their use of mHealth apps, and the tasks they want to achieve. By aligning our survey questions with these identified dimensions and the challenges identified earlier, we aimed to capture the essential aspects that users consider crucial in the context of data visualisations in mHealth apps. The discussion section of our research covers the Value Proposition part of the canvas. Here, we elaborate on how we address users' needs, overcome their challenges, and support the motivating factors identified earlier.

Figure 2 visually represents key dimensions derived from the application of the value proposition canvas, showcasing the specific areas of inquiry and the corresponding questions designed to explore each dimension.

B. SURVEY QUESTIONS

The survey consists of 17 questions that cover four key aspects, as depicted in Figure 2: (Section A) Understanding users and their experience level with mHealth apps, (Section B) Understanding user needs, (Section C) Expectations and preferences regarding data visualisation in mHealth apps, and (Section D) Key challenges encountered when using data visualisation in mHealth apps.

The survey questions were carefully designed to capture both quantitative and qualitative feedback from the participants. In Section A, focusing on survey questions Q1 to Q6, we employed quantitative questions that offered both single-choice and multiple-choice options. It is important to note that all questions except Q5 were designed as single-choice questions, while Q5 stood out as the only multiple-choice question in this section. This section focused on gathering specific information about users through structured responses.

In Sections B, C, and D of the survey, we employed a variety of question types to gather insights from users. These different question types allowed us to capture various aspects of users' preferences and experiences with data visualisation.

The first set of questions utilised a 1-10 scale to assess users' preferences and needs related to data visualisation. Q8 specifically focused on data tracking purposes, while question Q10 examined the frequency of specific tasks, providing insights into users' engagement patterns. Furthermore, participants were requested to rate influential factors for challenges (Q17) and factors that encourage app usage (Q14).

The statements for both Q14 and Q17 were formulated, taking into account our previous mHealth app reviews [14] and a systematic literature review [39]. By incorporating insights from these sources, we ensured a comprehensive compilation of relevant factors and issues that significantly impact user experiences with data visualisation in mHealth apps.

In addition to these questions, we incorporated two single-choice questions (Q7 and Q9) and one ranking question (Q11). Question Q13 involved multiple choices regarding the most understandable charts. To accommodate users with varying literacy levels, we provided chart samples for each available option, ensuring accessibility and ease of understanding.

To gain qualitative insights into users' experiences with data visualisation, three open-ended questions were incorporated into the survey. Q12 provided participants with the opportunity to provide written suggestions or upload sketches, enabling them to express their desired data visualisation designs in a detailed and personalised manner. Q15 encouraged participants to reflect on their experiences with their preferred apps and share the names of those apps. Lastly, question 16 aimed to gather specific insights into users' experiences with charts, inviting them to elaborate on their preferences and identify areas for improvement.

C. SURVEY MAPPING WITH RESEARCH QUESTIONS

To map the proposed research questions with our survey, we included Q15 to investigate the effectiveness of data visualisation in the top mHealth apps, addressing RQ1. Additionally, Q7 and Q13 were included to gather insights into users' preferences regarding chart readability and the optimal layout for presenting data through visualisation, aligning with RQ2. To understand users' purposes and interactions with data visualisation in their mHealth apps, questions Q8 to Q11 were incorporated. These questions aimed to explore the tasks users perform when utilising data visualisation and their desired ways of interacting with it, addressing RQ3. To address RQ4, questions Q14, Q16 and Q17 were included, which aimed to assess users' challenges and motivating factors related to data visualisation. Lastly, to address RQ5, question Q12 was included, allowing users to provide suggestions for features that could enhance their data visualisation experience.

D. EVALUATION METHODS

In addition to employing the mean for the majority of questions, we adopted alternative evaluation approaches for specific survey items. To evaluate the collected results, we employed the mean as the evaluation method. However, the following survey questions were evaluated in a different way: and gain insights into user challenges and encouragement factors (Q14 & Q17), we employed the Net Promoter Score (NPS). The NPS is a widely recognised metric used to measure customer satisfaction, ranging from -100 to $+100$. Higher scores indicate greater customer satisfaction [42]. By utilising the NPS, we were able to assess users' satisfaction with the different features of data visualisation.

To analyse the qualitative data obtained from open-ended text entry questions, we employed a systematic mapping technique. For Q12 and Q15, which were open-ended questions, each researcher independently analysed and filtered the responses based on predefined criteria. This involved verifying that the answers were written in English and contained meaningful content. Subsequently, a collaborative session was conducted to review and synthesise the individual analyses, resulting in a unified and comprehensive analysis of each validated response. In the case of Q16, another open-ended text entry question, each researcher mapped the responses to specific data visualisation components, including interaction, data, functional requirements, and style.

E. DATA COLLECTION

Our anonymous survey was presented on Qualtrics and advertised through several social media channels, including the Quantified Self forum, LinkedIn, Instagram, Reddit and Twitter. We specifically selected these channels due to the ability to share our survey flyer and mention relevant health tracker groups within each community. In addition, we added a link and QR code on the survey flyer to ensure we reached users interested in tracking their personal data.

To ensure the ethical treatment of our participants, the present study has been granted ethical approval by the Deakin Research Ethics Committee. Informed consent was obtained from participants online prior to the start of the survey. Participants were presented with a statement of the purpose of the study, the data collection process, and their right to withdraw. Participants were then asked to provide explicit consent to participate in the study. By obtaining informed consent, we aimed to ensure that participants were aware of the study's purpose and their role in it and that their participation was voluntary.

IV. SURVEY RESULTS

We received 56 completed responses, all of which were verified to be authentic human inputs by means of a thorough review of the written responses. The following subsections present the results and findings derived from these completed responses.

A. PARTICIPANTS PROFILE

This section provides a detailed analysis of the profile and preferences of the participants who took part in the study. The age distribution of the 56 participants who completed the study was as follows: 16 (28.57%) were aged 18-30, 20 (35.71%) were aged 31-40, 12 (21.43%) were aged 41-50, and 8 (14.29%) were above the age of 50. In terms of gender, 31 (55.36%) of the participants identified as female, 24 (42.86%) identified as male (Table 1). Furthermore, a significant proportion of the participants (50%) held Bachelor's degrees, while 30.36% held Master's degrees, 7.5% had completed post-secondary and upper education, and 12.50% held PhD degrees.

With respect to the number of mHealth apps used per person, we indicated that 41.07% of the participants reported using only one app to track their health data, 39.29% had installed fewer than five apps, 12.50% had installed more than five apps, and 7.14% had not found a suitable app yet. In addition, we explored the frequency of checking tracking apps among users of different age groups. Our findings reveal that 37.50% of users aged 18-30 checked their apps on a

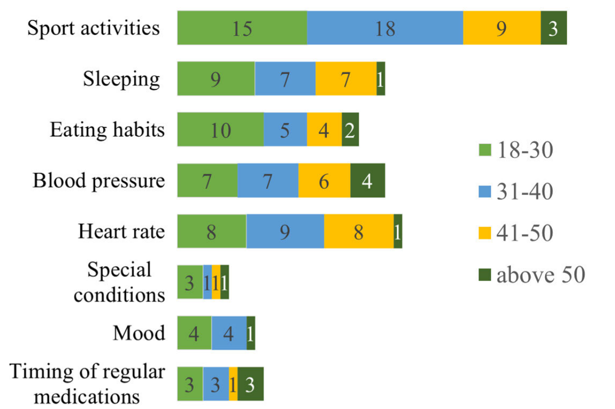

FIGURE 3. Age-Based Trends in Tracked Health Data.

weekly basis. In contrast, users aged 31-40 and above 50 were more inclined to check their tracking apps daily, with 40.00% and 58.33% respectively. Similarly, 44.44% of users aged 41-50 also reported checking their tracking app on a daily basis (Table 1).

The participants reported they used apps to track: sports activities (26.79%), heart rate monitoring (15.84%), blood pressure (14.29%), sleeping pattern (13,69%), eating habits (12.50%), medication reminder (5.95%), and mood tracking (4.76%) (see Figure 3). This could be justified as 64.28% of the respondents are in the age range of (18-40) years old (Figure 3). This data shows a reasonable and diverse range of participants' profiles in the survey.

RQ1: Top mHealth Apps in terms of good data visualisations After validating the responses to the open-ended question, we identified 16 different apps mentioned by participants. However, 5 apps consistently appeared in the collected responses. These apps include (1) Apple health app; (2) Sweatcoin; (3) Samsung health; (4) Fitness apps; and (5) Step tracker pedometer.

When considering the comprehensibility of charts across all the mentioned apps, it becomes evident that the bar chart emerged as the most frequently mentioned choice, with participants highlighting it a total of 23 times. Following closely behind was the pie chart, which received 14 mentions, while the line chart was mentioned 5 times. Furthermore, participants also made single mentions of other chart types, including star charts, tables, maps, timelines, and speedometers.

Table 2 shows the used charts and features of these 5 apps, mainly focused on the sports activities previously discussed as the highest-ranked activity users track using their mobile devices.

RQ2: Preferred data visualisation types Generally, based on the age distribution, 75% of the respondents from all age groups preferred to represent their data using both text and charts, while only 19.64% of the respondents selected only charts, which is still favoured over text only (5.3%). That was also the case when we checked the results based on educational level.

TABLE 1. Participants Portfolio.

Age	Gender	Educational Level					Apps Installed				Usage Frequency				
		Upper secondary	Post secondary	Bachelors	Master	Doctoral	Single app	< 5 apps	< 5 apps	Not finding the app yet	Hourly	Daily	Weekly	Monthly	Never
18-30	Female	1	1	7	3	0	6	4	2	0	1	3	5	2	1
18-30	Male	0	0	4	0	0	1	2	1	0	0	2	1	1	0
31-40	Female	0	1	6	3	0	5	4	0	1	1	6	2	1	0
31-40	Male	0	0	7	2	0	3	4	1	1	0	2	2	5	0
31-40	prefer not to say	0	0	0	1	0	1	0	0	0	0	0	1	0	0
41-50	Female	0	0	3	4	0	3	3	0	1	0	4	2	1	0
41-50	Male	0	0	1	2	2	2	2	0	1	0	3	1	1	0
above 50	Female	1	0	0	1	0	0	1	1	0	0	1	1	0	0
above 50	Male	0	0	0	1	5	2	2	2	0	0	3	2	1	0

TABLE 2. Top selected apps and it features.

Top application	Used charts	Main Features
Apple Health apps	Bar & line charts	track sleeping patterns, active energy, number of steps, walking and running distances
Sweatcoin	Doughnut chart	reward users based on their daily steps
Samsung health	Bar, line & waterfall charts	track activity taken sport sessions, calories, weight and sleeps patterns
Fitness apps	Bar, line & doughnut charts	track burnt calories, training time and average steps
Step tracker pedometer	Bar, map & doughnut charts	track steps using built-in sensors

Participants' preferences for chart types in mHealth apps varied significantly. The bar chart was the most favoured option, selected 46 times. Following closely was the pie chart with 33 selections. The timeline chart received 15 selections, while the line chart and stacked chart were chosen 14 and 13 times, respectively. On the other hand, charts such as the bubble chart, doughnut chart, area chart, and scatter chart received fewer than 10 selections. These results indicate the participants' preferences for different chart types in terms of ease of reading and understanding in mHealth apps.

B. USERS NEEDS

This section reflects on the survey's results around user needs - i.e. what users try to achieve from the data visualisations.

RQ3: Data visualisation goals and tasks *Goals:* The survey findings indicate that among the provided options for utilising data visualisation in mHealth apps, the goal of ''fun and curiosity'' received the highest mean score (8.20), followed by ''tracking goals'' (7.88), ''analysing habits and making decisions'' (7.45), and ''sharing achievements'' (5.24).

Furthermore, when analysing the responses across age groups, a distinct pattern emerges. The youngest age group (18-30) expressed a strong preference for the "fun and curiosity" aspect, rating it as the most important goal with a mean score of 13.25. On the other hand, the other age groups placed greater emphasis on "tracking goals" as their primary objective.

TABLE 3. Summary of critical tasks to create personas.

Age	Interaction	Current tasks	Wanted tasks
18-30	Read-only	Show progress	Finding pattern
31-40	Read and edit	Show progress	Showing history
41-50	Drill down	Finding min. & max.	Editing chart title
Above 50	Read-only	Comparison	Editing chart title

Critical tasks of interest: The findings related to the type of interaction, current tasks, and desired tasks are presented in Table 3, categorised by participants' age.

Regarding the preferred interaction methods with visualised data, we found a slight variation in the top three selected interaction methods: read-only (32.14%), read and edit visualisation (26.79%), and drill-down to show details (21.43%). These results suggest that users generally prefer to read visualisations with minimal interaction and are not interested in complex visualisations. Further Analysis by age group revealed that the read-only option was preferred by 55.55% of participants in the (18-30) and (above 50) age groups. In contrast, the read and edit visualisation option was favoured by 53.33% of participants in the 31-40 age group, while the drill-down to show details garnered a preference of 41.67% among participants in the 41-50 age group.

In terms of the most common tasks, finding the maximum and minimum was the most critical task, with 25.45% of participants ranking it at 10 (the highest importance score). Showing the progress of activity and comparison were the second most important tasks, with 20.74% of

TABLE 4. Summary of users' pains and gains to create personas.

Age	Users pain points	Users gains
18-30	Difficulty to drag points, I can't understand the charts, Charts don't assist in exploration	Easy to read presented data, Ability to set your own goal, Charts show progress
31-40	Can't change the chart type, Touch interface is not precise, Not showing the needed information	Data are complete and shown in the chart, Easy to read presented data, Easy to navigate
41-50	Overlapping text, missing charts, lack of consistency	Easy to read presented data, Easy to navigate, Control over data
Above 50	instability in the charted data, Small font size, Charts don't assist in exploration	Charts are fitted with screen size, Easy to read presented data, Colours are making chart data clear

participants ranking them highly. We further analysed the results by age group. We found that showing activity progress was favoured by the youngest age groups (18-30 and 31-40) while finding the minimum and maximum was preferred by the (41-50) age group. Participants aged 50 and above favoured the comparison option. Other tasks, such as filtering, ordering, showing a trend, details on demand, and identifying patterns and relationships, received similar mean scores.

Regarding preferred chart functionality and styling options, participants were most interested in controlling the chart and its presented data. Finding patterns (mean = 7.06) emerged as the most preferred option, followed by showing the history of previous data (mean = 6.94) and editing chart titles (mean = 6.92). We further analysed the results by age group and found that finding patterns was preferred by the youngest age group (mean = 7.47), showing the history of previous data was favoured by the (31-40) age group (mean = 7.53), and the two older age groups preferred the editing chart title option, with mean = 8.91 and 8.83, respectively.

C. USERS' PAINS AND GAINS

This section reflects on the results of the survey around pains and gains - i.e. the challenges users facing when using current mobile data visualisations.

Our analysis of the participants' feedback on the open-ended question revealed that the majority of respondents (14 responses) reported issues specifically related to the presented data in their mHealth apps. Conversely, only a minority of respondents (2 responses) identified interaction as a concern. Additionally, users reported general issues with the presented charts (8 responses) and the style of the charts (5 responses). On the other hand, the most frequently requested features were charts (14 responses) and interaction (8 responses), while style (7 responses) and data (5 responses) were deemed less important. However, due to the lack of specific details provided in the participants' responses, it was challenging to pinpoint the exact nature of the issues related to charts, interaction, presented data, and style.

RQ4: Issues and encouragement factors of mobile data visualisation *Top issues that affect mHealth data visualisation:* The overall NPS for the 27 provided options was negative, indicating the need for significant improvements in the design and development of data visualisation.

Based on user perspectives, the top five challenges across three main aspects of data visualisation (presented data, chart functionality, and chart interactivity) are as follows:

- Not showing the information (NPS = -9)
- Difficulty to drag points (NPS = -11)
- Touch interface is not precise (NPS = -13)
- Data displayed is too much (NPS = -15)
- I cannot see a chart of my entries (NPS = -17)

With an in-depth investigation of the importance of these challenges, we found some similarities and differences in ranking these challenges between users of different ages, as shown in Figure 4. The two youngest groups of participants selected not showing the needed information as one of the top challenges they encountered when exploring their tracking charts. Interestingly, participants in the 18-30 age group and above 50 selected charts do not assist in exploration as one of the critical challenges. The overlapping text was the top challenge based on the 41-50 participants. Summarising these results helped us understand users' pain points regarding different aspects of the presented charts and build the users' persona, as shown in Table 4.

Top factors that affect acceptance of data visualisation: Users were presented with 19 statements - shown in Figure 5 related to data visualisation design and development. Analysis of the responses revealed that eight of these statements received a positive NPS, indicating a high level of user satisfaction. The factors that influenced users' acceptance of data visualisation were found to be related to two aspects: presented data and chart interactivity.

- Easy to read presented data (NPS = 40.74)
- Data are complete and shown in the chart (NPS = 15.69)
- Ability to set your own goal (NPS = 14.81)
- Charts show progress (NPS = 13.73)
- Easy to navigate (NPS = 11.11)

Easy-to-read data was identified as one of the top factors for encouraging usage among all participants, regardless of age. Participants aged 18-30 appreciated the ability to set their own goals, while those aged 31-40 favoured the completeness of the presented data. Participants aged 41-50 preferred easy-to-navigate features, and those over 50 valued charts that fit the screen size. For a summary of the top positive factors, please see Table 4.

RQ5: Suggestions to improve data visualisation The findings from the open-ended question revealed that the majority of participants (86.96%) preferred to write their

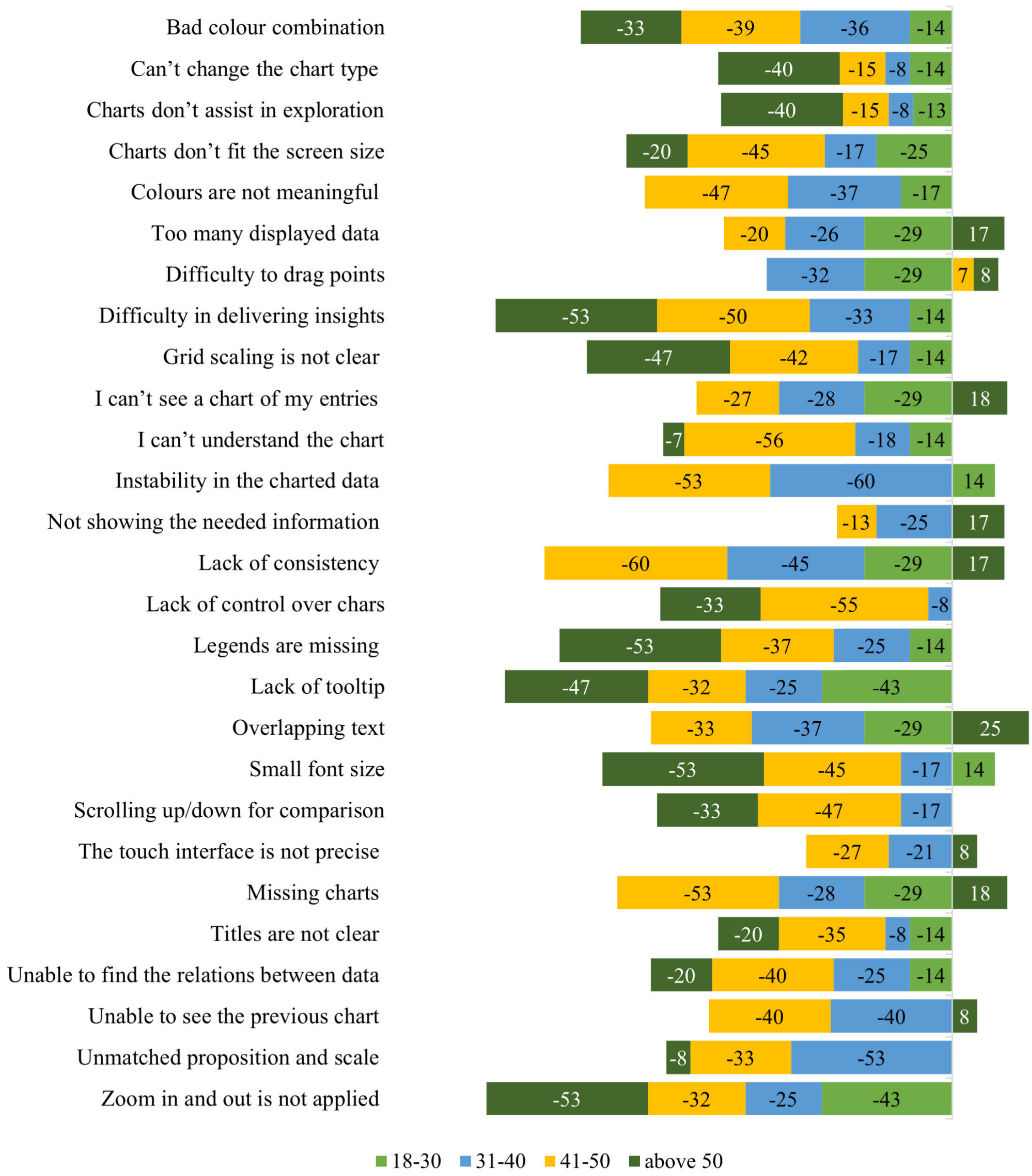

FIGURE 4. Distribution of Challenges in Data Visualisation by Age Group.

suggestions rather than uploading sketches. It should be noted that the uploaded sketches were found to be invalid and not considered in the analysis. The validated written responses encompassed various aspects of data visualisation components, which we categorised into five key areas. **Audiences:** Age-friendly data visualisation is one of the reported recommendations. Users wrote that some data visualisation could be more age-friendly in font size and colours. Also, Users repeatedly requested to make data visualisation user-friendly by providing straightforward access. **Functional requirements:** Users suggested multiple functional requirements. For example, they recommended adding a face scan to know the user's mood, comparing current and historical data, and the need for a daily dashboard in which users can personalise their presented data. Moreover, Additionally, one user expressed the need for a user guide that does not consume excessive memory and battery resources on the smartphone. **Data:** Users requested simpler data presentation. *"I think one of the most important things is for charts not to be crowded, and as a non-expert, I need to be able to understand the two parameters being compared easily, describing data more understandably"*. **Interactivity:**

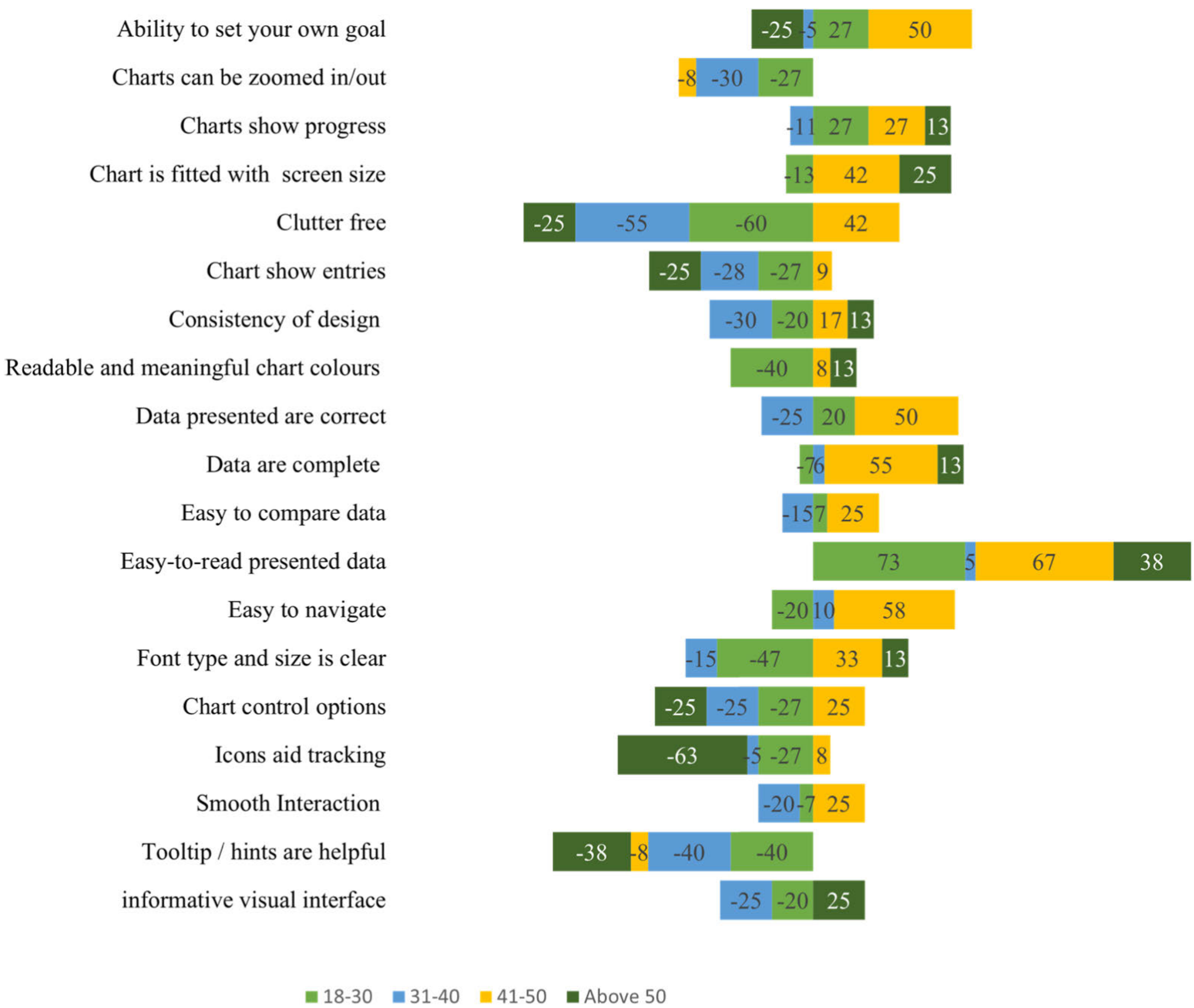

FIGURE 5. Factors Influencing Acceptance of Data Visualisation by Age Group.

One user reported a suggestion for having control over the charts *"I would like to add high and low limit lines to the Y-axis on a graph so that any Y values above the high limit are easily seen as above or below those lines"*. Additionally, users are looking for more interactive health tracker apps. They suggested adding fun and attractive features such as emojis and interactive charts representing their health data.

V. SURVEY ANALYSIS

Based on the participant profile presented in Table 1, the survey included a diverse range of individuals representing various demographics, professional backgrounds, and experience levels. A total of 56 participants took part in the survey, ensuring a comprehensive sample for analysis. In this section, we elaborate on the findings derived from the survey data, addressing the research questions that guided our study, and discussing the implications for improving user experiences in data visualisations.

RQ1:Top mhealth apps The most frequently mentioned health apps by the users in their responses were Apple Health, Sweatcoin, Samsung Health, Fitness App, and Step Tracker Pedometer. These apps consistently rank among the top apps in both the Google Play Store and App Store, indicating their popularity among users. These apps primarily focus on sports activities, which we previously identified (in Section IV) as the highest-ranked activities users track using their mobile devices. These apps are specifically designed to track and monitor sports-related data, such as step count, distance covered, calories burned, and workout intensity. This reflects the growing trend of individuals using mobile apps to monitor their fitness and actively participate in physical activities [25].

RQ2: Preferred data visualisation types and layouts When it comes to preferred visualisation types and layout, 75% of the respondents expressed a preference for presenting their data using a combination of text and charts. This finding highlights the importance of considering the data visualisation literacy of mHealth app users. It also suggests that providing a brief description or explanation alongside the presented charts could enhance user understanding and engagement. Further research is needed to examine the effectiveness of adding text to explain the presented charts to overcome the challenge found in [26].

In terms of the preferred chart types, the participants showed a strong preference for bar, pie, timeline and line charts. In line with these findings, Choe et al. [26] stated that bar charts and line charts have also been shown as the most used charts among 21 other visualisation charts. Additionally, Katz et al. [43] have stated that the pie chart scored high rates for being easy to read for participants. This reflects users' interest as they favour well-known traditional charts. Although studies have proposed a conflicting point of view concerning the pie charts' ease of reading and accuracy, it is still used regularly in multiple mHealth apps. However, the accuracy and readability of pie and doughnut charts have been criticised by [44] and [45] and visualisation community.[1] Therefore, it is suggested to conduct a detailed examination to understand how users interpret these charts.

RQ3: Data visualisation goals and tasks The results indicate that the majority of users track their data for fun and curiosity. This suggests that charts should be designed to be more interactive in order to enhance users' engagement. However, it is important to strike a balance and avoid complex interactive visualisations that may overwhelm users. Additionally, users express interest in simple analysis, such as comparing their data and identifying trends. These findings suggest that simplicity is a key principle that users value, aligning with the concept of universal design [46]. Future research could further explore universal design principles such as flexibility and inclusivity to enhance the design of data visualisations within the mhealth context.

Furthermore, the alignment between participants' chart preferences and their preferred tasks in mHealth apps reveals an intriguing finding. The most favoured chart types, including the bar chart, pie chart, timeline chart, line chart, and stacked chart, directly corresponded to tasks involving finding minimum and maximum values, showing progress and trends, and making comparisons [47]. This correlation highlights the importance of task relevance in influencing users' chart choices, emphasising the need for appropriate chart options that align with desired functionalities. By understanding this correlation, developers and designers can effectively cater to users' needs, enhancing the usability and user experience of mHealth apps.

RQ4: Challenges and encouragement factors Users' points of view were mainly bouncing between chart layout, styling, data and interactivity. As shown in the results section (IV), data visualisation design and development need to be refined as all of the concerning options were going to the negative side of the NPS. On the other hand, 8 encouragement factors were on the positive side, indicating users' acceptance of these features. Nevertheless, the remaining 11 options were going on the negative side, again indicating user dissatisfaction. Our findings align with [43], where the researchers examined users' experience using commercial diabetes apps. They found that users complained about the limitations of interactivity, inadequate data presentation, screen size limitations, and colour selection. Furthermore, although study [16] included suggestions for better chart layout and simple navigation guidelines, these two aspects still propose issues based on user perspectives. Hence, the current mobile data visualisation design and development practices must be revised and improved to address these challenges. As these gaps appear in multiple studies, we argue that connecting these research studies with industrial practices is necessary.

RQ5: Suggestions to improve data visualisation The provided suggestions shed light on the significance of considering universal design principles and data visualisation literacy. Participants' responses revealed two primary areas of concern regarding accessibility: the need for age-friendly visualisations and user-friendly access. Additionally, participants stressed the importance of presenting data in a simplified manner within charts, considering themselves as non-expert users.

Regarding functionality, users expressed a desire for advanced features in their tracking apps. These included mood recognition through face scanning, the ability to perform comparative analysis, the availability of tooltips and user guides, and the provision of personalised dashboards. It is worth noting that although tooltips were not identified as one of the top factors that encourage app usage, users still recommended their inclusion. This highlights the importance of ensuring inclusivity by incorporating a wide range of user needs and preferences. In terms of interactivity, users expressed a desire for greater control over chart scales. Furthermore, they emphasised the value of incorporating fun elements like emojis and interactive charts to effectively represent their health data, as these features enhance user engagement with the apps.

Taken together, the participants' suggestions highlight the importance of prioritising accessibility, user-friendly interfaces, and advanced functionalities in data visualisation design. By incorporating these recommendations, designers can create inclusive and engaging visualisations that cater to a diverse range of users' needs and preferences.

Approaches to address users needs and pains *Personas based on age grouping:* Based on the summarised information in Tables 3 and 4, it is evident that users of different ages have varying perspectives on chart presentation, styling, interactivity, and functionality. This knowledge has allowed us to gain insights into the characteristics of the primary audience of the mHealth tracking system and address their specific needs, pain points, and desired benefits. Furthermore, this analysis aligns with the recommendations put forth by Jena et al. [22], emphasising the importance of considering universal design principles and users' data visualisation literacy.

[1] https://www.data-to-viz.com/caveat/pie.html

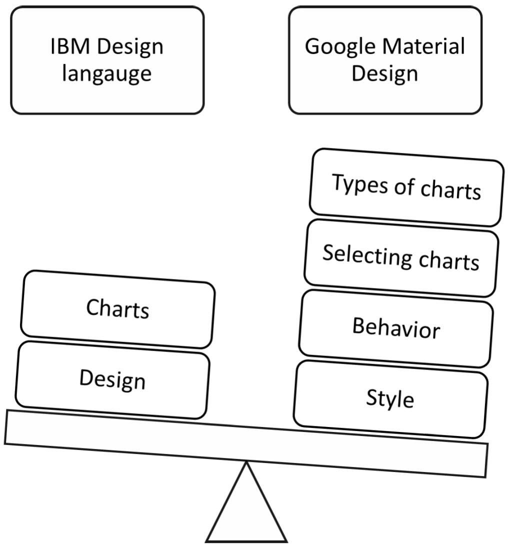

FIGURE 6. **Comparison between IBM and Google guidelines.**

By leveraging the insights gained from our survey results, we can develop personas[2] that capture the unique needs, pain points, and desired benefits of different user segments. These personas will be valuable tools for developers and designers, providing them with a deeper understanding of user characteristics and preferences. This understanding can guide the design and development of mHealth apps, particularly in relation to data visualisation perspectives.

However, in order to gain a comprehensive understanding of mHealth users and their interactions with the charts, further investigation is required to explore the user journey during chart exploration and interaction. This would provide valuable insights into the user experience and guide the development of a more user-centred mHealth charting system.

Emerging implications for data visualisation designers: The left side of the value proposition focuses on a value map that consists of products and services, pain relievers, and gains creator [41]. In our case, the service is to support end users to have a better experience when browsing and tracking their mHealth data using charts. Furthermore, our value proposition is to offer the best practice using these charts.

In order to reach this, the persona information that we captured previously from our survey results provides valuable insights for developers and designers in delivering well-designed and developed mHealth apps based on the data visualisation perspectives. Ideally, there should be frameworks or guidelines to help visualisation designers during this process.

We have identified two main industrial guidelines developed for data visualisation design: *Google material design* [49] (BETA version that would be changed based on research studies) and *IBM design language* [50]. These frameworks have 4 main limitations: a lack of consideration for non-expert users, the chart functionality, smartphones limitations and suitable data visualisations for different types of tracked data. The guidelines provided in Google's material design are more comprehensive than the IBM design language as shown in Figure 6. Google material design considered chart interactivity based on the mobile device platform. Its design language supported touch, tap interaction, pagination by swiping to the left to view the other charts, panning and zooming using 2 fingers to pinch. However, these guidelines lack support for other components related to data visualisation, such as considering non-expert audiences, presented data, chart requirements, chart interactivity and alignment of presented chart design and functionality with the used mobile devices. Thus, they are not appropriate, and hence there is a need for a revised framework.

VI. STUDY LIMITATIONS

Although our study provides valuable insights into user experiences when using data visualisation in mHealth apps, there are several limitations that may impact these results.

Firstly, the sample size of our study was 56 participants. While we aimed to include a diverse range of individuals, the small sample size may affect the generalisability of the findings. It is important to consider the representativeness of the participants in relation to the wider population.

Additionally, the distribution of our sample may be skewed due to the recruitment methods used, such as advertising through social media channels. This could result in a sample that is biased towards individuals with higher levels of education and technological literacy. Conducting future research with a larger and more diverse sample would provide a more comprehensive understanding of the user population and their experiences.

Another limitation is the reliance on self-reported user experiences and perspectives. This approach may introduce biases and subjective interpretations, as participants may provide responses based on their own perceptions and interpretations. Future studies could consider incorporating objective measures and observations to complement self-reported data, providing a more holistic view of user experiences.

VII. CONCLUSION AND FUTURE WORK

This paper presents a survey aimed at exploring user needs, challenges, and goals related to data visualisations in mHealth apps. The study employed the well-known value proposition canvas framework, which consists of three components that cover user tasks, pains, and gains. We have collected 56 complete responses, and our results show that bar and pie charts are more favoured as they are simple and easy to use. Curiosity and utility (such as tracking progress) are the primary drivers of using charts. The top challenges users encountered when using mHealth apps were lack of

[2] A persona is an ideal entity built from research on real users [48].

information displayed, user interaction with the charts (such as dragging points and touch interface), and crowded charts with data.

Based on the results of our survey, we were able to generate different general personas based on user age. This information can inform the design features that would meet user preferences and address their challenges. Our future research in this area aims to expand our understanding of users' needs and preferences related to data visualisation in mHealth apps. By personalising data visualisation in the context of mHealth apps, we can develop guidelines for designers and developers to create effective data visualisations that meet user needs. It is important to note that demographic factors such as socioeconomic and cultural factors should also be considered in developing a better understanding of the adoption of mobile data visualisation. Similarly, the number of completed responses may affect the diversity of the preferred options and reported challenges. Therefore, we plan to extend our work by contextualising each mHealth domain and studying its specific challenges to further refine our understanding of user needs and preferences.

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