Tailoring mobile health apps for lifestyle management: a discrete choice experiment

Chiara Seghieri[1]^, Tallys Feldens[1]^, Costanza Tortù[1]^, Natalya Usheva[2]^, Florian Toti[3]^, Ditila Doracaj[4]^, Natalia Giménez-Legarre[5,6,7,8]^, Eva Karaglani[9]^, Yannis Manios[9,10]^

[1]Department of L'EMbeDS, Institute of Management, Sant'Anna School for Advanced Studies, Pisa, Italy; [2]Department of Social Medicine and Health Care Organization, Medical University of Varna, Varna, Bulgaria; [3]Service of Endocrinology & Metabolic Diseases, University of Medicine of Tirana, Tirana, Albania; [4]Department of Biomedical Sciences, University of Medicine of Tirana, Tirana, Albania; [5]Growth, Exercise, Nutrition and Development (GENUD) Research Group, University of Zaragoza, Zaragoza, Spain; [6]Institute for Health Research Aragón (IIS Aragón), Zaragoza, Spain; [7]Biomedical Research Centre on Obesity Physiopathology and Nutrition (CIBERObn), Carlos III Health Institute, Madrid, Spain; [8]Aragon Agroalimentary Institute (IA2), University of Zaragoza-CITA, Zaragoza, Spain; [9]Department of Nutrition and Dietetics, School of Health Science and Education, Harokopio University, Athens, Greece; [10]Institute of Agri-Food and Life Sciences, Hellenic Mediterranean University Research Centre, Heraklion, Greece

Contributions: (I) Conception and design: C Seghieri, C Tortù; (II) Administrative support: Y Manios, E Karaglani; (III) Provision of study materials or patients: N Usheva, F Toti, D Doracaj, N Giménez-Legarre, Y Manios, E Karaglani; (IV) Collection and assembly of data: N Usheva, F Toti, D Doracaj, N Giménez-Legarre, Y Manios, E Karaglani; (V) Data analysis and interpretation: C Seghieri, T Feldens, C Tortù; (VI) Manuscript writing: All authors; (VII) Final approval of manuscript: All authors.

Correspondence to: Tallys Feldens, PhD. Department of L'EMbeDS, Institute of Management, Sant'Anna School for Advanced Studies, Via San Zeno, 2, Pisa 56127, Italy. Email: tallys.feldens@santannapisa.it.

Background: Health apps designed to monitor, motivate, and educate people towards their health goals are getting more users and features each time. These apps offer valuable support for self-managing health behaviors and achieving long-term objectives. However, there is limited understanding of user preferences regarding essential app features. The aim of the study is to get insights about potential users' preferences, in order to tailor better apps for lifestyle management.

Methods: We conducted a three-part web survey with 389 respondents from four countries as part of the DigiCare4You European Union (EU) project. In the first part, we collected the socioeconomic characteristics and health status of each respondent. In the following stage, we asked five questions on a Likert scale to ascertain the individual level of usage and general attitude towards technology. Finally, we performed a discrete choice experiment (DCE) using an unlabeled design and estimated the odds ratio for each feature using conditional logit analysis. We also ran alternative estimations stratifying by non-communicable disease (NCD) patients and non-NCD patients, and explored latent profile analysis (LPA) to understand whether the general attitude towards technology impacts the preference pattern between users.

Results: The DCE revealed that respondents showed a clear preference for monitoring physical health over emotional status. They favored receiving lifestyle achievement notifications weekly rather than daily, and daily rather than more frequently. Similarly, respondents preferred uploading body weight measurements on a weekly or monthly basis rather than daily. Users expressed a preference for collaborating with their doctors to set exercise and diet goals, rather than either deciding independently or delegating entirely to their doctors. End-users also show a pattern of preferring notifications for goals instead of challenging other users. Preferences regarding the subjects of health content between workout routines, food recipes, and new scientific evidence were not significant; also, no statistical significance was found for the decision between

^ ORCID: Chiara Seghieri, 0000-0002-3910-7775; Tallys Feldens, 0000-0002-1804-8315; Costanza Tortù, 0000-0003-2561-9726; Natalya Usheva, 0000-0003-4228-3152; Florian Toti, 0000-0002-2097-1766; Ditila Doracaj, 0000-0001-6198-8890; Natalia Giménez-Legarre, 0000-0002-2956-4219; Eva Karaglani, 0000-0001-5395-7023; Yannis Manios, 0000-0001-6486-114X.

follow-up visits with their doctor in person or remotely. LPA returned two groups regarding their general attitude towards technology: a lower, an intermediate, and a higher usage in their private life based on their responses to the questionnaire. Stratified DCEs have shown heterogeneity of users' preferences according to their specific attitude towards technology.

Conclusions: Our study indicates that potential mobile health (mHealth) app users managing chronic conditions prefer platforms that enable shared responsibility with their doctors in defining health goals while having an intermediate level of interaction frequency with the app. These findings are key to tailoring mHealth apps that can optimize motivation triggers, support healthier lifestyles, and empower patients with chronic conditions.

Keywords: Mobile health app (mHealth app); lifestyle management; preferences; discrete choice experiment (DCE)

Received: 07 May 2025; Accepted: 04 August 2025; Published online: 27 January 2026.
doi: 10.21037/mhealth-25-30
View this article at: https://dx.doi.org/10.21037/mhealth-25-30

Introduction

Mobile health (mHealth) apps that support self-monitoring lifestyle habits have evolved from a novelty to a widely utilized tool. As app development has expanded and the number of current and potential users continues to grow, the range of self-monitoring app alternatives has also increased (1-3). These apps engage users without geographical restrictions, through timely and customizable interfaces, relying solely on the usage of smartphones, whose penetration is overcoming socioeconomic disparities (2,3). With the advance of telemedicine use since the coronavirus disease 2019 (COVID-19) pandemic, novel digital health initiatives using self-reported data and telemonitoring via remote or wearable devices are becoming each time more widespread (4,5).

Lifestyle behaviors such as balanced dieting and regular physical activity play a significant role in preventing and controlling the advance of chronic conditions (6-8), while adherence to treatment is important to manage morbidity and achieve health goals (3,6,9-11). Diabetes type 2 and hypertension, among others, are responsible for the elevated global burden of disease and public health costs (4,12-15). So, mHealth apps can be used for patients and non-patients to trigger behavioral incentives into a healthier lifestyle, with a cost-saving potential (1,2,12).

Studies on the impact of digital health on chronic conditions so far have focused on the effectiveness of remote devices, together or not with mHealth apps (5,9,16-19). Some apps are directed to promote a specific lifestyle behavior, such as a change on the diet patterns (6,20) and promotion of physical activity (4). Others, instead, are comprehensive and focus on several lifestyle changes at once (9,21). Besides, there is a heterogeneity regarding the level of integration with the health system in allowing interactions patient-app-doctor, where the doctor can also access the data from the patient and give targeted recommendations (2,9,17,22).

Apart from the different approaches to the mHealth apps, several studies have been trying to understand the factors that predict acceptance, adherence, and usability of those apps beyond their effectivity (2,3,9,17,23-26). However, little evidence was gathered so far to understanding on a deeper level what are the preferences of the possible users to

Highlight box

Key findings
- Monitoring physical health is preferred over emotional status.
- Most users prefer less frequent notifications and data imputation than more.
- Attitude towards technology plays a role in explaining the appetite for notifications.

What is known and what is new?
- Well-constructed apps based on behavioral enforcement theories are key to enhance lifestyle self-management.
- Little is known about which are the features the users prefer in those apps, and how do these features change regarding the user's technology level of usage.

What is the implication, and what should change now?
- Apps allowing for monitoring physical health, with low data input and low to moderate notifications frequency match a bigger audience, thus having a higher adherence potential.

maximize the benefit of using these novel technologies. This is important because it affects the usability and adherence to the apps, characteristics that are generally related to improvement in health outcomes (5,12,24-28). Also, it lacks information about the possibility of heterogeneous preferences according to their health status and level of usage of technology.

In this study, our main objective is to reveal the baseline preferences of a multi-country population in tailoring a mHealth initiative focused on enhancing healthy behaviors. This investigation is part of the DigiCare4You Project (H2020), which spans across two high-income countries, Spain and Greece, as well as two middle-income countries, Bulgaria and Albania. Within DigiCare4You, the partners conducted a comprehensive analysis to gain insights into the attitudes and preferences of potential end-users of mHealth technologies through a Web Conjoint Survey (WCS) across all four implementation countries. The Web Survey collected information regarding baseline attitudes towards technology, in particular, usability of technology in their private lives, and it also included a discrete choice experiment (DCE) to elicit the respondents' preferences regarding the desired features of the mHealth app they might use, to report, monitor, and share with their doctor their lifestyle habits and health status in general. To explore the heterogeneity of the preferences, we also conducted a sub-analysis by health condition, trying to absorb the different perspectives that patients with chronic conditions may have when compared with individuals with no chronic conditions. Also, we run a latent profile analysis (LPA) to understand whether the participants with higher usage of technology have different patterns of preferences.

Methods

A mixed-methods approach, consisting of three consecutive steps: a literature review, expert recommendations, and focus groups, allowed to develop the survey questionnaire and identify potential attributes for the DCE.

Focus group

This study was targeted in four countries: Albania, Bulgaria, Greece, and Spain. In each country, the focus groups were organized to contain eight to ten people among chronic patients, representatives from associations of chronic patients, and other potential users of the mobile app who may benefit of monitoring health habits. The sessions were held between November and December of 2021, done by an external moderator and co-moderator who managed the sessions, clarified questions, and stimulated complete responses. Participants were asked to express their opinion on lifestyle behaviors, factors encouraging or discouraging the adoption of healthy habits, barriers and facilitators to compliance with a healthy lifestyle, and the willingness to adhere to a screening program of detecting early signs of chronic diseases. As this screening program was targeted to work on the school level, focusing on the parents and grandparents of the kids, also some questions regarding the role of the school in educating and preventing these diseases were asked. Further information about the focus group insights is available in Appendix 1.

Literature review

mHealth apps have been continuedly studied for their ability to promote self-monitoring. In this sense, push notifications or messages sent to the user, communication with the health care team, goal setting structure, action planning, a positive rewarding system, gamification strategies, and social support are important behavioral techniques that could be used to enhance mHealth interventions (2-4,9,24,25,29-33). In general, user engagement with mobile apps is linked to reinforcement, personalization, ease of communication and navigation, besides credibility (2,9,24,25).

While most of the findings agree with the general advice for mHealth apps, specific recommendations are lacking. For instance, reference (2) lists as recommendable design features "minimum input needed", "sending reminders", and "provision of relevant material". However, it lacks information from the end-users of how much data entry is "minimum", how often they should be receiving notifications, or what type of material they would prefer to access on the app, for example.

Recent DCE protocols focused on diabetes pointed to the importance of understanding patients' preferences in setting health goals with the health care team (34). Besides, new DCEs have assessed preferences for e-Mental health interventions regarding in-person versus online visits (35). Nevertheless, it is yet to be understood whether people prefer being assessed for their mental health or physical health, and what type of visits they prefer. No other DCEs were found so far to assess these preferences in a wider audience, such as a bigger group of non-communicable disease (NCD) patients and non-NCD patients, and there is no assessment on possible heterogeneity of these preferences.

Table 1 Attitude towards the usage of technological devices in private life

Question code	Question
1	"I think it is efficient to use mobile apps for shopping, delivering services, and booking services"
2	"When I go out, I prefer to pay through my virtual wallet, instead of using cash or cards"
3	"I like to manage my everyday activities and plans through a mobile app"
4	"I think technological devices and social networks represent fantastic tools to keep in touch with other people"
5	"I think technological devices help me to rapidly get access to various sources of information"

Few studies explicitly asked the patients and general population about their preferences for mHealth apps for self-monitoring. Only a few of them carried DCEs, and generally asked questions regarding the willingness to pay or to download rather than their favorite features on the app. One exception is Nittas *et al.* [2020] (36), who asked about individuals' preferences on costs, reminder customizability, the possibility to share their data with the health care provider, privacy control, and the method of collection of their data (manual or automatic). Respondents chose to have their data automatically retrieved, with multiple consents on data privacy control, shared with their health provider, for free, and with a customizable reminder. On another recent study that surveyed the ideal features of mHealth apps, Philip *et al.* [2022] (37) also reinforce the preferences for customizability, avoidance of too much data entry, and redundant features.

The insights of this literature review, together with the conversations between experts involved in the project and the themes that emerged from the focus group discussions, have given a baseline to choose the levels and attributes to perform the DCE on the third part of the web survey.

Web survey

The web survey was prepared in three parts. The survey was accompanied by a letter to the respondent in which, in accordance with the General Data Protection Regulation (GDPR), is clearly expressed that if the respondent completes and returns the questionnaire, by clicking the button "submit" he/her gives her consent to participate in the study. The questionnaire is anonymous, and participation and consent are totally voluntary and the respondent has the right to withdraw from the study at any time without any consequences. The letter also includes information about the project and the data storage, as recommended by the GDPR.

The first part collects health and socio-demographic characteristics for each respondent, such as age, employment status, years of education, marital status, family size, economic status, health status, and whether they are patient with NCDs with one or more diseases. All the respondents are adults. The respondents could also opt for not answering by skipping the question. The complete list of questions and alternatives of this first part of the survey is available in Appendix 1.

In the second section, the respondents were asked on a Likert scale between 1 (totally disagree) to 10 (totally agree) what was the level of agreement with five questions that were intended to capture the general attitude towards technology for each individual. *Table 1* displays a description of those questions. The third part of the survey required completing a DCE, which will be discussed in the next subsection.

The original survey was in English and then translated into the official languages of the four countries. Forward and backward translation were conducted by the project partners.

The questionnaire did not collect any personally identifiable information, nor any combination of data that could reasonably enable the identification of individual participants. Respondents' answers and data were not connected to their email addresses, and no incentives were provided for participation.

The study was conducted in accordance with the Declaration of Helsinki and its subsequent amendments. As the data collection does not affect the rights or freedoms of the participants, review by an Ethics Committee is not required. Informed consent was taken from all the participants.

DCE

While evaluating a mHealth app, users may gauge differently the components of the app. Discrete choice methods rely on eliciting the users' preferences using a stated-preference strategy, which has been found particularly

Table 2 Attributes and levels of the DCE

Attribute	Description	Levels
Monitoring perceptions	Which aspect the user wishes to daily monitor through the app	(I) On my emotional status
		(II) On my physical health
Frequency of notifications on my lifestyle achievements	Frequency on which the user wishes to receive push notifications on his/her lifestyle achievements in the app	(I) More than once a day
		(II) Once a day
		(III) Once a week
Frequency of uploading my body weight and circumferences	Frequency on which the user wants to upload his/her body measurements and his/her circumferences	(I) Daily
		(II) Weekly
		(III) Monthly
Additional wellness content	Additional content on wellness the user would like to see in the app	(I) Work-out routines
		(II) Food recipes
		(III) New scientific evidence
Follow-up visits with your doctor	Ways the user prefers to make his/her follow-up visits	(I) On person
		(II) On remote
Responsibility for setting goals to exercise and menu schedule	Who is responsible to set goals for menu and exercise	(I) My family doctor sets my goals
		(II) I set my goals independently
		(III) My family doctor and I set my goals together
Encouragement on exercise and menu goals	Mechanisms through which the user wants to be pushed to achieve his/her exercise and menu goals	(I) Challenge with another user
		(II) Notification for goals
		(III) Challenge with multiple users

DCE, discrete choice experiment.

useful to quantify preferences in health (38). It works by asking the preferred option between two competing scenarios, whose characteristics (attributes) provide different options (levels). The respondent then should select the preferred mobile app between two competing mobile apps that differ concerning the characteristics of some of their aspects. Users face pairwise comparisons (choice-sets), and the competing scenarios are randomly chosen through an appropriate randomized design.

Our design is unlabeled, which means that each column on one of the choice tasks represent a mix of the level's options without fixing any in particular. Within this design, the focus is on the attributes and levels and how the preferences are drawn from them. We selected seven attributes, with varying number of levels across the options. The analysis of the appropriate factorial design, the number of the choice settings and the data collection was performed by Qualtrics.

An example of the choice setting the respondents encounter is presented in Appendix 1, while *Table 2* displays the whole set of possible levels for the seven attributes.

Sample

The Web Survey was implemented through the online software platform named Qualtrics Experience Management (XM). The survey focused on the four targeted countries of the DigiCare4You project. The leading partners in each country shared survey links to potential end-users among their existing networks. The individuals who received the link were asked to further circulate it among their peers, using a snowball sampling approach (39). The aim with this chosen method was to reach the best sampling of possible end-users of the app, while trying to have a relevant number of NCD patients and non-NCD patients among them to be able to gather enough information to perform subgroup analysis. Subsequently, the survey link was shared by the local partners of each country with the patients, individuals, or members of associations they were in contact with.

According to the rule-of-thumb most used in the literature (40), the minimum sample size we should achieve for having a valid estimation from this DCE was 188 (without further subgroup analysis). Using this technique, the sample size retrieved from this experience was 389 respondents.

Statistical analysis

Choice data were analyzed using discrete choice models. In particular, we used conditional logit models, discrete choice models which selects probabilities from choice-specific attributes, developed by McFadden [1973] (41). In this setting, it is possible to quantify the impact of changes in attribute levels on the actual choices of the respondents (42). For instance, let $P(x|s,B)$ represent the conditional probability that an individual chooses the alternative x, given a set of attributes s, having available the set of alternatives B. The individual behavior can be depicted as a function h, drawn from a set of behavioral rules H, that tries to maximize the utility of the choice by taking into account the attributes and the alternatives. The probability that an individual drawn at random from the population will choose x is equal to the probability of occurrence of a decision rule accommodating this choice, hence

$$P(x|s,B) = \pi\left[\left\{h \in H \middle| h(s,B) = x\right\}\right] \quad [1]$$

By assuming that the odds of one alternative x being chosen over another y is independent of the presence or absence of others (independence of irrelevant alternatives), the exercise can be written in terms of binary odds, where, after some computation, can be expressed by Eq. [2]. The complete derivation of the formula and estimator is available in Appendix 1.

$$P(x|s,B) = \frac{e^{V(s,v)}}{\sum_{y \in B} e^{V(s,y)}} \quad [2]$$

The odds ratio in this case is estimated via maximum likelihood, and the maximized utility is a linear function of the observed attributes and alternatives.

Besides independence of irrelevant alternatives, the conditional logit also assumes that the utility to be maximized is homogenous among the individuals, which could be a limitation of the model (42). Although we do not have any reason to assume that the individuals within our sample are specifically heterogenous, we deal with this assumption by performing a sub-analysis using sub-sampling by NCD status and an LPA.

LPA tries to identify latent subpopulations within a sample based on profiles of personal attributes (43). In this study, we collected data regarding the usage of technology on the second part of the web survey, as shown in *Table 1*. Thus, we hypothesized that different profiles regarding technology usage and familiarity may have different patterns of preferences on the DCE. Henceforth, we conducted a sub-analysis to test this hypothesis.

All statistical analyses were performed using R Studio, version 4.3.1.

Results

Descriptive statistics

Table S1 presents the descriptive statistics of our sample according to the socio-demographic characteristics of the respondents. Most of our sample is composed of women (299 out of 389 respondents), mostly around 45–59 years old. Albania is the country with the highest count of participants, followed by Bulgaria. People with smaller to medium-sized families are more frequent in our sample, and the majority are highly educated, employed, with an intermediate level of easiness to cover their expenses. Although most individuals reported good or very good health status, nearly half of our sample reported suffering from at least one NCD.

Conditional logit model

Table 3 reports the estimation of the conditional logit model. The respondents of our sample prefer being assessed on the level of their physical health instead of on their emotional status. They choose receiving notifications about their lifestyle habits once a day rather than more than once a day, and once a week rather than once a day. This pattern shows a general attitude against too many notifications. The users would rather upload their weight and circumference measures weekly or monthly rather than daily; however, weekly uploads are slightly favored. On the additional wellness content, none of the alternatives was explicitly preferred, also with the follow-up visits with their doctor—the individuals of the full sample seem not to prefer one type of follow-up visit over another. On the responsibility for setting goals, the individuals show an inclination for setting them independently from their doctors alone; but put an even major preference on deciding their health

Table 3 Conditional logit model results

Attribute	Level	Estimates
Monitoring perceptions	Emotional status	Ref.
	Physical health	1.518*** (0.073)
Frequency of notifications	More than once a day	Ref.
	Once a day	1.402*** (0.089)
	Once a week	1.756*** (0.089)
Frequency of uploading body measures	Daily	Ref.
	Weekly	1.742*** (0.089)
	Monthly	1.677*** (0.09)
Additional wellness content	Workout routines	Ref.
	Food recipes	0.998 (0.09)
	New scientific evidence	0.996 (0.089)
Follow-up visits with your doctor	On person	Ref.
	On remote	0.906 (0.073)
Responsibility for setting goals	Doctor alone	Ref.
	Individual alone	1.169** (0.089)
	Doctor and individual together	1.403*** (0.09)
Encouragement on goals	Challenge other user	Ref.
	Notification for goals	1.319*** (0.089)
	Challenge multiple users	0.990 (0.089)
Concordance		0.629 (SE =0.015)
Likelihood ratio test		148.9 on 12 df (P<0.001)
Wald test		136.6 on 12 df (P<0.001)
Score (log-rank) test		144.6 on 12 df (P<0.001)

Estimates are presented as odds ratio (SE), unless otherwise stated. ***, P<0.01; **, P<0.05. df, degrees of freedom; ref., reference; SE, standard error.

goals together with their doctors. Our respondents prefer receiving notification for goals instead of engaging into challenges against other users, either individually or in groups.

In *Figure 1*, we depicted a summary of the findings representing the ideal app configuration according to our estimations. In the next section, we will introduce a sub-analysis on the sample heterogeneity.

Heterogeneous effects

NCD status

To check whether our results have heterogenous effects underlying the sample, we separated the sample between those who reported to have one or more NCDs (n=186) and those who did not (n=200). To this analysis, we grouped the patients of one and more than one NCDs together for sample size concerns. Then, we ran the conditional logit on those two groups separately. The results are available in *Table 4*.

Our results point out that both groups agree with the whole sample preferences when it comes to monitoring perceptions (physical over emotional) and frequency of notifications (weekly rather than more frequently). The two display a preference into uploading body measures in a slightly different way: NCD patients prefer uploading body

Figure 1 Ideal app configuration.

measures once a month, but non-NCD patients prefer it once a week. However, once a week and once a month is preferred over once a day for both groups.

As in the whole sample, additional wellness content and follow-up visits preferences were not statistically different. The type of encouragement for goals was only significant for the NCD group, who prefer to receive notification for goals, while the non-NCD group does not display a statistically significant preference. The preference for responsibility for setting goals was significant for the NCD group only, whose insights agree with the finding pointed out by the whole sample in the direction of shared goal-setting responsibility.

LPA

The LPA within our sample was selected to comprise the attitude towards the usage of technological devices in private life, reflected by the answers on the second part of the questionnaire (*Table 1*). As the answers were scored from 1 to 10, these values for each question were used to estimate two profiles: one that should depict the highest level of usage of technology, and another representing the lowest level. Further insight into the distribution of the responses to these questions can be found in Figure S1. To get meaningful classes, while having a sample size feasible enough to run a sub-sampled DCE, we restricted the algorithm to two classes and let the LPA be self-selected according to the methods described in the statistical analysis section.

The entropy estimate was 0.88, indicating a good fit of the data in separating into those two profiles. Also, the likelihood ratio test is significant, showing that the model with k=2 is better than the model with k=1. The model with k=3 is also significant and would be preferred according to the Akaike information criterion, but it would not be possible to run the sub-sampled DCE due to the smaller sample size. The complete table with the diagnostic statistics and the visualization of the distribution into the two classes are respectively in Table S2 and Figure S2.

According to our LPA group participants, we run a separate conditional logit for each sub-profile to check whether there is any difference in preferences according to the level of technology usage. Group 1 is the group with the least usage of technology, and Group 2 is the one with the highest usage level. *Table 5* represents the two DCE estimations.

Table 4 Conditional logit model results for the NCD subgroups

Attributes	Levels	NCD group (n=186)	No NCD group (n=200)
Monitoring perceptions	Emotional status	Ref.	Ref.
	Physical health	1.682*** (0.108)	1.362** (0.099)
Frequency of notifications	More than once a day	Ref.	Ref.
	Once a day	1.390* (0.129)	1.418** (0.12)
	Once a week	1.821*** (0.128)	1.620*** (0.122)
Frequency of uploading body measures	Daily	Ref.	Ref.
	Weekly	1.693*** (0.129)	1.782*** (0.123)
	Monthly	1.828*** (0.131)	1.506*** (0.123)
Additional wellness content	Workout routines	Ref.	Ref.
	Food recipes	1.165 (0.13)	0.86 (0.124)
	New scientific evidence	0.996 (0.13)	0.97 (0.12)
Follow-up visits with your doctor	On person	Ref.	Ref.
	On remote	0.809* (0.106)	1.014 (0.102)
Responsibility for setting goals	Doctor alone	Ref.	Ref.
	Individual alone	1.378* (0.128)	0.973 (0.12)
	Doctor and individual together	1.425** (0.132)	1.321* (0.124)
Encouragement on goals	Challenge other user	Ref.	Ref.
	Notification for goals	1.424** (0.129)	1.191 (0.122)
	Challenge multiple users	1.149 (0.128)	0.824 (0.125)
Concordance		0.648 (SE =0.023)	0.624 (SE =0.022)
Likelihood ratio test		91.39 (P<0.001)	66.5 (P<0.001)
Wald test		79.71 (P<0.001)	60.95 (P<0.001)
Score (log-rank) test		87.26 (P<0.001)	64.55 (P<0.001)

Estimates are presented as odds ratio (SE), unless otherwise stated. ***, P<0.01; **, P<0.05; *, P<0.1. NCD, non-communicable disease; ref., reference; SE, standard error.

Groups 1 and 2 also agree with the whole sample results, preferring physical health over mental health. Group 1 goes in the same direction as for the whole sample in its preference for weekly notifications, while Group 2 doesn't have an explicit and statistically significant preference at the 5% level.

On the frequency of uploading body measures, the group with higher usage of technology (Group 2) prefers uploading them weekly than monthly, when the opposite happens for the group with the least usage level (Group 1). Additionally, both groups follow the whole sample preference for shared responsibility in defining health goals.

Additional wellness content preferences, type of follow-up visits, and preference for encouragement on goals were not statistically significantly different in any of the subgroups.

We tested whether there is any difference in the group composition regarding socioeconomic and health characteristics of the respondents, using the Chi-squared test. We found that most of the groups are well balanced and do not show statistically significant differences across the variables, with only a few exceptions. The group with the lowest level of usage of technology has more participants in the 60–75 years old class, meaning that some of the older respondents were self-selected into this group. Bulgaria is the country that has statistically significantly more respondents pertaining to Group 1. Also, having fewer years

Table 5 Conditional logit model results for the LPA subgroups

Attributes	Levels	Group 1 (n=187)	Group 2 (n=161)
Monitoring perceptions	Emotional status	Ref.	Ref.
	Physical health	1.580*** (0.106)	1.518*** (0.114)
Frequency of notifications	More than once a day	Ref.	Ref.
	Once a day	1.433** (0.129)	1.233 (0.132)
	Once a week	2.053*** (0.128)	1.268* (0.134)
Frequency of uploading body measures	Daily	Ref.	Ref.
	Weekly	1.597*** (0.128)	1.913*** (0.138)
	Monthly	1.621*** (0.128)	1.773*** (0.139)
Additional wellness content	Workout routines	Ref.	Ref.
	Food recipes	0.960 (0.13)	0.976 (0.136)
	New scientific evidence	1.008 (0.131)	0.910 (0.136)
Follow-up visits with your doctor	On person	Ref.	Ref.
	On remote	0.976 (0.106)	0.847 (0.114)
Responsibility for setting goals	Doctor alone	Ref.	Ref.
	Individual alone	1.244* (0.129)	1.078 (0.134)
	Doctor and individual together	1.429** (0.13)	1.340** (0.142)
Encouragement on goals	Challenge other user	Ref.	Ref.
	Notification for goals	1.280* (0.128)	1.285* (0.137)
	Challenge multiple users	0.877 (0.129)	1.011 (0.136)
Concordance		0.649 (SE =0.023)	0.613 (SE =0.025)
Likelihood ratio test		85.54 (P<0.001)	57.65 (P<0.001)
Wald test		75.4 (P<0.001)	52.46 (P<0.001)
Score (log-rank) test		81.89 (P<0.001)	55.85 (P<0.001)

Estimates are presented as odds ratio (SE), unless otherwise stated. Group 1 is the group with the least usage of technology, and Group 2 is the one in the highest usage level. ***, P<0.01; **, P<0.05; *, P<0.1. LPA, latent profile analysis; ref., reference; SE, standard error.

of education is a factor that induces self-selection to Group 1. Table S3 with the results of the Chi-squared test is available in Appendix 1.

Discussion

Our results, estimated with the conditional logit model, reveal statistically significant stated preferences among respondents. We further analyzed subgroups based on NCD patient status and technology usage to assess if these preferences varied by background. Below, we compare our findings with existing literature.

First, respondents preferred monitoring physical over mental health via the mHealth app. Although research indicates benefits for both (34,44-46), no prior study has explicitly asked respondents to choose. This preference might stem from mental health stigma (45), low awareness, or the perceived separation of mental and physical health, which may lead individuals to overlook mental health's impact on chronic conditions (47-49).

Frequent notifications are linked to app adherence and effectiveness (2-4,24,26,28,31,32), yet excessive notifications can deter users (19). Our analysis shows that technology-savvy users are indifferent to notification frequency, while NCD patients prefer less frequent notifications explicitly. These results suggest the value of customizable notifications, as noted in previous studies (2,24,26,36,37).

During the focus group sessions, some participants expressed avoidance to enter too much data in the health app, but others also conveyed the idea that frequent measurements have a motivating effect. The estimates of our conditional logit model show that the preferences for body measurements were heterogeneous amongst the groups. Users less used to technology and NCD patients prefer more spaced upload of body measurements, a trend that was reversed for the group with higher technology usage and non-NCD patients. This preference suggests both a desire for customization and some reluctance for manual data entry (2,37).

Although other authors may have found that evidence-based content, food recipe suggestions, and work-out routines may be engaging (2,24,33), this is the first time, to the best of our knowledge, that these possible additional contents are compared with each other regarding the general preferences. Our estimations did not find statistically significant coefficients in any of the models, which probably shows our sample is indifferent to these features.

While some studies suggest that preferences towards telemedicine favor in-person visits instead of on-remote visits (48), our data does not support this finding. Instead, our respondents do not display a precise preference for the format of the appointments with their doctors. Although these preferences might be a sign of a higher acceptance of telemedicine, this may also mean that they are favoring other attributes and giving relatively less importance to this feature. For instance, the respondents of our survey demonstrated to have stronger preferences for participating actively in the setting goals process, as already demonstrated previously (33). Specifically, the respondents of our survey prefer to share the responsibility to set goals together with their doctor; probably because it enables them to discuss the context of their everyday lives, their concerns, priorities, and difficulties (49). Respondents that use less technology and NCD patients also have a stronger preference for collaboration on setting goals.

Several studies have pointed that gamification and social support features can enhance adherence to lifestyle apps (2-4,28,31-33); and our focus group analysis also mentioned rewarding and social incentives schemes. Nonetheless, little information was known about what feature of gamification is the most preferred amongst the possible end-users. In our estimation, we found that not only for the global sample but also for the NCD patients, receiving notifications for goals would motivate more than challenge-style interactions with other users. This finding is relevant because it contrasts with the preconception of challenging interactions as inherently motivating. Our results suggest that, once the respondents are faced with other options such as notification for goals, this is the alternative they would prefer.

One of our key findings relates to the heterogeneity of preferences about the app functionalities. According to previous research (24,50), personalization can be a key element to determining users' adherence and engagement with the app, thus improving the chances of effectiveness of the intervention. Also, app personalization can be helpful for defining the preferred settings of specific patient groups with different diseases, for example (50).

Our study has noteworthy limitations. Firstly, DCE designs offer insights that are limited to the attributes and levels that were chosen. In this sense, we could not reject the possibility that other attributes and levels outside the ones of our choice could be deemed relevant. We tried to consider the most comprehensibly as possible the recent literature gaps on selecting the presented options.

Secondly, we tried to approximate two profiles of technology usage by applying the machine learning technique of LPA. Under this method, we are assuming that all answers regarding the day-to-day technology usage have the same weight into defining a person's profile, which might be an oversimplification. However, by using this data-driven technique, we tried to avoid preconceptions about the underlying mechanisms that may influence the preferences.

Although we gathered health status information from the respondents, we could not have a sizeable sample to run sub-analysis by type of disease. Considering that, we could not ascertain the disease-specific expectations and preferences about the app, although we acknowledge they may vary. We believe, though, that personalization would allow for a bigger control and enhance the capacity of fine-tuning the needs of specific patient groups, as already found in the literature (50).

We also attempted to assess further socioeconomic and health effects on our findings, but lack of minimal sample size constrained the feasibility of this sub-analysis.

Our survey was meant to focus mainly on patients, as the app tries to enhance agency and self-monitoring skills. However, we do not know whether the same preferences would hold in case the eventual caregivers were the ones dealing with the app. As our sample design did not focus on this population, further studies should investigate in detail the caregivers' preferences and opinions about the monitoring app. Still, we believe that the customizability of these tools can enhance adaptability also in this setting.

Lastly, we also recognize the possibility of our answers suffering from hypothetical bias. As the respondents were asked to answer about a hypothetical app, without actually using it, it is possible that on real-life settings their preferences could be changed. In any case, our results could be seen as a reference point to preferences of this gender, and further studies could benefit of comparing their results with ours. We cannot ascertain beforehand the preferences we have found will impact health outcomes of future patients. Future works evaluating the short- and long-term effects of this hypothetical app should assess its efficacy and the role of these preferences in the near future.

As far as we know, this is the first study comparing the features of a mHealth app for potential end-users between four different European Union (EU) countries. Not only these preferences were gathered and compared, but also our sample allowed us to understand how subpopulations divided by NCD status or usage of technology have their preferences stated.

Conclusions

In this work, we collected and analyzed preferences about mHealth apps for lifestyle management. We found that users prefer less data input, less notifications, monitoring their physical status over emotional status, and there is some heterogeneity of the preferences according to their subgroup.

Our results have important implications for public and private health care initiatives aiming to develop or enhancing health monitoring apps. Our results support the hypothesis that end users of chronic conditions believe that mHealth apps are useful for adhering, and keeping a healthy lifestyle, especially when they are customizable, permit the integration with the health care systems, and allow for a better communication between doctors and patients.

Acknowledgments

We thank all patients and collaborators of the Digicare4You project (https://cdn.amegroups.cn/static/public/mhealth-25-30-1.pdf).

Footnote

Data Sharing Statement: Available at https://mhealth.amegroups.com/article/view/10.21037/mhealth-25-30/dss

Peer Review File: Available at https://mhealth.amegroups.com/article/view/10.21037/mhealth-25-30/prf

Funding: This study is conducted within the DigiCare4You Project, which has received funding from the European Union's Horizon 2020 Research and Innovation Program (grant agreement No. 945246).

Conflicts of Interest: All authors have completed the ICMJE uniform disclosure form (available at https://mhealth.amegroups.com/article/view/10.21037/mhealth-25-30/coif). The authors have no conflicts of interest to declare.

Ethical Statement: The authors are accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved. The study was conducted in accordance with the Declaration of Helsinki and its subsequent amendments. As the data collection does not affect the rights or freedoms of the participants, review by an Ethics Committee is not required. Informed consent was taken from all the participants.

References

1. Corsica JA, Kelly MC, Bradley LE, et al. Mobile apps for diabetes self-management: An updated review of app features and effectiveness. J Behav Med 2025;48:137-48.
2. Wei Y, Zheng P, Deng H, et al. Design Features for Improving Mobile Health Intervention User Engagement: Systematic Review and Thematic Analysis. J Med Internet Res 2020;22:e21687.
3. Aguiar M, Cejudo A, Epelde G, et al. An approach to boost adherence to self-data reporting in mHealth applications for users without specific health conditions. BMC Med Inform Decis Mak 2025;25:16.

4. Domin A, Spruijt-Metz D, Theisen D, et al. Smartphone-Based Interventions for Physical Activity Promotion: Scoping Review of the Evidence Over the Last 10 Years. JMIR Mhealth Uhealth 2021;9:e24308.
5. Kario K, Harada N, Okura A. Digital Therapeutics in Hypertension: Evidence and Perspectives. Hypertension 2022;79:2148-58.
6. Carter MC, Burley VJ, Cade JE. Weight Loss Associated With Different Patterns of Self-Monitoring Using the Mobile Phone App My Meal Mate. JMIR Mhealth Uhealth 2017;5:e8.
7. Hurst JR, Dickhaus J, Maulik PK, et al. Global Alliance for Chronic Disease researchers' statement on multimorbidity. Lancet Glob Health 2018;6:e1270-1.
8. Halpin, HA, Morales-Suárez-Varela, MM, Martin-Moreno, JM. Chronic Disease Prevention and the New Public Health. Public Health Rev 2010;32:120–54
9. Cao W, Milks MW, Liu X, et al. mHealth Interventions for Self-management of Hypertension: Framework and Systematic Review on Engagement, Interactivity, and Tailoring. JMIR Mhealth Uhealth 2022;10:e29415.
10. Qiu SH, Sun ZL, Cai X, et al. Improving patients' adherence to physical activity in diabetes mellitus: a review. Diabetes Metab J 2012;36:1-5.
11. Theodoridis X, Chourdakis M, Chrysoula L, et al. Adherence to the DASH Diet and Risk of Hypertension: A Systematic Review and Meta-Analysis. Nutrients 2023;15:3261.
12. Hagelsrum KDa, Andermo S, Svedberg T, et al. Users' perceptions of an mHealth service to support healthy lifestyle habits among adult individuals with type 2 diabetes in Sweden – A qualitative study. BMC Digit Health 2025;3:17.
13. Institute for Health Metrics and Evaluation. Global Burden of Disease (GBD). Available online: https://www.healthdata.org/research-analysis/gbd
14. Sun H, Saeedi P, Karuranga S, et al. IDF Diabetes Atlas: Global, regional and country-level diabetes prevalence estimates for 2021 and projections for 2045. Diabetes Res Clin Pract 2022;183:109119.
15. World Health Organization. Global report on hypertension: the race against a silent killer. Geneva: World Health Organization (WHO); 2023.
16. Xu H, Long H. The Effect of Smartphone App-Based Interventions for Patients With Hypertension: Systematic Review and Meta-Analysis. JMIR Mhealth Uhealth 2020;8:e21759.
17. Lee EY, Cha SA, Yun JS, et al. Efficacy of Personalized Diabetes Self-care Using an Electronic Medical Record-Integrated Mobile App in Patients With Type 2 Diabetes: 6-Month Randomized Controlled Trial. J Med Internet Res 2022;24:e37430.
18. Mikulski BS, Bellei EA, Biduski D, et al. Mobile Health Applications and Medication Adherence of Patients With Hypertension: A Systematic Review and Meta-Analysis. Am J Prev Med 2022;62:626-34.
19. Creber A, Leo DG, Buckley BJR, et al. Use of telemonitoring in patient self-management of chronic disease: a qualitative meta-synthesis. BMC Cardiovasc Disord 2023;23:469.
20. Payne JE, Turk MT, Kalarchian MA, et al. Adherence to mobile-app-based dietary self-monitoring-Impact on weight loss in adults. Obes Sci Pract 2021;8:279-88.
21. Sakane N, Suganuma A, Domichi M, et al. The Effect of a mHealth App (KENPO-app) for Specific Health Guidance on Weight Changes in Adults With Obesity and Hypertension: Pilot Randomized Controlled Trial. JMIR Mhealth Uhealth 2023;11:e43236.
22. Persell SD, Peprah YA, Lipiszko D, et al. Effect of Home Blood Pressure Monitoring via a Smartphone Hypertension Coaching Application or Tracking Application on Adults With Uncontrolled Hypertension: A Randomized Clinical Trial. JAMA Netw Open 2020;3:e200255.
23. Cavero-Redondo I, Martinez-Vizcaino V, Fernandez-Rodriguez R, et al. Effect of Behavioral Weight Management Interventions Using Lifestyle mHealth Self-Monitoring on Weight Loss: A Systematic Review and Meta-Analysis. Nutrients 2020;12:1977.
24. Jakob R, Harperink S, Rudolf AM, et al. Factors Influencing Adherence to mHealth Apps for Prevention or Management of Noncommunicable Diseases: Systematic Review. J Med Internet Res 2022;24:e35371.
25. Meyerowitz-Katz G, Ravi S, Arnolda L, et al. Rates of Attrition and Dropout in App-Based Interventions for Chronic Disease: Systematic Review and Meta-Analysis. J Med Internet Res 2020;22:e20283.
26. Patail K, Pai HH, Greenfield G, et al. What are the perceptions and experiences of adults using mobile applications for self-management in diabetes? A systematic review. BMJ Open 2025;15:e086671.
27. Robertson MC, Raber M, Liao Y, et al. Patterns of self-monitoring technology use and weight loss in people with overweight or obesity. Transl Behav Med 2021;11:1537-47.
28. Yang Y, Boulton E, Todd C. Measurement of Adherence to mHealth Physical Activity Interventions and Exploration

of the Factors That Affect the Adherence: Scoping Review and Proposed Framework. J Med Internet Res 2022;24:e30817.
29. Aromatario O, Van Hoye A, Vuillemin A, et al. How do mobile health applications support behaviour changes? A scoping review of mobile health applications relating to physical activity and eating behaviours. Public Health 2019;175:8-18.
30. Eaton CK, McWilliams E, Yablon D, et al. Cross-Cutting mHealth Behavior Change Techniques to Support Treatment Adherence and Self-Management of Complex Medical Conditions: Systematic Review. JMIR Mhealth Uhealth 2024;12:e49024.
31. Shabir H, D'Costa M, Mohiaddin Z, et al. The Barriers and Facilitators to the Use of Lifestyle Apps: A Systematic Review of Qualitative Studies. Eur J Investig Health Psychol Educ 2022;12:144-65.
32. Edwards EA, Lumsden J, Rivas C, et al. Gamification for health promotion: systematic review of behaviour change techniques in smartphone apps. BMJ Open 2016;6:e012447.
33. Zhou Y, Li SJ, Huang RQ, et al. Behavior Change Techniques Used in Self-Management Interventions Based on mHealth Apps for Adults With Hypertension: Systematic Review and Meta-Analysis of Randomized Controlled Trials. J Med Internet Res 2024;26:e54978.
34. Sommer J, Dyczmons J, Grobosch S, et al. Preferences of people with type 2 diabetes for telemedical lifestyle programmes in Germany: protocol of a discrete choice experiment. BMJ Open 2020;10:e036995.
35. Phillips EA, Himmler SF, Schreyögg J. Preferences for e-Mental Health Interventions in Germany: A Discrete Choice Experiment. Value Health 2021;24:421-30.
36. Nittas V, Mütsch M, Braun J, et al. Self-Monitoring App Preferences for Sun Protection: Discrete Choice Experiment Survey Analysis. J Med Internet Res 2020;22:e18889.
37. Philip B, Abdelrazek M, Barnett S, et al. Towards better mHealth apps: Understanding current challenges and user expectations. In: Proceedings of the 9th IEEE/ACM International Conference on Mobile Software Engineering and Systems. 2022:33-7.
38. Bridges JF, Hauber AB, Marshall D, et al. Conjoint analysis applications in health--a checklist: a report of the ISPOR Good Research Practices for Conjoint Analysis Task Force. Value Health 2011;14:403-13.
39. Goodman LA. Snowball sampling. Annals of Mathematical Statistics 1961;32:148-70.
40. Johnson R, Orme B, editor. Getting the Most from CBC. Sawtooth Software Research Paper Series. Sequim: Sawtooth Software, Inc.; 2003.
41. McFadden D. Conditional Logit Analysis of Qualitative Choice Behavior. In: Zarembka P, editor. Frontiers in Econometrics. New York: Academic Press; 1973:105-42.
42. Hauber AB, González JM, Groothuis-Oudshoorn CG, et al. Statistical Methods for the Analysis of Discrete Choice Experiments: A Report of the ISPOR Conjoint Analysis Good Research Practices Task Force. Value Health 2016;19:300-15.
43. Spurk D, Hirschi A, Wang M, et al. Latent profile analysis: A review and "how to" guide of its application within vocational behavior research. Journal of Vocational Behavior 2020;120:103445.
44. Patel J, Hung C, Katapally TR. Evaluating predictive artificial intelligence approaches used in mobile health platforms to forecast mental health symptoms among youth: a systematic review. Psychiatry Res 2025;343:116277.
45. Yuting Z, Xiaodong T, Qun W. Effectiveness of a mHealth intervention on hypertension control in a low-resource rural setting: A randomized clinical trial. Front Public Health 2023;11:1049396.
46. Zheng S, Edney SM, Goh CH, et al. Effectiveness of holistic mobile health interventions on diet, and physical, and mental health outcomes: a systematic review and meta-analysis. EClinicalMedicine 2023;66:102309.
47. Bharadwaj P, Pai MM, Suziedelyte A. Mental health stigma. Economics Letters 2017;159:57–60.
48. Moulaei K, Sheikhtaheri A, Fatehi F, et al. Patients' perspectives and preferences toward telemedicine versus in-person visits: a mixed-methods study on 1226 patients. BMC Med Inform Decis Mak 2023;23:261.
49. Murdoch J, Salter C, Ford J, et al. The "unknown territory" of goal-setting: Negotiating a novel interactional activity within primary care doctor-patient consultations for patients with multiple chronic conditions. Soc Sci Med 2020;256:113040.
50. Jacob C, Sanchez-Vazquez A, Ivory C. Social, Organizational, and Technological Factors Impacting Clinicians' Adoption of Mobile Health Tools: Systematic Literature Review. JMIR Mhealth Uhealth 2020;8:e15935.

doi: 10.21037/mhealth-25-30
Cite this article as: Seghieri C, Feldens T, Tortù C, Usheva N, Toti F, Doracaj D, Giménez-Legarre N, Karaglani E, Manios Y. Tailoring mobile health apps for lifestyle management: a discrete choice experiment. mHealth 2026;12:3.