Adaptive User Interfaces for Software Supporting Chronic Disease

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ABSTRACT

mHealth interventions hold promise for supporting the self-management of chronic diseases, yet their limited utilisation remains a problem. Given the significant variability among individuals with chronic diseases, tailored approaches are imperative. Adaptive User Interfaces (AUIs) may help to address the diverse and evolving needs of this demographic. To investigate this approach, we developed an AUI prototype informed by existing literature and used it as the basis for a focus group and interview study involving 22 participants. Concurrently, a quantitative survey was carried out to extract preferences for AUIs in chronic disease related applications with 90 participants. Our findings reveal that user engagement with AUIs is influenced by individual capabilities and disease severity. Additionally, we explore user preferences for AUIs, expanding the adaptation literature by uncovering usage challenges, proposing practical strategies for enhanced AUI design, and acknowledging potential trade-offs between usability and adaptation. Lastly, we present design considerations for AUIs in chronic disease applications, aiming to prevent user overload and maintain critical software functionality and usability aspects.

CCS CONCEPTS

• **Human-centered computing → Graphical user interfaces**; **User interface programming**.

KEYWORDS

adaptive user interface, AUI, chronic disease, mHealth applications

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LAY ABSTRACT

Almost half of Australians are estimated to have one or more chronic diseases in 2020–21. Mobile health tools show promise in helping people manage chronic diseases, but these are not commonly used among many individuals with chronic conditions. People with chronic diseases have diverse needs, so a one-size-fits-all approach does not work well. Adaptive User Interfaces (AUIs) offer a solution by tailoring the user experience to individual needs. In our study, we created an AUI prototype based on our investigation of the existing research. We tested our prototype through focus group sessions and interviews. At the same time, we conducted a survey to learn more about their preferences for AUIs in apps related to chronic diseases. Our research revealed that how much users engage with AUIs depends on their individual abilities and the seriousness of their illness. We also discovered what users like and dislike about AUIs, highlighting some challenges in their use. To make AUIs better, we suggested some practical ideas and recognised that there can be a balance between making them easy to use and adaptive. Lastly, we provided some tips for designing AUIs in apps for chronic diseases to ensure they are user-friendly, without making them too complicated, and still offering important features.

1 INTRODUCTION

Chronic diseases, including conditions like asthma, cardiac disease, and diabetes, have emerged as significant challenges for the health-care system [97]. Managing these enduring health conditions extends beyond biological parameters alone, with a growing emphasis on empowering patients to actively participate in *self-management* [97]. mHealth technologies have seen increasing use in promoting self-management by enhancing medication adherence and enabling self-tracking capabilities [41]. However, research indicates that those who could benefit the most from mHealth solutions often under-utilise them [43]. To scale up the deployment of mHealth applications, it is imperative to create more *user-friendly systems* that can accommodate the *diverse needs of users* [43]. However, several challenges need to be addressed to achieve this objective. Firstly, chronic diseases are inherently *heterogeneous*, impacting individuals in various ways, including triggers, symptoms, and severity [8, 47]. Secondly, it is crucial to consider the *developmental stages of chronic diseases* when designing the mHealth technology, as chronic diseases may co-occur with other medical or psychological disorders, which further adds to the complexity of chronic disease self-management [8, 24]. Thirdly, chronic diseases typically persist over an individual's *lifetime* [47, 97]. Therefore, mHealth technologies must maintain user engagement and motivation over a long term. Patients have diverse backgrounds, expertise, demographics, and psychological and cognitive traits [64, 94].

Adaptive User Interfaces (AUIs) are frequently advocated for accommodating the significant variability of patients by customising the **user interface (UI)** to suit individual needs, goals, and contexts of use in mHealth technologies [71]. Despite the increasing interest in employing AUIs within chronic disease related applications [84, 88], they tend to overlook different user characteristics and interactions [38, 67]. Additionally, there is a lack of information concerning the development processes for AUIs in the early design stages [9]. The main AUI evaluation methods focus on evaluating the effectiveness of the application as a whole, which makes it difficult to draw conclusions about the usefulness of the AUI and user preferences [9]. There is also limited understanding of how individuals with chronic diseases utilise AUIs, as they may not fully leverage the benefits of adaptations [55].

In this paper, we examine users' perspectives concerning the usage of AUIs in chronic disease related applications. Firstly, we developed an AUI prototype focused on AUI in chronic disease related applications. This prototype served as the basis for our qualitative investigation into how individuals experience AUIs in the context of chronic diseases (interview and focus group study). At the same time, we conducted a quantitative survey to collect user preferences regarding different aspects of the adaptation process. This work offers three key research contributions:

- our work sheds new light on the influence of users' cognitive capabilities and severity of symptoms of those with chronic diseases on their interaction with AUIs;
- we investigate user preferences for AUIs, expanding the adaptation literature by uncovering challenges in AUI usage, suggesting practical strategies for improved AUI design, and acknowledging potential trade-offs between usability and adaptations; and
- design considerations for AUIs in chronic disease applications are proposed to avoid overburdening the user or compromising aspects of software functionality and usability valued by the user.

2 RELATED WORK

Prior research has explored the use of AUIs in systems designed for healthcare professionals [28, 37, 95]. Eslami et al. [28] used interviews and observations to gather health information system requirements, primarily focusing on healthcare professionals. Vogt and Meier [95] examined AUI design issues in specific contexts like smart hospitals. Greenwood et al. [37] introduced a novel approach using reactive agents for AUIs in diabetes treatment decision support, customising data display based on clinicians' preferences. There is an increasing number of papers describing applications, approaches, tools and algorithms for patient-focused AUIs.

Recognising that mHealth app users are very diverse, a growing number of papers describe approaches, applications and tools for patient-focused AUIs. Existing AUI framework studies have tended to focus on specific adaptive components or specific aspects of patient management [32, 85, 98]. For example, Shakshuki et al. [85] proposed an AUI architecture for patient monitoring with an emphasis on health-related information adaptation. Yuan and Herbert [98] designed a fuzzy-logic-based context model for personalised healthcare services in chronic illness, prioritising health issue prediction and preventive measures based on user data rather than UI adaptation to individual user needs and context.

AUIs have been implemented in various mHealth applications, including stroke rehabilitation [15], type 2 diabetes [73], cardiac disease [69], dementia [10, 39] and Parkinson's disease [51]. These applications adapt in different granularity, such as exercise activity difficulty levels [15], health-related information [10, 39], navigation [10, 73], multimodal interfaces [73], information architecture [69], and graphic design [39, 51, 69, 73]. However, most of these studies lack detailed explanations of their AUI development process, particularly in the early stages involving their diverse end users. Additionally, the common evaluation approach for AUIs focuses on overall application effectiveness without appropriate comparisons to non-adaptive UIs, making it challenging to draw specific conclusions about the AUI's impact. Some AUI research in other domains indicates that AUIs can enhance user performance and satisfaction compared to non-adaptive baselines [34, 61, 75, 91], while disruptive adaptations, which changes the way users are accustomed to interacting with the system or breaks conventions, can lead to frustration or dissatisfaction [29, 80].

3 METHODOLOGY

We wanted to understand how AUIs can be used to provide better mHealth apps for people with chronic disease, an increasingly important societal challenge area. To do this, we built a set of proof-of-concept adaptive mHealth apps and then gathered representative user feedback on these prototype apps.

3.1 Adaptive User Interface prototype

Building upon insights from an earlier **systematic literature review (SLR)** [9], our study advances the formulation of adaptation categories and incorporates all of them into one prototype which encompasses three main types of adaptation: presentation adaptation, content adaptation, and behaviour adaptation.

Presentation adaptation entails the modification of interface element parameters (e.g., colour, size, positioning, font) to enhance user experience, subdivided into ***1) graphic design*** and ***2) information architecture***. Graphic design manipulates visual aspects, like theme, and layout, while information architecture pertains to the structural organisation of information within the system.

Content adaptation modifies interface content, including text, semantic elements, images, or explanatory text, to suit users' needs. We propose two primary subcategories: ***1) content complexity***, simplifies content for better comprehension, considering users' cognitive abilities, education, and comprehension. This category comprises three subcategories. Easy-to-understand language employs clear, concise wording for enhanced comprehension. Minimalist design reduces visual clutter, presenting content more succinctly. Text-to-image conversion translates intricate text into easily comprehensible visual representations. ***2) interface elements rearrangement***, involves reorganising elements to enhance content presentation and accessibility, encompassing position adjustments and selective element concealment.

Behaviour adaptation involves adjusting navigation methods, enabling/disabling interface elements, and modifying interaction

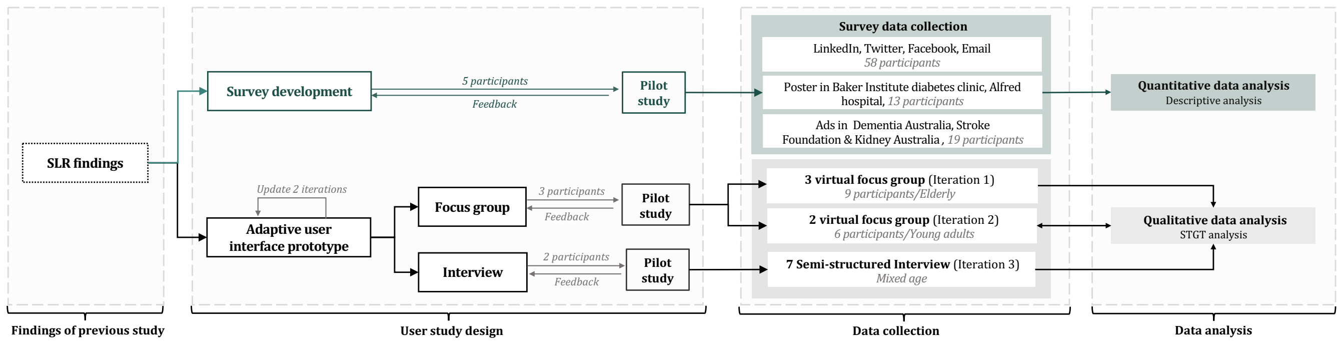

Figure 1: User study approach

modes within an application. This complex form of adaptation often spans multiple steps and can encompass content and presentation adjustments. We group it into five subcategories: ***1)*** *navigation adaptation*, altering user navigation permissions or suppressing specific modules; ***2)*** *add-on functions*, incorporating new features to enhance user assistance and application usability; ***3)*** *pervasive strategies*, adapting motivation techniques for effective behavioural changes tailored to user types/status; ***4)*** *multimodal interaction*, adjusting interface modalities based on varied usage contexts; and ***5)*** *difficulty level adjustment*, modifying game/exercise difficulty to balance engagement and challenge based on user motivation/performance. The AUI prototype underwent evaluation by three co-authors and was tested on two real users with experience in mHealth apps. For each adaptation, we provided transitions, sample rationales, and additional instructions, to facilitate user navigation and interaction with various adaptations.

3.2 User study design

Our user study comprises two parts, as shown in Figure 1. Firstly, we developed an AUI prototype for applications related to chronic diseases based on earlier SLR findings. With our prototype, we conducted a qualitative investigation to examine how individuals experience AUIs in the context of chronic diseases. We also conducted a quantitative survey to collect user preferences regarding different dimensions of adaptation.

Focus group study and interviews. Both focus group and interview sessions underwent one round of pilot testing involving varying numbers of participants. We utilised a theoretical sampling method [48] to recruit participants for both focus groups and interview studies. In this sampling approach, as data collection and analysis progress and yield concepts and categories, new participants are selected based on specific criteria, hinged on whether there is a need to deepen or expand existing concepts and categories. Qualitative data collection and analysis followed an iterative process encompassing three data collection iterations. Upon obtaining ethics approval from the university's ethics board,[1] we commenced our focus group study by recruiting participants through a mailing list of a previous chronic disease research program. In this iteration, we mainly targeted older individuals (aged over 55) (*Iteration 1*). Subsequently, using our personal connections we recruited several young adults with chronic diseases (aged under 44) (*Iteration 2*). [2] To enhance data reliability and validity through multiple data collection methods (*methodological triangulation*) [21], we employed semi-structured interviews alongside focus group studies. Interview participants were recruited via local community channels, at Baker Institute Diabetes Clinic and Alfred Hospital, as well as via advertisements in Dementia Australia, Stroke Foundation, and Kidney Australia (*Iteration 3*). During the interview and focus group sessions, participants started by viewing a brief adaptation video with audio explanations, offering comprehensive introductions to each adaptation, which was then followed by hands-on interaction. Additionally, a help page was presented during the session, allowing participants to reference instructions if needed. All participants received an AU$30 virtual gift voucher as a token of appreciation.

Survey. In parallel, we conducted an anonymous online survey using Google Forms, targeting participants with chronic diseases. The survey consisted of four main sections, each focusing on specific topics to ensure participants' ease of understanding: demographic information, health status, mHealth application use patterns, and AUI preferences. To ensure participants' understanding of AUIs, a brief explanation with two examples of AUIs in the health domain is provided at the start of the AUIs section. This section focuses on participants' preferences regarding various adaptations, different types of data, data collection methods, and desired level of involvement in the adaptation process. Survey questions are informed by a previous SLR [9], and the survey underwent a three-stage pre-test process following Dillman's recommendations [25], involving expert reviews, user feedback, and pilot testing with five participants. Survey data collection occurred from January to July 2022 through various recruitment channels, with a total of 90 respondents (Figure 1).

3.3 Data analysis

Qualitative data analysis. We used the **Socio-Technical Grounded Theory (STGT)**'s data analysis procedures [48] to analyse our focus group and interview recordings. STGT can be selectively applied by incorporating its fundamental data analysis procedures instead of being used solely for theory development. We transcribed the audio recordings with participants' consent and subsequently

[1]Monash Ethics Review Manager (ERM) reference number: 36568

[2]The first author, who is afflicted by a chronic condition, engages with both online and offline support groups for individuals in similar circumstances.

stored and analysed the data using NVivo. We employed open coding for the transcripts, along with constant comparison and memoing techniques across different transcripts. The data collection and analysis were iterative and interleaved (Figure 1). Qualitative data was analysed by the first author and shared with the rest of the authors to facilitate discussion at each stage of the process and determine the best ways to present the findings, across all data collection iterations. Key categories and underlying concepts from STGT analysis are presented in Section 4.

Quantitative data analysis. Descriptive statistics are presented as percentages for all respondents. Chi-square tests are used for the univariate comparison of categorical variables, including age, gender, nationality, education, and chronic disease conditions. To ensure that the data distribution met the prerequisites for the Chi-square independence test, we grouped related variables into categorical variables beforehand. If a significant association is found, we subsequently employ **binary logistic regression (BLR)** or multinomial logistic regression to model the relationship between these variables. We chose the common significance level of $\alpha = 0.05$.

3.4 Participants

Focus groups and interviews. Participant demographics are detailed in Table 1, encompassing a diverse range of nationalities including Australian, Chinese, Indian, British, Filipino, Malaysian, American, and Tamil, with a predominant Australian representation. The sample comprises a greater proportion of females (15) than males (7), spanning various age groups (18-34: 7, 35-54: 6, 55-74: 10), as well as a wide spectrum of chronic diseases, such as type 2 diabetes, rhinitis, chronic gastritis, depression, epilepsy, anxiety, hypertension, chronic depressive disorder, post-traumatic stress disorder (PTSD) and different mental health conditions. All participants are either current or past users of the mHealth applications. A majority (17/22) possess a university degree. Participants are numbered according to their study involvement: FP1-FP15 for focus group participants, and IP1-IP7 for the interview participants.

Table 1: Participants for focus groups and interviews

#	Age	Gender	Ed*	Nationality	Chronic diseases
Iteration1: Each focus group study took 60-70 minutes.					
FP1	55-64	Female	M	Australian	Type 2 diabetes
FP2	55-64	Female	M	Australian	Type 2 diabetes
FP3	65-74	Female	M	Australian	Type 2 diabetes
FP4	65-74	Male	P	Australian	Type 2 diabetes
FP5	25-34	Female	M	Chinese	Asthma, Allergic rhinitis & Chronic gastritis
FP6	65-74	Female	P	Tamil	Type 2 diabetes
FP7	55-64	Female	T	Australian	Type 2 diabetes
FP8	18-24	Female	B	Malaysia	Depression
FP9	65-74	Male	B	Australian	Type 2 diabetes, Heart disease, Epilepsy&Asthma
Iteration2: Each focus group study took 60-70 minutes.					
FP10	25-34	Male	M	Chinese	Type 2 diabetes
FP11	25-34	Female	B	Filipino	Over weight & Anxiety
FP12	25-34	Male	M	Chinese	Rhinitis & Anxiety
FP13	35-44	Male	B	India	Overweight & Type 2 diabetes
FP14	35-44	Male	B	India	High blood pressure
FP15	25-34	Female	M	Chinese	Mental health conditions
Iteration3: Each interview study took 30-60 minutes (aimed at saturation).					
IP1	55-64	Female	A	Australian	Type 2 diabetes
IP2	35-44	Male	B	British	Mental health conditions
IP3	65-74	Female	A	Australian	Type 2 diabetes
IP4	45-54	Female	M	Australian	High blood pressure & Type 2 diabetes
IP5	45-54	Female	M	Chinese	Anxiety, Insomnia & Mental health conditions
IP6	18-24	Female	B	American	Anxiety & Mental health conditions
IP7	55-64	Female	B	Australian	Major chronic depressive disorder & PTSD

Ed:Education (M=Master, B=Bachelor, A=Associate, T=Technical training)*

Survey participants. Among the 90 survey participants (Table 2), the majority are male (56%) with varying ages (18-74 years) and education levels. The most commonly repeated education level is a bachelor's degree (44%). We collected responses from participants in diverse countries, with roughly 50% of the responses originating from individuals residing in Australia. Given the limited sample sizes in specific chronic disease categories, we grouped chronic health conditions into four broader groups: cardiometabolic (e.g., diabetes, high blood pressure, obesity and heart disease), respiratory (e.g., allergies, asthma and chronic lung disease), immune-related (e.g., cancer, parkinson disease and compromised immune system), and mental health conditions [16]. The most common chronic conditions reported are cardiometabolic diseases (52%).

Table 2: Survey participants (n = 90)

Demographics	#	% of Participants
Age of the Participants		
18-24, 17/19% | **25-34**, 30/33% | **35-44**, 19/21% | **45-54**, 10/11% | **55-64**, 11/12% | **65-74**, 3/4%		
Gender of the Participants		
Female, 38/42%, | **Male**, 50/56%, | **Prefer not to say**, 2/3%		
Countries of the Participants		
Australia	44	49%
China	21	23%
USA	12	13%
UK	6	7%
Other (Nigeria, Canada, Korea, Spain and Sri Lanka)	7	8%
Education information of the Participants		
Less than Bachelor's degree	31	34%
Bachelor's degree	40	44%
Postgraduate (Master's and Doctoral degree)	19	21%
Categories of chronic disease (Some participants have multiple chronic diseases)		
Cardiometabolic	47	52%
Immune-related	31	34%
Mental health conditions	7	8%
Respiratory	11	12%

4 RESULTS OF QUALITATIVE DATA ANALYSIS

We identified four challenge categories that participants encountered when using our AUI mHealth prototype, and three strategies to mitigate the identified challenges, presented in Figure 2.

4.1 Challenges participants face in using AUIs

Drawing upon STGT data analysis and existing literature [1, 9], our we categorise identified challenges into four distinct categories, each of which is explored in detail below.

4.1.1 What to adapt. The **predictability of the UI** emerged as a crucial concern, aligning with prior research [52, 68]. Participants emphasised the importance of spatial stability within the UI (IP 4,5,7, FP2). IP7 articulated, *"system makes lots of changes would confuse me because I get used to finding things in the same place. When it changes, hard to see what comes next"*. This observation is supported by the study [42], which highlights that even slight changes that impact predictability can result in errors. Some participants found UI adaptation concepts and generated adaptations challenging to understand (FP 2,4,7,9,12,15,16, IP3). This lack of **comprehensibility** could hinder adaptation's effectiveness, potentially resulting in reduced user performance and satisfaction, and ultimately causing users to consider switching to other apps (FP2). In the context of chronic diseases, the intricacies of adaptation can be exacerbated [98]. For example, the AUI prototype featured an avatar displaying

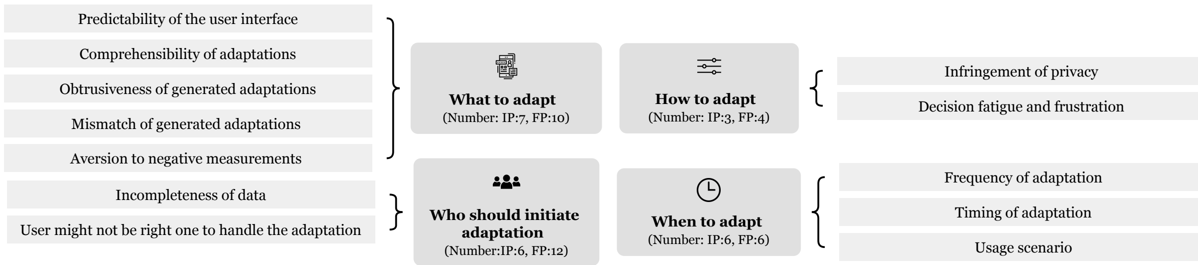

Figure 2: The challenges reported by participants

a concerned expression in response to unfavourable measurements. Older participants (aged over 65) (FP4, IP3) indicated that this simple visual cue may not alleviate their concerns and may even increase their confusion. By contrast, younger participants (aged under 44) appreciated such avatars, finding them a way to *"make all serious things more fun"* (IP7, FP 5,8 10,13). This difference aligns with prior research suggesting gamified design appeals more to younger audiences due to tech proficiency and familiarity with games [12].

Some adaptations, such as the inclusion of additional comfort words and gamified design elements to convey health information, are perceived to be **obtrusive and potentially distracting** from primary tasks by most participants (IP 1,3,4,6,7, FP 4,5,6,7,9). IP3, for instance, emphasised that: *"I don't talk about my comfort level. I don't talk about my feelings. I talk about my medical issues. Any adaptation that does not relate to my health status is not useful and very distracting"*. Participants like FP4, IP1, and IP7 also questioned the presence of unrelated visuals or adaptations in a serious health-related app. However, participants with more experience in using mHealth applications had a less negative view of certain *"distracting"* adaptations (FP5, IP6). Visual elements can vary in impact and relevance based on user experience and cognitive abilities [66].

Some participants expressed concerns about potential **mismatched adaptations** (FP 4, IP 2,3,6). They worried about becoming trapped in an adaptation process triggered by *"wrong measurement or the wrong input data"* (FP4, IP6). IP2 shared similar feelings, stating he *"felt overwhelmed due to the uncertainty of what the system would understand and what it would not"*. Such instances of expectation mismatches often result in a decline in trust in the generated adaptation [36]. Additionally, few younger (aged under 34) participants appreciated the value of certain adaptations like font size adjustments or simpler UI designs (FP 8,11,15, IP6). However, they frequently perceived value not for themselves, but rather for others with varying disabilities and independence. Their reluctance to embrace certain adaptations may stem from their strong sense of self-sufficiency and independence [90], which can make them overlook the immediate benefits of the adaptation.

Participants in our study display mixed feelings regarding measurement results, especially in the context of recording health data like blood glucose levels, stress levels, and blood pressure. Some participants expressed **aversion towards the bad measurement** and preferred not to be constantly reminded of negative outcomes (IP 1-5, FP 8,9). Likewise, IP1 shared her inclination to avoid doctors and attempt to deny the measurement when confronted with unfavourable health data. Participants recommended that presenting data in a *"non-critical"* (IP4) and positive reinforcement manner would be beneficial (IP3). These struggles indicate the influence of users' symptoms and health conditions on their interactions with technologies [55]. In contrast, other participants especially those with mental health issues, found value in the reminders and clear presentation of such data as an important signal for their health management (IP5, FP 5,8,10-13,15). For instance, IP5, who deals with mental health issues, expressed that: *"Bad data serves as an important signal. I prefer frequent and clear reminders for any negative measurement. That's the whole purpose of the app"*. IP5 also described how tracking bad health measurements made her feel *"proactive and empowered"*.

4.1.2 Who should initiate adaptation. In typical app usage scenarios, users already face challenges of continuously logging various types of data, such as heart rate, blood pressure, blood sugar levels, and body composition [76]. The introduction of AUIs in these applications can further complicate matters, primarily due to the role of data in UI adaptation [6]. Most participants already find it challenging to consistently record their daily data, leading to **incomplete data records** (FP 4-6,9,11,12,15, IP 3,6). For instance, FP9 mentioned how frequently he forgets to take blood tests, similar to FP5, who stated that even after setting up three reminders, she often forgets to record her daily mood. This inconsistency in data recording is a common issue in chronic disease related applications [86]. Furthermore, IP3 admitted that she sometimes *"fakes some data"* to complete records artificially, which can *"make the progress and reports look really good"*. These participants emphasised that having various adaptations becomes pointless if the underlying data is unreliable. Building upon the discussion of data collection, participants expressed concerns about **whether users are the right ones to handle the adaptation process**. Firstly, older participants (aged over 45) mentioned the ***added mental workload*** of handling adaptations alongside their existing responsibilities related to managing their chronic conditions (IP 1,4,7, FP 4,6,7,9). They found it challenging to learn and navigate the adaptation process, which could counteract the time and effort-saving benefits that automation of adaptations aims to offer [34, 45]. There are several participants opposed to complete automation as it might leave them in the dark about what's happening (IP 3,6, FP 1,2,3). Furthermore, IP7 expressed concerns that: *"If you think adaptation is the answer, now, you have to suffer from adaptation solution. And then it makes your chronic disease worse"*. This suggests that mHealth apps could pose risks to user safety when their design is not well-controlled [2]. Secondly, considering the app's intended purpose, situations may arise where a ***user's preferences conflict with the app's intended use*** (FP 4,6,7-9,11,12, IP 2). For instance, in the context of rearranging elements on the UI, some participants expressed concerns that *"certain essential functionalities, such as recording blood sugar levels for diabetes management, might be inadvertently hidden because you forget or not access them frequently"*. FP11 and FP12 suggested that some users might manipulate the system to obtain adaptations they want, deviating from an app's original design and purpose.

4.1.3 How to adapt. Several younger participants (aged under 44) in our study voiced worries about potential **privacy infringements** related to adaptation (IP2, FP11,13). IP2 emphasised that he *"probably wouldn't allow any audio-based input for every app"* because he feared that the app is listening all the time. This observation implies that smartphone users may feel violated when they discover that applications access their data without their knowledge [60], potentially leading individuals with greater privacy concerns to avoid using such apps [62]. By contrast, other participants expressed confidence in the reputation of the application (FP 1,2,3,4,6) or the organisation (FP 14,15, IP 1,3,5,7) that developed the application, suggesting that they are not overly concerned about privacy issues. This is deemed reassuring given the prevalent privacy issues surrounding mHealth apps [40].

Excessive control over adaptation can result in **decision fatigue and frustration**, especially concerning individuals with chronic diseases already facing making numerous decisions related to their treatment and lifestyle adjustments [83]. Requesting participants to decide on adaptations might make them feel more drained as the day progresses (IP 2,3,4, FP 7,9), as this forces them to make more decisions [82]. Participants expressed desire for *"a system-driven approach to adaptation decisions"* (IP2) and frustration with *"constant interruption to make adaptation choices"* (IP3).

4.1.4 When to adapt. While participants appreciated the ability to adapt the app, they found it challenging to engage with **frequent adaptations** (FP 4,6,8,9, IP 4,7), especially if they needed to perform these operations in a daily manner. For example, FP9 with type 2 diabetes noted: *"There are times when I try to log my blood sugar levels, but I often forget to do so. If introducing a new adaptation, I might forget that as well, and it could be more challenging if things keep changing frequently"*. Moreover, certain participants wished the UI to remain unchanged after the initial setup, particularly for functions they seldom used (FP 4,6). They recognised the need for dynamic adjustments for frequently used functions. The preference for adaptation frequency can also be influenced by factors such as the ratio of infrequent to frequent feature use and users' familiarity with the interface, as suggested by Bunt et al. [14].

The **timing of adaptation** is a crucial aspect of UI adaptation [1, 14], and participants in our study expressed varying preferences in this regard. Some participants who were knowledgeable about their health conditions and app usage preferred setting up the adaptation upon logging in (IP 6, FP 8,10), aligning with the idea that upfront customisation is efficient when users have a clear understanding of their needs [14]. By contrast, the majority of participants preferred adaptations to occur at regular intervals and should wait until they had familiarised themselves with the application (FP 4,6,7, IP 1,3,4). IP3 explained, *"I would go through all relevant features for managing my health, and then I can get a better idea of how the app should appear and work"*. FP7 expanded on this point, emphasising that immediate adaptation upon initial login could be overwhelming, particularly for those who had just been diagnosed with chronic diseases.

Being mindful of different **usage scenarios** helps ensure that the app remains relevant and valuable to a diverse user base [87, 93]. For example, FP2 mentioned that she often watches TV and uses the mHealth app simultaneously, which highlights the importance of clear and efficient navigation within the app, as multitasking can lead to errors in attention and attribution [87, 93]. Furthermore, some participants noted that they might use the app together with their families (FP 8,9,10, IP 1,3,4,5,7). In these cases, users have to *"look over the health data"*, *"understand the app's features"*, and *"set up some reminders in the app"* for their family members (IP 1,3,4, FP 9). This additional layer of complexity emphasises the multifaceted need for generated adaptations. IP7, for example, expressed the desire to understand why specific adaptations were made for their parents, which might not align with the parents' priorities of using the app. Similarly, IP5, FP8, and FP10 mentioned the need to monitor their parents' health while their parents are in a different country. For instance, IP5's mother, who is almost 80 years old and lives alone in China, has limited technological proficiency. To address this, IP5 bought a smartwatch for her mother and set up the app on her own phone to remotely monitor her mother's daily physical activity and health status. This usage pattern where the app is used by individuals other than the intended user, can potentially lead to unforeseen consequences [59], such as misinterpreting data, incorrect health decisions and feature misuse, especially when the primary user's health needs differ from the secondary user [5, 59]. IP3 also mentioned that she occasionally explains the information in the app to her husband or children. This interaction between users and potential users, including informal carers (e.g. children, spouses) and formal carers (e.g. doctors, nurses), is also highlighted in the study by Martin-Hammond et al. [65].

Summary. We identified four categories of challenges related to users' perceptions of what should be adapted on the UI, who should control the adaptation, how the adaptation should occur, and when it should take place.

4.2 Strategies to mitigate AUI challenges

Participants in our study proposed three distinct categories of strategies to address the challenges associated with incorporating AUIs into the mHealth technologies (Figure 3).

4.2.1 Controllability and Autonomy. Participants in the study stress-ed the importance of having control and autonomy over the adaptation process. While autonomy and controllability are distinct concepts, they are closely related and can influence each other in the context of user interactions [52]. Some participants expect to have a **dedicated adaptation panel** that allows them to manage all adaptations (FP 7, IP 3,7). In this panel, they envision different levels of adaptation that provide varying degrees of complexity. For instance, IP3 explained: *"I can access several adaptations in this*

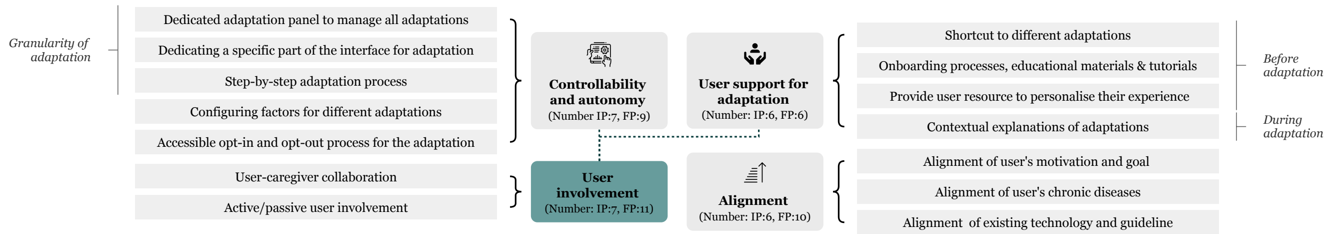

Figure 3: Strategies for adaptations suggested by participants

dashboard, where level three is everything, level two is simple and easy to understand and level one is minimalised design".

In contrast to controlling over adaptation in multiple places on the UI, some participants preferred to have **a specific part of the system dedicated to adaptation** which introduces only minimal distortion to the original interface (FP 4,6,9, IP 1,4,5). This preference aligns with findings from previous studies [23, 34, 61], which may be attributed to the desire for high spatial stability in the UI [22]. IP1 explained that she would feel more confident exploring the system's adaptation features if there was a designated adaptation section within the app, as it would prevent *"accidentally making changes to different parts of the app"*. This concern about unintentional changes is not uncommon among some elderly users (mentioned by FP 4,6,9), who may feel anxious about unintentionally altering the adaptation settings, often requiring assistance to address such issues.

One of the challenges mentioned earlier is that users may not always know the adaptation that suits them initially. One approach identified by participants is to provide a **step-by-step adaptation** process that gradually introduces more complex adaptations (IP 1,3, FP 3,10,11,12). FP3 noted, *"If you find it difficult to understand, there is always the option of switching to the simplified, plain English version. If simple English is still challenging, you can rely on visual aids. This adaptation hierarchy seems promising to me."* This approach aligns with research indicating that individuals tend to choose tasks of intermediate difficulty, which can boost their sense of competence [20]. However, it's essential to adapt in an unobtrusive manner that remains easy for users to notice and follow up on, as some participants expressed concerns regarding the engagement of older individuals (aged over 65) with frequent adaptation (FP 4,6).

These different kinds of controllability and autonomy are achieved on **various levels of granularity** which vary from broad UI presentation changes to more fine-grained adaptations that impact dialogues, navigational flows, or specific content elements (Figure 3) [1, 18, 31]. Our study uncovered a spectrum of preferences for adaptation granularity level. Some favoured one-time adaptations that encompassed the entire application, others leaned towards more specific adaptations targeting particular interaction objects.

Another important aspect of controlling adaptation is to **configure multiple factors for different adaptations** (IP 2,3,4-7, FP 3,7,9). Participants called for more autonomy over the level of automation of the adaptation and the importance or sequence of the adaptation. Offering *"user control over the automation level and scope of adaptations"* (IP3), *"capability to prioritise UI elements based on their usage frequency, significance, or sequence"* (IP2), and *"options to mark specific adaptations as favourites for increased use or for similar adaptation scenarios"* (FP9) are noted by participants.

Providing users with an **easy and accessible opt-in and opt-out process** for adaptation is crucial to ensure user autonomy and positive user experience (IP 1,3,4,6,7, FP 3,5,7,11,12,15). Participants desire a system that allows them to easily enable adaptations with a simple click (FP 3,7,11, IP4), while also valuing the ability to revert adaptations if needed (FP 3,5). These practices for enhancing controllability empower users to maintain control over their app experience, a factor that has been shown to significantly contribute to users' sustained engagement with the application [72].

4.2.2 Providing user support for adaptation. It is essential to provide comprehensive user support and resources to help navigate and comprehend adaptations. We identified two phases for this support: prior to adaptation and during adaptation (Figure 3). Before users engage in adaptation, participants expressed a need for the system to offer straightforward and easily accessible **shortcuts for making these adaptations**, avoiding navigating through complex menus (IP 2,3, FP 10,11,13). For instance, IP2 shared his experience of not noticing the adaptation feature in a mental health app for an entire year because it is buried deep within the settings menu. Additionally, incorporating **onboarding processes or interactive tutorials** can effectively introduce users to the concept of adaptation, demonstrate its benefits and facilitate a better understanding of the underlying principles and purposes of adaptations (FP 1,7,9, IP 1,5,7). For example, FP7 and FP9 both mentioned: *"I would appreciate some assistance before any adaptation is implemented because certain adaptation concepts are challenging for me."*

Furthermore, the **availability of ample resources and meaningful suggestions** plays a significant role in the desirability of adaptations. Participants have shown their appreciation for the option to select from a catalogue of adaptations offered by the application (IP 3,4,7, FP 7,9). As IP7 put it: *"A suggested system interaction could be, "I've noticed that you haven't been using these two features frequently. Would you like to remove them from your dashboard?" This way, I have the option to decide whether to accept or decline the suggestion."* This approach ensures that users have access to relevant suggestions while still maintaining the flexibility to tailor the technology to their preferences.

Providing **contextual explanations for adaptations** within the application to help users understand the adaptation process and interpret perceived information is essential for transparency in the adaptation process [50]. Participants frequently expressed the need for a detailed justification regarding the relationship between user data and generated adaptations, as well as the reasons behind why the system believes a particular adaptation is needed or desired (IP 3,4, FP 7,8,9,13). Some participants also anticipated features like *"highlighting the adapted parts on the interface"* (IP3) or *"using animated transitions to visualise the adaptation process"* (FP8). These thoughts over adaptation have been explored in prior research [30] and reflect the importance of transparency in the mHealth applications' operations [36, 65]. FP13 valued the ability to check and verify the generated adaptations. However, it is worth noting that not all participants share this perspective. IP2, for example, believed that contextual reasoning for adaptations is unnecessary if users have no control over what is suggested. Additionally, IP7 and FP4 cautioned against overly complex reasoning, which they believed could *"confuse and distract users from their primary tasks"*. This divergence in opinion highlights the need to tailor support and explanations to users' interests and cognitive abilities [36].

4.2.3 Alignment. Achieving **alignment in chronic disease management** involves standardising and simplifying medical terminology and processes. Older participants (aged over 55) expressed a need for the system to provide standardised, non-academic terminology for drug names (FP 1,2,3,4,6,9, IP 1,3). This request arises from the challenge of remembering medication names, particularly when managing multiple chronic conditions with frequently changing prescriptions. For instance, FP9, who deals with heart disease, type 2 diabetes, epilepsy, and asthma, takes several medications concurrently. He struggled with the variability in medication appearances, and names and stated: *"I receive generic medication for a week, and then I receive the brand name for the following week. Occasionally, the tablets appear different, which means I might be taking a different medication each time I receive a new prescription order."* FP1, FP3, and FP7 expressed similar sentiments, desiring a simple and standardised naming system to assist with memory. Additionally, some participants also wished for the opportunity to learn and understand medical terms to engage in more informed discussions with doctors (IP 3, 7). They acknowledged that: *"I would ultimately be speaking with doctors, who often use medical terminology. This is when knowing medical terms becomes important for having meaningful discussions with them."* This indicates the need for a balanced approach that simplifies terminology for better comprehension while providing opportunities for users to expand their medical knowledge. AUIs may potentially lead users to acquire less domain-specific knowledge compared to non-adaptive systems [58], highlighting the importance of considering users' willingness to trade off knowledge acquisition for ease of use when designing AUIs. Many participants (FP 1,4,6,7,9, IP 1,3) recommended the incorporation of relevant visuals related to the app's topic to enhance user understanding and engagement. For example, IP1 suggested the inclusion of a doctor's image to denote critical health issues. Participants managing type 2 diabetes (FP 4,6,7) specifically emphasised the utility of visual representations, such as images of familiar food items like steak, potatoes, beans, and vegetables, to quantify dietary recommendations. However, it's worth noting that introducing anthropomorphic visuals could potentially shift users' perceptions of responsibility from themselves to the system [50], as indicated by the doctor image example.

It is crucial to recognise that **user motivation to use applications relies heavily on their perceived value**. Regardless of the presence of adaptation, if users do not see the practical benefits or relevance of an application to their needs, they are unlikely to be engaged in the long run [72, 86]. Participants commented that some adaptations are nice to have but overall provided no essential value to their chronic disease management (FP 5,8,13, IP 3,4,7). One participant said, *"people who are motivated by adaptation only might be hard to keep then using the application"* (IP3). This highlights the need for mHealth apps to deliver substantial value for effective chronic disease management [90].

To boost user engagement and familiarity, it is crucial to **integrate applications with technology that users are already familiar with** to enable natural and simple interactions. Incorporating voice assistants like Amazon Echo or Google Home was suggested by some participants (FP 3,4,6,7, IP 1,4,6) as a means to provide an intuitive user experience. Furthermore, using established icon sets and standardised symbols can help users quickly understand the intended message, as discussed by IP 2,4, FP 1,9. Participants often compared the app's design with the familiar aesthetics and conventions of contemporary smartphone interfaces, especially in cases where users were less accustomed to encountering UI adaptive features [66]. For instance, one participant (IP4) mentioned that: *"I am confused about the icon's meaning, it's more like a settings button rather than a portal for adaptation."*

4.2.4 User involvement. The strategies that entail user participation, including user support and controllability, are significantly influenced by the level of user involvement. User involvement refers to the extent to which users engage with a system and develop their understanding of it, either actively or passively [26]. **Active user involvement** is exemplified by participants who proactively experiment with various data sources to understand how they impact the system's output (FP 4,6,7, IP 3), desire for active participation and a sense of control over the adaptation process (FP 8,11). In contrast, **passive user involvement** characterises individuals who are more inclined to seek information about how the adaptation works but do not actively provide feedback or corrections to the system (IP 2,4,6, FP 1,2,3,5,9). Participants with a passive involvement with the app, with some admitting they *"have not fully explored what app can do"* (FP9), others expressing *"a lack of concern about the system's adaptation process"* (IP2), some indicating tolerance for most generated adaptations (FP5), and some preferring minimal interaction with the app (FP2). Beyond primary users, other individuals, such as **caregivers and family members**, may also interact with the app (FP 8,9,10, IP 1,3,4,5,7). As discussed in the challenges section 4.1.4, it is crucial to consider the potential influence of these secondary users on the app and how the app's adaptation may affect their experiences and interactions with it.

Summary. Participants recommend effective adaptation strategies, emphasising user control, autonomy and support over the adaptation, and alignment with chronic disease management, existing technology and user goals.

5 RESULTS OF QUANTITATIVE ANALYSIS

Different types of adaptation. Different types of adaptation are preferred by survey respondents, with no single type dominating the others. We conducted a Chi-square independence test to examine the impact of demographic variables on user adaptation preferences. The results reveal significant associations of age, nationality, and chronic diseases with a preference for content complexity, add-on functions, persuasive strategy and multimodal interaction. A BLR analysis was performed to test the relationships between different adaptations and significant results from the previous Chi-square test (Table 3). Compared to Australian participants, individuals from other nationalities (UK: OR = 0.066, China: OR = 0.125) are less inclined to prefer adaptations related to content complexity. Participants with cardiometabolic diseases are significantly more inclined to expect adaptations such as different persuasive strategies (OR = 11.264), additional functions (OR = 8.093), and content complexity (OR = 12.215) compared to those with respiratory diseases. Participants with mental health conditions also place notable value on content complexity (OR = 4.173). These preferences may stem from the self-management nature of cardiometabolic and mental health diseases, for which many specialised applications are available [17, 19, 89]. Participants aged over 45 are notably more inclined to seek multimodal interaction (OR = 5.824) and additional function (OR = 3.764) adaptations compared to those under 45. This may be due to older users seeking minimal interaction effort and requiring extra assistance with app navigation [12, 65, 90].

Data source of adaptation. Participants had diverse preferences for the source of adaptation data, with nearly half wishing the app could adapt based on physiological, physical, and psychological characteristics, user preferences, and user goals. We conducted a Chi-square test and BLR analysis, which revealed participants from the USA, China and the UK are less inclined to desire AUIs that cater to their needs regarding physiological or physical characteristics, users' preferences, users' feedback for the app, goals or motivations for using the app (details can be found in the supplementary material). The dominant methods of data collection are smartphone sensors (68%) and wearable sensors (64%). No significant correlations between the data collection method and demographic variables are found.

Preferred level of involvement in the adaptation. Most participants preferred a semi-automatic adaptation approach (54%) that involves collaboration between the system and end-users to achieve the adaptation [1, 70]. Conversely, only a small minority of participants (8%) showed a preference for a fully manual system, where users have complete control to modify specific UI elements to suit their needs [3]. No significant correlations between the level of involvement and demographic variables are found.

Table 3: Binary logistic regression results of the adaptation types and demographic aspects

Variables	Categories	CC*	AD*	DP*	MI*
Age group	45-74	3.212/(0.065)	3.764/(0.02)	0.637/(0.43)	5.824/(0.002)
Nationality	UK	0.066/(0.016)	0.825/(0.843)	0.889/(0.908)	0.133/(0.095)
	USA	0.276/(0.107)	0.299/(0.178)	1.504/(0.567)	0.346/(0.193)
	China	0.125/(0.003)	0.215/(0.025)	1.179/(0.796)	1.081/(0.896)
	other	0.783/(0.803)	0.341/(0.264)	1.2/(0.845)	0.533/(0.492)
Chronic diseases	Mental health	4.173/(0.033)	0.358/(0.093)	2.126/(0.181)	0.661/(0.475)
	Cardiometabolic	12.215/(0.013)	8.093/(0.029)	11.264/(0.006)	1.782/(0.471)
	Immune-related	0.536/(0.554)	3.823/(0.168)	2.293/(0.339)	1.463/(0.664)

* *Odds Ratios/(P-value),(CC=Content complexity, AD=Add on functions, DP=Different persuasive strategy, MI=Multimodal interaction)*

Summary. Survey participants exhibited diverse preferences for various adaptations and the types of data they wanted to adapt. Smartphone and wearable sensors are the preferred data collection methods among respondents, and they desired a semi-automatic adaptation approach. These preferences are influenced by demographic variables such as nationality, age, and types of chronic diseases.

6 DISCUSSION

Trade-off between user burden, user support and controllability. The relative challenges encountered in the effectiveness of AUI may be attributed to the complexity of providing users with the appropriate level of control [75]. While user control over adaptation can be beneficial [54, 74], our findings also emphasise the importance of considering users' competence, the added cognitive load, and the potential for these adaptation processes to become intrusive [57]. Our participants expected some level of control, whether through the dedication of a dashboard for adaptation, the adaptation of a specific part of the system, or configuring certain factors of adaptation. However, allowing too much control may lead to distraction and inefficiency, especially among users lacking the necessary knowledge or interest to make informed decisions [53]. Furthermore, as discussed by Kay [54], user preferences for control can vary significantly. Some users may be less inclined towards control, and overwhelming them with excessive control options can lead to distraction and inefficiency [54]. In such scenarios, providing support materials to assist users in making adaptation decisions may not be effective as well, as users may have difficulty understanding the support provided, leading to increased cognitive demands [56]. In conclusion, controllability and support enhancements come at a cost, and it is important to consider what kind of control or support is really needed.

User groups and control. Some studies recommend offering a variety of control [53, 74, 96] and support [14, 26] options to cater to diverse user groups' preferences and needs. Based on our findings, we categorise user groups according to four key characteristics: **1)** ***Domain Knowledge.*** User decision-making strategies may depend on their expertise in a given domain [11]. Novice users may struggle to understand certain adaptation concepts and the possible benefits of such adaptations. Conversely, expert users with more domain knowledge can harness the system's potential by exercising greater control [7]. **2)** ***User involvement.*** We found that users exhibit varying levels of involvement when interacting with the system. Some participants are active in the adaptation process, willingly exploring and approving various adaptation suggestions [33]. Conversely, passive participants may cease exploration once they believe the current user interface meets their minimum requirements [26, 74]. **3)** ***User experience with mHealth applications.*** Previous experience with mHealth applications influences users' propensity to control adaptations. Experienced users are more inclined to explore control options for adaptations, possibly because their prior experience with the system reduces their cognitive load, encouraging them to explore new actions and functionalities [4]. **4)** ***Health conditions.*** Chronic diseases exert varying physical, psychological, and mental impacts on participants [24, 47, 63, 97]. Our findings suggest that providing extensive control and support for adaptation may not be suitable for individuals lacking the capacity to make such decisions, especially if they are dealing with numerous treatment and lifestyle choices [83]. This is particularly relevant for those with severe health conditions or newly diagnosed individuals with chronic diseases [77]. Certain participants who consider themselves experts in managing their health conditions tend to become their own primary caregivers and exhibit a greater willingness to explore diverse adaptation possibilities.

Usability issues for adaptation. AUIs offer solutions to various usability issues in mobile applications, such as enhancing accuracy, efficiency, and user learning, as well as tackling information overload and aiding in the use of complex systems [13, 49]. However, prior research on AUIs has consistently demonstrated a trade-off between the benefits of adaptive mechanisms and usability concerns [14, 22, 34–36, 50, 52, 68, 75, 92]. We found several usability challenges associated with AUIs, including privacy concerns, predictability issues, comprehensibility difficulties, and UI obtrusiveness in our study. Interestingly, our study highlights that user preferences for adaptation can either alleviate or exacerbate these usability challenges. For instance, aligning visual elements and icons with user preferences can reduce UI obtrusiveness. However, attempts to improve control or privacy may introduce extra user interactions, data inputs, or system notifications, potentially increasing the risk of disruption and diverting the user's attention from their previous focus [23, 52]. Similarly, aligning with chronic disease guidelines and providing explanatory materials can improve adaptation comprehensibility. Still, an excessive and overt provision of support content can be very obstructive and challenging to grasp [26]. Mitigating specific usability challenges in AUI design often entails trade-offs with other usability goals.

Dealing with usability trade-offs: Our findings highlight two key considerations to deal with this trade-off: ***1) User priorities.*** Users often have varying priorities regarding conflicting usability goals [78, 79]. Providing alternative solutions that align with the various usability priorities of users is a promising strategy [14, 35]. This approach assumes that different users may be open to trade-offs among different usability aspects. For instance, in one study by Harper et al. [46] found that users reported usability issues with a system but remained satisfied overall because the benefits of having control options outweighed the encountered inconveniences. ***2) Granularity.*** Usability objectives such as predictability, comprehensibility, and controllability can be achieved at different levels of granularity [14, 52]. Our observations revealed that making minor adjustments during the adaptation process might not significantly impact the overall user experience. Instead, making small, incremental changes might disrupt the user's familiarity with the UI, leading to a less consistent and less predictable user experience [14, 34]. On the other hand, these low-level granularity adaptations may have a limited impact on controllability, and comprehensibility [1]. High-level granularity, modifying most aspects of the design [18, 99], could introduce more usability challenges, but its infrequent use may compensate for these issues. This approach is more advantageous when users initially engage with the system, as they lack a preconceived notion of how the system should appear [14]. Finding the right balance between these factors is essential for designing AUIs that effectively manage the trade-off between adaptation and usability.

Certain usability challenges introduced by AUIs can be mitigated without necessarily enhancing the user's mental model of the adaptive system [75, 81]. However, systems that assist users in overcoming usability issues tend to foster a deeper understanding and trust in the adaptation over time, which can promote sustained engagement with mobile health applications [65].

7 LIMITATIONS

Threats to external validity. For the interview and focus group study, we adopted STGT and theoretical sampling which are aimed at representative samples, so the qualitative part of our study can not claim generalisability. Instead, we aimed to provide insights into how users perceive AUI for those with chronic diseases. Future research should confirm our findings with more diverse populations, including those with lower digital literacy [44]. Secondly, our study is based on a high-fidelity design prototype, potentially leading to disparities between the prototyped adaptations and operational applications. For example, the prototype presents challenges in forecasting adaptations' interactions with other functionalities and users' allocation of time to specific adaptations [14, 34, 35].

Threats to internal validity. Respondents may have been confused about some of our questions or adaptive UI examples. We provided pre-focus group training and help documents to try and mitigte this. We derived our survey questions from a prior SLR [9] and took measures to enhance clarity, including providing an explanation of the AUI within the survey. For the interview and focus group sessions, we employed the STGT approach for qualitative data analysis and engaged in extensive team discussions on the analysis, findings, and presentation to minimise potential biases.

Threats to conclusion validity This study addresses various chronic diseases, which might restrict the relevance of our findings. However, it is consistent with the common practice of including individuals with multiple chronic conditions in research [27]. Some of the participants in our study have multiple chronic diseases, which is reflective of real-life scenarios where individuals often experience not just one chronic condition but also comorbidity [24]. The actionable nature of our findings need to be tested in user evaluation of prototype adaptive eHealth apps.

8 CONCLUSION

Society demands better mHealth apps for aiding diverse users in self-managing their chronic diseases. In this study, we evaluated users' perspectives on diverse Adaptive User Interface (AUI) approaches in chronic disease management applications. We uncovered key challenges faced regarding the use of such AUIs and the strategies proposed for improving adaptation design. Our findings highlight a vital role of AUIs in accommodating diverse needs of users with various chronic diseases. We address the trade-off between adaptation and usability, offering insights into how AUIs can enhance user control and overall user experience. Our results reveal participant preferences for different adaptations, data types, collection methods, and involvement levels.

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