

Assessment

Cite this article: Gc VS, Iglesias CP, Erdem S, Hassan L, Peek N, Manca A (2022). Using discrete-choice experiments to elicit preferences for digital wearable health technology for self-management of chronic kidney disease. *International Journal of Technology Assessment in Health Care*, **38**(1), e77, 1–9
<https://doi.org/10.1017/S0266462322003233>

Received: 28 February 2022
Revised: 05 July 2022
Accepted: 29 August 2022


Key words:

patient preferences; chronic kidney disease; wearable devices; mixed methods; discrete-choice experiment; conjoint analysis

Author for correspondence:

*Andrea Manca,
E-mail: andrea.manca@york.ac.uk

Using discrete-choice experiments to elicit preferences for digital wearable health technology for self-management of chronic kidney disease

Vijay S Gc¹ , Cynthia P Iglesias^{2,3}, Seda Erdem⁴, Lamiece Hassan⁵, Niels Peek⁵ and Andrea Manca^{1*}

¹Centre for Health Economics, University of York, York, UK; ²Department of Health Sciences, University of York, York, UK; ³Danish Centre for Healthcare Improvement (CHI), Aalborg University, Aalborg, Denmark; ⁴Management School, University of Stirling, Stirling, UK and ⁵Division of Imaging, Informatics and Data Sciences, University of Manchester, Manchester, UK

Abstract

Objectives: Wearable digital health technologies (DHTs) have the potential to improve chronic kidney disease (CKD) management through patient engagement. This study aimed to investigate and elicit preferences of individuals with CKD toward wearable DHTs designed to support self-management of their condition.

Methods: Using the results of our review of the published literature and after conducting qualitative patient interviews, five-choice attributes were identified and included in a discrete-choice experiment. The design consisted of 10-choice tasks, each comprising two hypothetical technologies and one opt-out scenario. We collected data from 113 adult patients with CKD stages 3–5 not on dialysis and analyzed their responses via a latent class model to explore preference heterogeneity.

Results: Two patient segments were identified. In all preference segments, the most important attributes were the device *appearance*, *format*, and *type* of information provided. Patients within the largest preference class (70 percent) favored information provided in any format except the audio, while individuals in the other class preferred information in text format. In terms of the style of engagement with the device, both classes wanted a device that provides options rather than telling them what to do.

Conclusions: Our analysis indicates that user preferences differ between patient subgroups, supporting the case for offering a different design of the device for different patients' strata, thus moving away from a one-size-fits-all service provision. Furthermore, we showed how to leverage the information from user preferences early in the R&D process to inform and support the provision of nuanced person-centered wearable DHTs.

Introduction

The prevalence of chronic conditions and multimorbidity is increasing, imposing an enormous burden on patients and the healthcare system. Living with multimorbidity can affect patients' quality of life in significant ways (1). It is argued that investing in self-management interventions has the potential to improve health outcomes and ease the pressure on healthcare systems (2;3). Self-management requires patients to engage in a collaborative partnership with their families or carer and their health professionals, with a view to learn (and commit) to look after themselves while managing their condition (4). Patient's knowledge, confidence, and skills to self-manage their own health and care refereed as “patient activation” (5) play important role in managing their health and has better health outcomes.

The emerging use of (innovative) digital technologies in healthcare offers a potentially effective option for delivering self-management support strategies to some individuals. Examples include education, support, and self-management in diabetes, chronic obstructive pulmonary disease (6;7), and epilepsy (8). Despite their rapid diffusion, important scientific and practical challenges need to be overcome to ensure that digital health technologies (DHTs) are adopted by healthcare systems and, just as importantly, by patients (9).

Chronic kidney disease (CKD) is a slow, progressive, and irreversible decline in renal function, leading to end-stage renal disease and cardiovascular morbidity, with significant health and healthcare cost implications (10;11). The management of CKD includes: slowing down the disease progression to kidney failure; and reducing cardiovascular disease risk by managing kidney functions and CKD progression risk factors, such as hypertension and diabetes. As CKD progresses toward end-stage, long-term CKD management requires a high-level patient

involvement to reduce the overwhelming impact of CKD. Self-management of CKD incurs a high burden of implementation for patients, who are expected to manage aspects ranging from: attention to dietary and medical management to recognizing early warning signs, regulation of fluid intake, blood pressure, and electrolytes (12). The increasing use of self-management interventions for CKD in recent years demonstrates the growing importance of such interventions in managing this condition to improve health outcomes (13). Hypertension management is a key outcome of CKD self-management, and technology-enabled interventions can control blood pressure in CKD (14).

Clinically and cost-effective DHTs that can transform health and social care delivery must also be patient-centered. Research and Development (R&D) effort to support the creation of DHTs, particularly those used by patients, should be informed by strong clinical evidence and patients' values, priorities, and preferences (15;16). If an R&D team, the target patients, and their (informal) carers do not co-produce the design of an innovative DHT from the earliest stages of development, the potential benefits of these technologies may never come to realize (17;18). Thus, it is important to invest in co-designing any new form of collaborative care to help individuals manage health in their daily lives, respond more quickly to changes in symptoms, and prevent relapse.

This study is a part of the UK Engineering and Physical Sciences Research Council-funded "Wearable Clinic" aimed to create a set of software tools for wearable technology to support patient self-managing their long-term conditions. In this exploratory study, we aimed to investigate and elicit the preferences of individuals with CKD toward wearable DHTs to support self-management of their condition. This is the first effort in the context of using early health technology assessment methods to support the development of new wearable DHT.

Methods

Discrete-choice experiments (DCEs) are survey-based methods commonly used to explore preferences for services or products (19). They involve presenting individuals with hypothetical choices which differ in attributes and their magnitude or levels and ask participants to choose the alternative they prefer in each choice set. This enables researchers to understand the value that individuals place on various levels of the attributes that characterize the technology under development. The study was designed and reported in line with published recommendations (20–22). We describe below the process involved in identifying the important aspects of wearable DHT used in the DCE.

Phase 1: identification of the characteristics of a wearable DHT to support self-management of chronic conditions

A literature review was conducted to identify published studies that (i) investigated reasons why individuals with CKD may choose (or refuse) to use wearable DHTs to support their self-management activities, as well as any study that (ii) attempted to understand people's preferences for, and perceptions of technology-based interventions (e.g., wearables, mHealth, telehealth, smartphone apps). The search terms used are provided in Supplementary Material S1. Two researchers independently screened the titles and abstracts of all the articles identified through the electronic search, and one reviewer extracted data for all included studies. An

initial set of generalizable characteristics of wearable DHTs (i.e., attributes) was compiled for further use in Phase 2.

It included their appearance, choice of settings, the format in which feedback information is provided to users, degree, and extent of data entry, capabilities/functionalities, style of engagement with the user (frequency and type of information the device provides), and the time required by the user to interact with it. A brief description of these features is provided in Supplementary Material S2. Furthermore, we conducted qualitative interviews with technology developers to identify the potential purposes of the technology under development. This resulted in a list of nine purposes of DHT which was used in Phase 2.

Phase 2: qualitative interviews

The findings from Phase 1 were used to define a topic guide for a semi-structured focus group meeting (Supplementary Material S3). Focus groups involve organized discussions with individuals to gain information about their views and experiences of a topic. In contrast to individual interviews, focus groups capitalize on stimulating interaction between participants, often yielding additional insights (23). In this study, the focus group was used for two purposes: (i) to identify DCE attributes and attribute levels; and (ii) to shed light on individuals' views of the role and potential uses of wearable DHTs to support collaborative management of their condition.

We used multiple platforms to recruit people with CKD into our focus groups, such as patient/consumer groups, charities, social media, existing patient and public involvement networks, and online research recruitment platforms. As a result, 10 volunteers who initially expressed an interest in contributing to our research were invited to participate in the focus group, and four were subsequently accepted (based on scheduling and availability).

Data from the focus group were transcribed verbatim and qualitatively analyzed using the framework approach (24). To provide context, participants were asked about what strategies they used to manage their health and prior experiences of using DHTs and/or wearable devices (e.g., wearable blood glucose monitoring devices). When asked about the features that would persuade them to use a wearable device to support their self-management efforts, respondents preferred a small, multifunctional device. Individuals indicated they were willing to compromise on aspects such as the portability, aesthetic, and appearance (how discreet it is) of the device as long as this was able to help them with more than just one task of their self-management routine. Participants valued features that allow them to (i) monitor symptoms, (ii) pick up any warning signs, (iii) track progress and alert them when extra support may be needed, (iv) provide flexibility in interacting with a care team, and (v) help manage the time and frequency of appointments with the care team (for detailed results, see Supplementary Material S4).

Phase 3: designing, piloting, and fielding the online DCE

The outcomes of Phases 1 and 2 provided us with a list of attributes and attribute levels to use in DCE, based on which we have designed the pilot survey. In DCE, participants were asked to choose between two hypothetical wearable DHTs presented to them and a "none of them" option to mimic the real-world scenario where individuals are free not to choose a device for whatever reason. Responses to these choice-based questions enabled us to analyze trade-offs people made. In turn, this allowed us to inform the design of technologies that have the greatest potential to maximize adoption,

adherence, patient satisfaction, health outcome, and possibly reduce costs for the healthcare system.

DCE experimental set-up

We adopted a full profile balanced-overlap, nearly orthogonal experimental design (25) using Sawtooth Software Lighthouse Studio v9.6 to create alternative profiles of a hypothetical wearable DHT from different combinations of its attributes and associated levels (reported in Table 1). The final set of attributes and their levels were determined by the investigative team based on the feedback received from the patients during piloting. The experimental design included ten choice tasks, each having two alternatives described by five attributes with a number of levels (see Table 1 for the full list). As it was not feasible for a participant to respond to the full factorial design (i.e., sixty-four combinations of attribute levels), we blocked the full factorial design into ten blocks (versions). Each participant was then randomly assigned to each block when they clicked on the survey link.

The experimental design ensured one-way and two-way frequency balance such that each attribute level appeared an almost equal number of times in the survey and paired with other levels of the attribute in choice tasks as an equal number of times as possible (two-way frequencies). The balanced overlap between choice tasks in the experimental design allowed us to measure marginal utilities put on attribute levels when controlling for any cases where certain level(s) might appear all the time. An example choice task can be found in Figure 1.

Pretesting and piloting the online choice survey

The online survey was piloted via four in-depth face-to-face interviews using the think-aloud method (26) before deploying the final survey. The purpose of this exercise was to: investigate the face validity, test the understanding and relevance of the wording used to characterize attributes of the wearable DHT, as well as, assess the overall presentation and interpretation of the DCE survey. In this pilot, we recruited individuals with CKD purposively based on technology use experience, demographics, and disease stage. Participants were presented with choice tasks and asked to complete them using a think-aloud approach while responding to survey questions. In addition to any issues raised by participants while reading and completing the questionnaire, we looked at visual hints (e.g., body language, facial gestures, pauses) that may reveal the

need to clarify and discuss specific aspects of the survey. Three researchers facilitated the process, clarified any issues that participants had, and documented issues related to the presentation and description of any of our online survey items, for example, wording, display of the survey.

Overall, pre-testing participants completed the choice tasks without difficulty. They suggested changing some of the wordings to add clarity and maintain consistency. For example, one of the suggestions was to rename option 3 “none of them” to “neither option 1 nor option 2.” In addition, there was confusion on the levels of two attributes, that is, information it provides (medical and non-medical) and the format of information it provides (number, text, image, audio). In the revised version, we provided examples of medical and non-medical information and images, and audio. Following the think-aloud interviews, the wording and display of the survey introduction and the choice tasks were revised and simplified. Altogether, the final design included ten choice tasks, each comprising two hypothetical technologies and one opt-out scenario, which were randomly allocated to participants.

Survey participants, measures, and procedures

We recruited patients with CKD using online advertisements circulated to patient/consumer organizations (e.g., HealthWatch), charities (e.g., Kidney Care UK), social media (e.g., Facebook groups, Twitter), patient and public involvement networks, and online recruitment platforms between July and October 2019. The eligibility criteria for the participants were being aged ≥ 18 years and diagnosed with stage 3 CKD and onwards, but not on dialysis. As a token of appreciation, participants were given a £20 Amazon gift voucher.

There is no formal basis for sample size calculation for choice surveys in healthcare, and estimation methods are currently developing (27). Therefore, the sample required for this study was estimated based on pragmatic considerations, and these included taking into account likely participation rates based on prior experience recruiting individuals with long-term conditions. The required minimum sample size to estimate preferences was 100 respondents. However, a larger sample was targeted to allow for the analysis of preferences heterogeneity.

The online survey began with a patient information sheet, followed by screening questions to identify eligible respondents. Participants were provided with a consent form, information on the

Table 1. Final attributes and levels used in the experiment

Attributes	Levels	Description
Its appearance	Discreet (e.g., unnoticeable) Noticeable (e.g., obvious, eye-catching)	The appearance of the device
Format of the information it provides	Numbers Text Images (e.g., graphs or pictures) Audio (e.g., reading information for you, signaling with sound)	Format of the information devices provides
How it engages with me	Explains my options and tells me what to do Offers me options and allows me to make a choice	Engagement style of the device
Type of information it provides	Non-medical information, such as what I do and how I do things that influence my condition (e.g., lifestyle, diet) Medical information related to the progression of my condition (e.g., GFR results, blood pressure, trends)	Type of information device communicates
How much time I need to spend	Up to 30 min/day Between 30 min and 1 hr/day	Time investment for the use and maintenance of the device

GFR, glomerular filtration rate.

If a digital wearable device with the following sets of characteristics was offered to you to help manage your condition now, which one would **you** prefer **the most**?

	Option 1	Option 2	Option 3
Its appearance	Discreet (e.g. unnoticeable)	Noticeable (e.g. obvious, eye-catching)	
Format of the information it provides	Text	Numbers	
How it engages with me	Offers me options and allows me to make a choice	Tells me what to do	Neither Option 1 nor Option 2
Type of information it provides	Medical information	Non-medical information	
How much time I need to spend	Between 30 minutes and one hour/day	Upto 30 minutes/day	
	dce_Random1	dce_Random1	dce_Random1
	Select	Select	Select

Next

Figure 1. Example of choice sets used in the discrete-choice experiment.

study, and instructions on how to complete the choice task. Respondents were asked to select the top five purposes from a list of nine non-mutually exclusive potential purposes of a wearable health technology that emerged from Phase 2. The survey concluded with questions about their health, prior experience of using any digital wearable devices to monitor and control their condition, socio-demographics, and views on the survey.

The study was approved by the University of Manchester's Research Ethics Committee (reference no. 2019-3263-10408) and was conducted in accordance with the General Data Protection Regulation.

Statistical analyses

The analysis of data from the choice task in our online survey was based on the random utility maximization theory (28;29). As individuals might have different preferences, we used a latent class modeling approach (30;31). The underlying theory for the latent class model (LCM) posits that participants' preferences can be segmented into Q latent segments (classes). Preferences within each class are assumed to be the same (i.e., homogeneous) but differ across classes. The model allows us to explain individuals' preferences from their choice data and simultaneously show how respondents' characteristics, such as gender and age, influence class membership. The optimal number of classes (i.e., segments) is identified using model fit criteria such as Bayesian Information Criterion (BIC), Akaike Information Criterion (AIC), log-likelihood values, and the principle of model parsimony. Socio-demographics and other data collected as part of the online survey were analyzed using descriptive statistics. All

statistical analyses were undertaken using *Apollo* package in R (32). We also fit mixed logit and multinomial logit regression models but they performed worse than latent class model (Supplementary Material S5).

Furthermore, we performed scenario analyses for a number of policy-relevant scenarios to demonstrate the implications of our findings. We assume that there are three scenario options for wearable digital devices:

- Scenario 1: Device which has a discreet appearance, presents non-medical information with numbers and images, offers options to patients, and takes up a maximum of 30 min per day for an individual.
- Scenario 2: Device which has a noticeable appearance, presents medical information with numbers and texts, tells patients what to do, and takes up between 30 and 60 min per day for an individual.
- Scenario 3: No device

Using the LC model estimates, we calculate the predicted choice probabilities of these scenarios at an aggregate level (Table 2). We used Krinsky and Robb (33) technique to calculate confidence intervals (CIs) for the predicted update probabilities for given scenarios. This technique is based on taking a large number of draws (in our case $r = 10,000$) from a multivariate distribution with mean probabilities calculated using the estimated coefficients and covariances from their covariance matrix of the estimated coefficients. So, based on this r number of draws, we produced r simulated values of predicted probabilities. These values are then used to calculate the 95 percent CI. More detail on the calculator can be found in Supplementary Material S6.

Table 2. Scenario analyses

Scenario	Choice probability (95% CI)	Choice probability for Latent Class 1 (95% CI)	Choice probability for Latent Class 2 (95% CI)
1	0.50 (0.40, 0.59)	0.54 (0.43, 0.64)	0.41 (0.23, 0.60)
2	0.35 (0.26, 0.44)	0.43 (0.32, 0.54)	0.16 (0.07, 0.32)
3	0.15 (0.10, 0.24)	0.03 (0.02, 0.06)	0.43 (0.26, 0.61)

Results

The survey weblink was shared on multiple online platforms. In total, 233 unique hits on the survey website led to 142 (61 percent) completed surveys. We excluded twenty-nine responses that were completed in <5 min or were duplicates, and the final sample included 113 respondents.

Socio-demographic and health responses

Among the 113 respondents (Table 3), the sample included a slightly higher proportion of women (67 percent). Respondents were predominantly white, and over three-quarters of them were aged ≥ 45 years. The majority were not in full-time employment, and 51 percent of the respondents had a degree-level qualification or higher. Almost two-thirds of the participants (63 percent) had CKD stage III disease, and 61 percent of the sample received their CKD diagnosis more than 5 years ago. Only 6 percent of the respondents had previously used any digital wearable devices to self-manage their condition. Over four-fifth (81 percent) agreed that “they have the knowledge, skills, and confidence to take an active role in managing their own care.”

Latent class model results

We analyzed the choice data using LCMs with up to four latent classes. Comparing the information criteria, log-likelihood measures, and model parsimony of these models, we decided on the model with two classes (Table 4). We also note that due to the small sample size, we also considered the size and composition of the latent classes when deciding on the final model. For example, a latent class as small as 5 percent of the sample (i.e., around eight people) would not give much reliable information; thus, it is useful

Table 3. (Continued)

	All	Percent
25–34 yr	10	(8.8%)
35–44 yr	15	(13.3%)
45–54 yr	32	(28.3%)
55–64 yr	34	(30.1%)
65–74 yr	19	(16.8%)
75+yr	1	(0.9%)
<i>Ethnicity</i>		
White	107	(94.7%)
Mixed	1	(0.9%)
Black	4	(3.5%)
Other	1	(0.9%)
<i>Employment status</i>		
Full-time student	3	(2.7%)
Full-time employment	37	(32.7%)
Part-time or self-employed	22	(19.5%)
Unemployed	22	(19.5%)
Retired	29	(25.7%)
<i>Level of education</i>		
Secondary school	14	(12.4%)
Vocational/Trade /college qualification	29	(25.7%)
“A” level / “AS” levels	12	(10.6%)
Degree level qualification(s) or higher	58	(51.3%)
Mean EQ-5D-5L score (SD)	0.655	(0.264)
<i>CKD stage</i>		
Stage IIIa/IIIb	71	(62.8%)
Stage IV	21	(18.9%)
Stage V	21	(18.9%)
<i>Time since CKD diagnosis</i>		
<1 yr	9	(8.0%)
1–2 yr	14	(12.4%)
2–5 yr	21	(18.6%)
>5 yr	69	(61.1%)
<i>Used any digital wearable devices to self-manage their condition</i>		
Yes	7	(6.2%)
No	106	(93.8%)
<i>Confidence in managing own care</i>		
Strongly agree	43	(38.05%)
Agree	48	(42.48%)
Neither agree nor disagree	8	(7.08%)
Disagree	10	(8.85%)
Strongly disagree	4	(3.54%)

CKD, chronic kidney disease; SD, standard deviation.

Table 3. Sample characteristics

	All	Percent
Sample (n)	113	
<i>Gender</i>		
Male	36	(32.9%)
Female	76	(67.3%)
Prefer not to reveal	1	(0.9%)
<i>Age groups</i>		
18–24 yr	2	(1.8%)

(Continued)

Table 4. Results of the latent class model

	Preference Class 1	Preference Class 2
Attribute level	Coefficients (SE)	Coefficients (SE)
<i>Preference class proportions</i>	70%	30%
<i>Constants</i>		
Asc(left)	1.88 (0.27)***	−2.56 (0.44)***
Asc(right)	1.92 (0.28)***	−2.55 (0.45)***
Asc(sq)	Reference	
<i>Appearance</i>		
Discreet	0.57 (0.13)***	1.96 (0.35)***
Noticeable	Reference	
<i>Format of the information it provides</i>		
Numbers	0.41 (0.16)**	0.69 (0.39)*
Text	0.34 (0.15)**	0.94 (0.37)**
Images/graphic	0.63 (0.16)***	0.43 (0.40)
Audio	Reference	
<i>How it engages with me</i>		
Tells me what to do	−0.09 (0.10)	−0.10 (0.23)
Offers me options	Reference	
<i>Type of information it provides</i>		
Non-medical information	−0.91 (0.10)***	−0.97 (0.24)***
Medical information	Reference	
<i>How much time I need to spend</i>		
Up to 30 min/day	0.17 (0.11)	0.38 (0.22)*
30–60 min/day	Reference	
<i>Class membership</i>		
Intercept	1.83 (0.60)***	Reference
Age (18–34 yr) (=1, yes)	−0.27 (0.83)	
Age (35–54 yr) (=1, yes)	−0.64 (0.53)	
Male (=1, yes)	0.04 (0.53)	
Employed (=1, yes)	−0.37 (0.50)	
CKD stage (=1, stage 3)	−0.71 (0.50)	
Log-likelihood	−930	
R ²	0.23	
AIC	1,910	
BIC	2,057	
N(parameters)	24	
N(observation)	1,130	

****p* < .01;***p* < .05;**p* < .10.

AIC, Akaike information criterion; ASC, alternative specific constant; BIC, Bayesian information Criterion; SE, standard error.

to consider the sample size along with other measures when choosing the final model.

Class 1 accounted for 70 percent of the sample, and Class 2 accounted for 30 percent of the sample. The socio-demographic

characteristics used in the class membership function were not statistically significant, indicating that none of the gender, age, employment status or CKD stage significantly determined the preference-class membership.

Focusing on the estimates for each attribute and their relative magnitude in both latent classes, we see that appearance and format are perceived to be the most important features of the digital wearable devices, as compared to engagement and information type a device can offer, as well as the time requirement from patients.

The majority (Class-1) preferred to have a wearable digital device, the minority (Class-2) preferred not to have it, as evident from significant and negative coefficients on alternative specific constants (*asc*). Despite this difference, both patient groups preferred a discreet wearable device, which uses numbers or texts and presents only medical information. While the use of images was favorable to the largest latent class, the smallest latent class did not prefer them. As for the engagement style, both groups did not indicate significant preferences, but looking at the coefficients, we can say that all patients were leaning toward wearable devices offering them options rather than telling them what to do. Another difference between the two patient classes was about the time they were prepared to spend. Whilst the large class was indifferent, the small class was more favorable toward a device requiring less than 30 min per day.

Overall, the majority of the patients preferred to have a wearable device, which has a discreet appearance, non-audio features when sharing information with users, and shares only medical information. The remaining small group did not prefer to have a wearable device. However, if they were using one, they preferred to have a device with discreet appearance, utilizing only numbers and texts, sharing only medical information, and requiring only up to 30 min per day.

What are the most relevant purposes of wearable health technology?

The survey asked participants to choose the top five potential purposes of wearable health technology from a list of nine. The most frequently selected relevant purposes were (i) help monitor or track symptoms of condition between follow-up appointments, (ii) help track their own progress and alert them at times when they may need extra support, (iii) educate them with new knowledge or skills relevant to their condition, (iv) prevent relapse by detecting warning signs that they may have missed, and (v) monitor (and remind when necessary) whether or not they have done specific tasks including following routines as part of care plan such as taking medications. Managing the time and frequency of appointments with people in the care team, sharing progress with others, and alerting when extra support is needed were the lowest-ranked relevant purpose of the wearable DHT.

Scenario analysis

We found that Scenario 1 had, on average, a 50 percent chance of being selected and Scenario 2 has a 35 percent chance of being chosen by patients. No-device option (Scenario 3) has a 15 percent chance of being chosen by patient groups. This demonstration highlights that the choice and adoption of a wearable digital device is highly dependent on the weights patients put on the attributes of these devices.

Considering the observed and unobserved heterogeneity, we can further explain the choice predictions using the LC estimates,

including the class membership covariates. According to these choice probabilities, on average, we see that the largest latent class (class-1, 70 percent) chooses scenario 1 with 54 percent probability, scenario 2 with 43 percent probability, and a minimal likelihood of choosing no device option. However, the latent class-2 seems to favor having a no-device (43 percent), followed by scenarios 1 and 2.

Discussion

Over the past decade, there have been advances in technological innovations of wearable DHT and the rise of consumer health wearables (34;35). However, while these technologies can improve the quality of care, can be adapted on a large scale and at a low cost (36), their wider adoption remains hindered by acceptability, usability, and cost-effectiveness (37). This research investigated patients' preferences for wearable DHTs that aim to help individuals manage CKD.

The results provide insights into what generalizable characteristics of wearable digital devices are more likely to be valued or accepted by target users (in this study, people with CKD) and how these preferences might differ for different patient groups. More specifically, we found that, on average, participants preferred a wearable DHT that is discreet, interacts with the user by providing options, provides medical information related to the monitoring of the condition and provides information in text, image or graphic formats.

However, our econometric analysis showed preference heterogeneity, indicating the need for considering different versions of wearable DHTs for different CKD patient groups. These initial results indicate users' preferences toward wearable DHTs, how these differ between patient subgroups, and support the case for designing the device functionalities to meet the requirements of different subgroups of patients. The findings also provide insights to technology developers in the healthcare technology sector on how best to meet the needs of different CKD patients regarding their conditions. Incorporating user preferences early in the development pathway of DHT could help design targeted, person-centered technologies and improve adherence and disease management, facilitate shared decision-making, and lead health innovations. With the recent global growth in mobile/digital technology, involving patients earlier in adopting such technologies in healthcare can promote both clinical control and patient self-management.

There is an emerging consensus that users (e.g., patients and healthcare providers) should be involved at crucial decision points in developing the medical product life cycle (38). Previous studies mainly looked at the use and effectiveness of technology-enabled interventions to support self-management of CKD (14;39), and indicated a positive effect of such interventions on clinical outcomes but did not consider patients' perceptions and preferences which are crucial aspects for improving adherence and uptake of the resulting interventions. In their review, Jeddi et al. (14) described the features of technology-based interventions to improve CKD self-management but did not indicate what features mattered the most to individuals with CKD. Moreover, patients' preferences, perspectives, and values are often not included in formal health technology assessment processes (40).

Our findings showed that CKD patients' preferences toward wearable DHTs differ between patient groups. In line with these findings, a recent review by Lin and Hwang (41) showed that

different levels of engagement and eagerness are required for a patient-centered approach to self-management support in CKD. In other chronic conditions, such as chronic obstructive pulmonary disease (COPD), a qualitative study on the use of wearables and self-management apps in patients with COPD found that people wanted to maintain control of the information and connect with the data (42). Involving patients (and informal carers) in the co-design of wearable technology will be crucial to overcome potential barriers for use and ensure that technology design and development incorporates key components and/or features that may aid the self-management of chronic conditions.

In our study, patients with CKD preferred a wearable DHT that provides medical information as opposed to non-medical information, such as lifestyle advice. It is possible that they preferred the wearable DHT that provides disease-specific information in order to be alerted when a possible exacerbation occurs and that they can get non-medical information from other sources. In this regard, Vosbergen et al. (43) used mixed methods (qualitative interviews and online survey) using members of the general public to develop tailored health education messages and elicited chronic heart disease patients' preferences for multiple message features. They found that patient-centered tailored messages using individual-based methods produced a manageable set of tailored messages, leading to increased patient engagement and improved processing of the message's content.

Furthermore, the majority (80 percent) of the respondents agreed with the statement "I have the knowledge, skills, and confidence to take an active role in managing my own care", indicating a certain degree of patient activation (44) and identifying the patient as a good target for self-management support. An important question that emerges, as the self-management tasks become more demanding, is the relationship between health literacy (including digital health literacy), health awareness, and self-care behaviors is complex (45). It has been found that limited health literacy disproportionately affects people with CKD with low socioeconomic status and of non-white ethnicity (46); thus, healthcare providers must be aware of the potential equity implications associated with implementing a digital health-driven self-management support intervention in this patient population.

To the best of our knowledge, this is the first study that looked at CKD patients' preferences to inform the development of a wearable DHT, which has the main function of supporting people with CKD to self-manage their condition. Inclusion of preference exploration (qualitative) and elicitation (quantitative) methods provide useful information for decision-making at different stages of the medical product development lifecycle. We used a patient-oriented approach to develop the DCE by involving patients and members of the public. This approach contributes to greater transparency, acceptability, and appropriateness of methods; and increases participation in research (47).

Conducting choice surveys in the design phase of DHT raised a number of methodological considerations. Given the early phase of technology development, we used a pragmatic approach to estimate the sample size for our online choice survey. The fact that we were in an early stage of technology development meant that the attributes included in the choice task scenarios had to be kept broad. The list of attributes and levels can be refined further in the next phase of developing our wearable DHT.

The survey was administered online, and data were collected electronically. As it is typical with all online and offline surveys, it is possible that participants self-selected themselves into the study, which might cause the study results to be skewed toward this group.

We see, for instance, that white female respondents were over-represented compared to the distribution of the general population of people with CKD in the UK. Increasing our sample's size and diversity would help us further investigate preference heterogeneity; and the association between class membership, individual socio-economic characteristics (e.g., age, gender, and employment status), and disease severity.

Conclusion

The development of wearable DHTs to support people's self-management of their condition must take into account their preferences to facilitate a move away from one-size-fits-all provisions. This will likely result in population health gains. Although this study focuses on designing and developing a specific technology in self-management for CKD, our research methodology is generalizable to inform and support the provision of nuanced person-centered products and services across a range of different health technologies and chronic conditions.

Supplementary material. To view supplementary material for this article, please visit <https://doi.org/10.1017/S0266462322003233>.

Acknowledgments. The authors would like to acknowledge and thank all participants who took part in the focus group and think-aloud interviews for providing insight into their experience; the individuals who responded to the questionnaire; public contributors Ms Suzy Bourke and Mr Rob Finnigan, for their comments on the earlier version of the online survey; and Dr Paul Laboi, York Teaching Hospital NHS Foundation Trust, for clinical input. The authors are grateful to Stella O'Brien for her comments on the earlier version of this manuscript from a PPI perspective; to John Mills (Vasculitis UK), Katherine Grady (Research for the Future), and Kidney Care UK, who supported and facilitated the recruitment of study participants. The authors appreciate the support from Kath Wright (University of York) and Paolo Fraccaro (University of Manchester) with the literature review.

Author contributions. C.P.I., S.E. and A.M. developed the study concept; V.S.G., C.P.I., S.E. and L.H. were involved in data curation; V.S.G. and S.E. performed formal statistical analysis; C.P.I., S.E., and A.M. designed the methodology; V.S.G. and L.H. recruited study participants. V.S.G. wrote the first draft of the manuscript and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Funding statement. This research was funded by the Engineering and Physical Sciences Research Council (grant EP/P010148/1; The Wearable Clinic: Connecting Health, Self and Care).

Conflicts of interest. The authors declare that they have nothing to disclose.

Consent to participate. Patients had to provide electronic consent before taking part in the study.

Ethics approval. The study was approved by the University of Manchester's Research Ethics Committee and was conducted in accordance with the General Data Protection Regulation.

Availability of data and material. The datasets generated during and/or analyzed during the current study are not publicly available as no consent was sought from participants to allow sharing of data with third parties.

References

1. Damarell RA, Morgan DD, Tieman JJ. General practitioner strategies for managing patients with multimorbidity: A systematic review and thematic synthesis of qualitative research. *BMC Fam Pract*. 2020;**21**:131.
2. Taylor SJC, Pinnock H, Epiphaniou E, et al. A rapid synthesis of the evidence on interventions supporting self-management for people with long-term conditions: PRISMS - Practical systematic review of self-management support for long-term conditions. *Health Serv Deliv Res*. 2014;**2**:1–580.
3. Barlow J, Wright C, Sheasby J, Turner A, Hainsworth J. Self-management approaches for people with chronic conditions: A review. *Patient Educ Couns*. 2002;**48**:177–187.
4. Grey M, Schulman-Green D, Knafl K, Reynolds NR. A revised self- and family management framework. *Nurs Outlook*. 2015;**63**:162–170.
5. Hibbard JH, Stockard J, Mahoney ER, Tusler M. Development of the patient activation measure (PAM): Conceptualizing and measuring activation in patients and consumers. *Health Serv Res*. 2004;**39**:1005–1026.
6. Morton K, Dennison L, May C, et al. Using digital interventions for self-management of chronic physical health conditions: A meta-ethnography review of published studies. *Patient Educ Couns*. 2017;**100**:616–635.
7. Slevin P, Kessie T, Cullen J. A qualitative study of chronic obstructive pulmonary disease patient perceptions of the barriers and facilitators to adopting digital health technology. *Digit Health*. 2019;**5**:2055207619871729.
8. Bruno E, Simblett S, Lang A, et al. Wearable technology in epilepsy: The views of patients, caregivers, and healthcare professionals. *Epilepsy Behav*. 2018;**85**:141–149.
9. Singh K, Drouin K, Newmark LP, et al. Many mobile health apps target high-need, high-cost populations, but gaps remain. *Health Aff (Millwood)*. 2016;**35**:2310–2318.
10. Go AS, Chertow GM, Fan D, McCulloch CE, Hsu CY. Chronic kidney disease and the risks of death, cardiovascular events, and hospitalization. *N Engl J Med*. 2004;**351**:1296–1305.
11. Elshahat S, Cockwell P, Maxwell AP, et al. The impact of chronic kidney disease on developed countries from a health economics perspective: A systematic scoping review. *PLoS One*. 2020;**15**:e0230512.
12. Peng S, He J, Huang J, et al. Self-management interventions for chronic kidney disease: A systematic review and meta-analysis. *BMC Nephrol*. 2019;**20**:142.
13. Donald M, Kahlon BK, Beanlands H, et al. Self-management interventions for adults with chronic kidney disease: A scoping review. *BMJ Open*. 2018;**8**:e019814.
14. Jeddi FR, Nabovati E, Amirazodi S. Features and effects of information technology-based interventions to improve self-management in chronic kidney disease patients: A systematic review of the literature. *J Med Syst*. 2017;**41**:170.
15. Iglesias Urrutia CP, Erdem S, Birks YF, et al. People's preferences for self-management support. *Health Serv Res*. 2022;**57**:91–101.
16. Krahm M, Naglie G. The next step in guideline development: Incorporating patient preferences. *JAMA*. 2008;**300**:436–438.
17. Edelman N, Barron D. Evaluation of public involvement in research: Time for a major re-think? *J Health Serv Res Policy*. 2016;**21**:209–211.
18. Shields GE, Brown L, Wells A, Capobianco L, Vass C. Utilising patient and public involvement in stated preference research in health: Learning from the existing literature and a case study. *Patient*. 2021;**14**:399–412.
19. Clark MD, Determann D, Petrou S, Moro D, de Bekker-Grob EW. Discrete choice experiments in health economics: A review of the literature. *Pharmacoeconomics*. 2014;**32**:883–902.
20. 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**:403–413.
21. Lancsar E, Louviere J. Conducting discrete choice experiments to inform healthcare decision making: A user's guide. *Pharmacoeconomics*. 2008;**26**:661–677.
22. Hollin IL, Craig BM, Coast J, et al. Reporting formative qualitative research to support the development of quantitative preference study protocols and corresponding survey instruments: Guidelines for authors and reviewers. *Patient*. 2020;**13**:121–136.
23. Kitzinger J. Qualitative research. Introducing focus groups. *BMJ*. 1995;**311**:299–302.
24. Gale NK, Heath G, Cameron E, Rashid S, Redwood S. Using the framework method for the analysis of qualitative data in multi-disciplinary health research. *BMC Med Res Methodol*. 2013;**13**:117.
25. Chrzan K. Using partial profile choice experiments to handle large numbers of attributes. *Int J Mark Res*. 2010;**52**:827–840.

26. Kjøgaard ME, Bech M, Sogaard R. Designing a stated choice experiment: The value of a qualitative process. *J Choice Model*. 2012;5:1–18.
27. de Bekker-Grob EW, Donkers B, Jonker MF, Stolk EA. Sample size requirements for discrete-choice experiments in healthcare: A practical guide. *Patient*. 2015;8:373–384.
28. Thurstone LL. A law of comparative judgment. *Psychol Rev*. 1927;34:273–286.
29. Manski CF. The structure of random utility models. *Theory Decis*. 1977;8:229–254.
30. Cunningham CE, Deal K, Rimas H, et al. Using conjoint analysis to model the preferences of different patient segments for attributes of patient-centered care. *Patient*. 2008;1:317–330.
31. Erdem S, Thompson C. Prioritising health service innovation investments using public preferences: A discrete choice experiment. *BMC Health Serv Res*. 2014;14:360.
32. Hess S, Palma D. Apollo: A flexible, powerful and customisable freeware package for choice model estimation and application. *J Choice Model*. 2019;32:100170.
33. Krinsky I, Robb AL. On approximating the statistical properties of elasticities. *Rev Econ Stat*. 1990;72:189–190.
34. Piwek L, Ellis DA, Andrews S, Joinson A. The rise of consumer health wearables: Promises and barriers. *PLoS Med*. 2016;13:e1001953.
35. Frist WH. Connected health and the rise of the patient-consumer. *Health Aff (Millwood)*. 2014;33:191–193.
36. Kvedar J, Coye MJ, Everett W. Connected health: A review of technologies and strategies to improve patient care with telemedicine and telehealth. *Health Aff (Millwood)*. 2014;33:194–199.
37. Loncar-Turukalo T, Zdravevski E, Machado da Silva J, Chouvarda I, Trajkovik V. Literature on wearable technology for connected health: Scoping review of research trends, advances, and barriers. *J Med Internet Res*. 2019;21:e14017.
38. Hoos A, Anderson J, Boutin M, et al. Partnering with patients in the development and lifecycle of medicines: A call for action. *Ther Innov Regul Sci*. 2015;49:929–939.
39. Campbell J, Porter J. Dietary mobile apps and their effect on nutritional indicators in chronic renal disease: A systematic review. *Nephrology (Carlton)*. 2015;20:744–751.
40. Brooker AS, Carcone S, Witterman W, Krahn M. Quantitative patient preference evidence for health technology assessment: A case study. *Int J Technol Assess Health Care*. 2013;29:290–300.
41. Lin CC, Hwang SJ. Patient-centered self-management in patients with chronic kidney disease: Challenges and implications. *Int J Environ Res Public Health*. 2020;17:9443.
42. Wu RC, Ginsburg S, Son T, Gershon AS. Using wearables and self-management apps in patients with COPD: A qualitative study. *ERJ Open Res*. 2019;5:00036–2019.
43. Vosbergen S, Mulder-Wiggers JM, Lacroix JP, et al. Using personas to tailor educational messages to the preferences of coronary heart disease patients. *J Biomed Inform*. 2015;53:100–112.
44. Hibbard J, Gilbert H (2014) *Supporting people to manage their health: An introduction to patient activation* [Internet]; [Cited 2021 Aug 10]. Available at: https://www.kingsfund.org.uk/sites/default/files/field/field_publication_file/supporting-people-manage-health-patient-activation-may14.pdf.
45. Wong KK, Velasquez A, Powe NR, Tuot DS. Association between health literacy and self-care behaviors among patients with chronic kidney disease. *BMC Nephrol*. 2018;19:196.
46. Taylor DM, Fraser S, Dudley C, et al. Health literacy and patient outcomes in chronic kidney disease: A systematic review. *Nephrol Dial Transplant*. 2018;33:1545–1558.
47. Aguiar M, Harrison M, Munro S, et al. Designing discrete choice experiments using a patient-oriented approach. *Patient*. 2021;14:389–397.