Patient preferences for using remote care technology in heart failure: A discrete choice experiment

Ahmed Al-Naher, Jennifer Downing, Dyfrig Hughes, Munir Pirmohamed

Submitted to: JMIR Cardio
on: October 26, 2024

Table of Contents

Patient preferences for using remote care technology in heart failure: A discrete choice experiment

Ahmed Al-Naher[1] PhD, BSc, MBBS; Jennifer Downing[1] PhD; Dyfrig Hughes[1] PhD; Munir Pirmohamed[1] PhD, MB ChB

[1]Institute of Systems, Molecular and Integrative Biology (ISMIB) University of Liverpool Liverpool GB

Corresponding Author:
Jennifer Downing PhD
Institute of Systems, Molecular and Integrative Biology (ISMIB)
University of Liverpool
Block A: Waterhouse Buildings
1-5 Brownlow Street
Liverpool
GB

Abstract

Background: Remote care technology can bridge the gap between healthcare and community settings, provide more continuous and frequent monitoring of the disease process, and aid in self-care. A common barrier however is the lack of patient engagement with remote care technologies.

Objective: This discrete choice experiment elicits the preferences of heart failure patients with regard to remote care technologies, and in turn, creates a hierarchy of factors that can affect engagement.

Methods: A discrete choice experiment survey was designed with input from a patient group. The experimental attributes were based on five central themes (each of which had positive and negative levels): communication, clinical care, education, ease of use, and convenience. The survey allowed participants to trade attributes according to their preferences.
The survey was distributed to 93 participants with heart failure. The results were analysed using binary logit to obtain preference weights for each attribute.

Results: The binary logit created coefficients for each attribute, all of which were significant ($p<0.01$), and which equated to the relative preference of the associated themes: clinical care (2.022), education (1.252), convenience (1.245), ease of use (1.155) and communication (1.040). The most preferred factor, clinical care, had enough value to be traded for approximately any two other factors. Communication was the least preferred attribute.

Conclusions: Technology designers can use the associated preference weights to determine the relative increase of value perceived by patients by adding in certain attributes, and thus increase engagement from patients most likely to benefit from remote care.

(JMIR Preprints 26/10/2024:68022)
DOI: https://doi.org/10.2196/preprints.68022

Preprint Settings

1) Would you like to publish your submitted manuscript as preprint?
✓ **Please make my preprint PDF available to anyone at any time (recommended).**
Please make my preprint PDF available only to logged-in users; I understand that my title and abstract will remain visible to all users.
Only make the preprint title and abstract visible.
No, I do not wish to publish my submitted manuscript as a preprint.
2) If accepted for publication in a JMIR journal, would you like the PDF to be visible to the public?
✓ **Yes, please make my accepted manuscript PDF available to anyone at any time (Recommended).**
Yes, but please make my accepted manuscript PDF available only to logged-in users; I understand that the title and abstract will remain v
Yes, but only make the title and abstract visible (see Important note, above). I understand that if I later pay to participate in <a href="http

Original Manuscript

Patient preferences for using remote care technology in heart failure: A discrete choice experiment

Al-Naher Ahmed[1], Downing Jennifer[1], Hughes Dyfrig[1,2], Pirmohamed Munir[1]

[1]Institute of Systems, Molecular and Integrative Biology (ISMIB), University of Liverpool, UK
[2] Centre for Health Economics & Medicines Evaluation, Bangor University, UK

Corresponding author:
Dr Jennifer Downing
Institute of Systems, Molecular and Integrative Biology (ISMIB), University of Liverpool,
Block A: Waterhouse Buildings,
1-5 Brownlow Street,
Liverpool, UK, L69 3GL
E-mail: j.downing@liverpool.ac.uk

Word count: 2624

Patient preferences for using remote care technology in heart failure: A discrete choice experiment

Structured Abstract

Background:

Remote care technology can bridge the gap between healthcare and community settings, provide more continuous and frequent monitoring of the disease process, and aid in self-care. A common barrier however is the lack of patient engagement with remote care technologies.

Objective:

This discrete choice experiment elicits the preferences of heart failure patients with regard to remote care technologies, and in turn, creates a hierarchy of factors that can affect engagement.

Methods:

A discrete choice experiment survey was designed with input from a patient group. The experimental attributes were based on five central themes (each of which had positive and negative levels): communication, clinical care, education, ease of use, and convenience. The survey allowed participants to trade attributes according to their preferences.

The survey was distributed to 93 participants with heart failure. The results were analysed using binary logit to obtain preference weights for each attribute.

Results:

The binary logit created coefficients for each attribute, all of which were significant ($p<0.01$), and which equated to the relative preference of the associated themes: clinical care (2.022), education (1.252), convenience (1.245), ease of use (1.155) and communication (1.040). The most preferred factor, clinical care, had enough value to be traded for approximately any two other factors. Communication was the least preferred attribute.

Conclusions:

Technology designers can use the associated preference weights to determine the relative increase of value perceived by patients by adding in certain attributes, and thus increase engagement from patients most likely to benefit from remote care.

Keywords

Heart failure, Telehealth, Remote care, Engagement, Discrete choice, Medical devices

1 Introduction

1.1 Statement of Significance

Issue	Remote care technologies can provide access of care to those with chronic conditions such as heart failure. However, the drop-off rate for these devices are extremely high in this elderly population.
What is Already Known	A qualitative systematic review identified five themes that affect user engagement with remote care: communication, clinical care, education, ease of use, and convenience.
What this Paper Adds	This questionnaire elicits the preferences of these factors from the heart failure community, and so displays their relative importance for patients. This is significant as it helps the design and implementation of future remote technologies to improve engagement and access to care in this hard-to-reach cohort.

1.2 Background

Remote care technologies which can gather clinical data remotely enable closer monitoring of patients who are at high risk of day-to-day clinical variation.[1, 2] When designing new remote care interventions, it is essential to consider user engagement. Our systematic review of the perceived benefits and drawbacks of remote care, from a clinician, patient and carer viewpoint,[3] identified five common themes that can be used to describe the experiences of users when engaging with remote care technology: communication (increasing interaction between patients and healthcare staff/carers/ other patients), clinical care (improving the quality of care compared to established practice), education (providing tailored information to help with self-care and reduce uncertainty), ease of use (the technical aspects of the intervention are easy to handle without issues) and convenience (the intervention fits well around the patient's lifestyle and requires minimal effort). These themes capture user experience with minimal overlap. They are also amenable to being delineated in questionnaire form, which lends itself well to a choice-based survey.[4]

1.3 Aim

Our aim for this study was to understand the stated preferences of patients with heart failure in relation to remote care technology, using these 5 themes. This can be done using choice-based surveys [5] such as discrete-choice experiments (DCE). In a DCE, remote care technologies can be described by variables of interest or 'attributes'. Respondents' willingness to trade one attribute against another in different scenarios allows a quantification of the relative importance of each attribute,[6] and provides evidence on respondents' stated preferences for a given technology. We therefore designed a DCE to gather opinions from patients living with heart failure on preferences in remote care using our five themes.[3]

2 Methods

Since our themes were generated from grounded theory, their titles may be interpreted in a variety of ways. We therefore created clear descriptions for each attribute in relation to remote care (see Table 1). For each attribute we chose two 'levels', positive and negative, corresponding to the level of attainment of any given attribute, with 'neutral' included as a 'negative' level. [7, 8]

2.2 Questionnaire construction

Each question forced the participant to choose between two hypothetical remote care technologies with opposing attribute levels i.e. a positive level in an attribute in one choice means that the alternative choice will have the negative level of that same attribute. The forced choice design reduced the complexity of adding an opt-out alternative to each question; which minimised questionnaire fatigue.[9]

The choice sets (the combination of levels of each attribute that were grouped together per question) were assigned based on a pre-determined, orthogonal design algorithm.[10] For a discrete choice questionnaire containing 5 attributes each with 2 levels, this resulted in 16 questions. The order of the questions was randomised to mask the pattern of the choice sets. The attributes were listed in alphabetical order in each question.[11, 12]

2.3 Sample size

We used an established method for determining the minimum sample size for conjoint analyses:[13]

$$N > \frac{500 \times c}{t \times a}$$

Where (N) is the minimum sample size; (c) is the number of levels; (t) is the number of questions; and (a) is the number of alternative answers.

For a 16-question survey with 2 choices, the recommended minimum response size is 32 participants. We took this as a minimum, and left the online survey open until the end of the study window to capture as many responses as possible.

2.4 Criteria for patient participation

Inclusion criteria:

1. Aged 18 years or over.
2. Diagnosis of chronic heart failure.

Exclusion criteria:

1. Diagnosis of acute heart failure without any chronic component.
2. Non-English speaking patients (questionnaire only available in English).

2.5 Patient and Public Involvement

A patient participation group was formed to aid the outputs of the research consisting of five patients from local cardiology clinics. The group piloted the questionnaire, and had input into the patient information leaflet. Design changes were made due to this feedback, including shortening the questions and formatting for better readability. Furthermore, they helped to distribute the survey to online heart failure communities (see Supplementary Data 1-4).

2.6 Consent and ethics

As per HRA guidance,[14] responses to online surveys imply consent as long as participants are provided with sufficient information to reach an informed decision. We worked with our patient group to develop substantial participant information. This study was approved by the REC at the University of Liverpool (ref: 3314).

2.7 Analysis

Responses were analysed using limited dependent-variable models to determine preference weights of each attribute.[15] From this, we can infer which attributes participants are willing to trade in favour of others. Our DCE is a forced-choice, five-attribute, two-level, two-alternative questionnaire. As both the choices and the levels were binary, binary logit[15] was used determine the likelihood of the outcome. The logarithmic function ensures the likelihood values are constrained between 0 and 1.[16] The logit definition is as follows:[17]

Logit(P) = log(odds) = log(P/(1-P))

As part of the regression, we assign logit(P) as a linear function of any given attribute Xi, so that:

$$\log \frac{P}{(1-P)} = \alpha + \beta Xi = Ui$$

Where: P = probability (of choosing this option); α = reference value or constant; β = coefficient of attribute X; i = attribute number; U = utility

The logit value is proportional to the odds of an attribute, affecting the probability of choosing an alternative. Thus, these values can be compared directly as preference weights for each variable. The preference value for each attribute is known as utility, which is the measure of importance of each attribute or combination of attributes. In order to standardise for participant heterogeneity, random effects were added to create a mixed binary logit model.[17, 18]

The utility value of each combination of attribute level was obtained by adding the constant coefficient of attribute X from the logit model, with the coefficients of each positive attribute present. The odds were obtained by exponentiating the utility. To convert this to percentage probability, i.e. the likelihood of choosing this remote care device as opposed to the alternative, we divided the Odds by 1+Odds.[19] The dataset was analysed using RStudio version 1.0.136. These calculations were also corroborated using STATA/MP 13.0.

3 Results

The survey was open to the public for 133 days (3/6/18 – 14/10/18) and was initiated by 164 participants. The completion rate was 57%, giving 94 completed responses. A limited trial of the paper questionnaire was undertaken in local heart failure clinics, but this generated only 1 completed response. Response non-differentiation was identified, and two responses were omitted due to non-trading (all responses from a participant were either the A choice or the B choice). This left 93 valid responses. The raw data for the online responses are available in Supplementary Data 5.

We identified some positive attribute dominance in the responses (respondent always chose the option with a positive level in a single attribute): 10 participants had positive dominance for 'clinical care', three for 'education', two for 'ease of use' and one for 'communication'. There were no cases of negative attribute dominance. The main outputs of the mixed binary logit are displayed in Table 2.[20]

Each coefficient was highly statistically significant, indicating that there was a sufficient sample size and significant effect of each attribute on patient choice. The goodness of fit was evaluated using the pseudo R-squared of the logit model, which showed a value 0.1833. The attributes presented in the model thus explain 18% of the variance in choice of each participant, a typical result for a DCE of this size.[21]

We calculated the utility value, odds ratio and percentage probability of choosing each combination of attribute levels (Table 3). The utility represents the preference value for choosing each alternative and can be compared for evaluating complete choice sets (different combinations of attributes). This contrasts with coefficient values for each attribute, calculated from the logit model, which indicates preferences for individual attributes.

3.1 How to use the data for comparative analysis: a worked example

To compare two different types of intervention, e.g. with and without a certain attribute included, we calculate the ‘marginal probability’ or difference in preference percentage probabilities between the two interventions. This can be done by choosing the row which most corresponds to each individual remote care device, and then subtracting the percentage probabilities from each other to get the difference in probability. For example, in a remote care intervention with no attributes present (0/0/0/0/0), the percentage probability of choosing this device compared to one with 0 utility is 3.37% (Table 3). The marginal probability gained by adding the attribute of ‘communication’ to this intervention (1/0/0/0/0) is 8.98 – 3.37 = +5.61%. However, the marginal probability of adding ‘clinical care’ instead (0/1/0/0/0) is 20.83 – 3.37 = +17.46%. Taking the mean of marginal probabilities for adding the attribute to each permutation which excludes it gives a quantitative measure of patient preference. We found the mean marginal probabilities per attribute to be as follows: ‘communication’ = +18.04%, ‘ease of use’= +20.1%, ‘convenience’ = +21.76%, ‘education’ = +21.9%, and ‘clinical care’ = +37.55%. These values could also be interpreted as the relative increase in patient preference gained by adding this attribute to an intervention that lacks it.

4 Discussion

The analysis ranked the remote care attributes in the following order of importance: 1. Clinical Care; 2. Education; 3. Convenience; 4. Ease of Use; and 5. Communication. Based on the coefficients of the logit fit, ‘clinical care’ was almost twice as important as the lowest scoring variable, ‘communication’. Remote care technology design should therefore prioritise clinical care improvements first and foremost. The attributes of ‘education’ and ‘convenience’ had similar preference values, which were around 20% greater than ‘communication’. ‘Ease of use’ was 11% more important than ‘communication’. Therefore, if a trade-off is required, any other attribute may be sacrificed for the sake of preserving ‘clinical care’, whilst still incentivising patient engagement.

Among the advantages of our experiment was that each possible combination of levels and attributes was presented to the participants, resulting in a full factorial design. This establishes a more accurate statistical value for each preference as fewer assumptions are made. By contrast, partial factorial designs sacrifice comprehensiveness for brevity.[22] Another strength is that the attributes used were based on evidence from a grounded theory qualitative systematic review, specific to the subject. This means that the outputs of the review were tailored to this questionnaire design, resulting in relevant attributes derived from high quality evidence.

There have been no other DCEs evaluating remote care technologies in this patient cohort. Therefore the study provides a valuable insight into the factors of remote care devices that encourage engagement.

In a post-COVID era, remote care technologies have gained greater importance in healthcare. Heart failure patients are a vulnerable cohort, and so are more likely to be offered remote consultation. Therefore these preference rankings are all the more vital at this time, to help remote care become better established in medical practice for those that need it most.

Our study does have some limitations. The statistical model assumes each participant will always choose the option which maximises their utility, which could lead to bias. We tried to mitigate this by adding a random effect to model heterogeneity of preference choices, even if they might be irrational (or of less utility). This study therefore presents the preference values in terms of a probability of choosing each option, which means the likelihood of a non-rational choice still exists. Also, the effects of the recorded attributes are presented in relation to one another, and relies on the foundation of its supporting research to substantiate the list of tested attributes.[6] Finally, the experiment assumes that the participant is equally attentive on question 1 as they are on question 13, and this may not always be the case.[23]

In many DCEs, the alternative choices are based on existing interventions or ones which are ready to market. In this study, we asked participants to imagine theoretical technologies. This enables the outputs to be applied to a wide variety of technology designs in the future. A disadvantage is the potential for hypothetical bias which can lead to a discrepancy between patient stated preference and the actual preference.[24]

The online self-selection method may reduce the generalisability of the study findings to other cohorts such as in-person heart failure clinics. However, these cohorts may be fewer in a post-COVID era, where patients are more likely to be familiar with remote care. Our findings should nevertheless be interpreted within the context of patients who are generally supportive of new technology.[25]

We had the option of creating either an 8-question design or a 16-question design. We opted for the latter to obtain a greater statistical effect from each respondent. In hindsight this may have led to the large percentage of non-completers. Future questionnaire designers should consider that reducing the number of questions, while limiting the range of the alternatives presented, could lead to a higher completion rate.[23]

5 Conclusions

We demonstrate an intuitive and simple way to predict the level of engagement and preference of patients based on the attributes of remote care. Technology designers should consider the use of these findings to check the effectiveness of an intervention's features in engaging the patient user-base. This will help develop a working plan of improvement for devices based on their missing attributes. While this study focuses on patient preference, it will be up to the third party to determine other practical aspects of technology refinement such as cost, administration, and resources, to judge whether the change is worthwhile. However, by taking the first steps to quantify the level of engagement gained from each change, we hope to make this decision easier for those that seek to bring remote care technology to these patients in an effective and engaging manner, to reduce the burden of morbidity from heart failure.

6 Acknowledgements

We acknowledge the vital input from the heart failure patient group at Liverpool Heart and Chest Hospital, in overseeing the questionnaire and patient information leaflets. We would in particular like to thank Lynn Hedgecoe who was instrumental in distributing the survey to patient groups as well as reviewing the manuscript from a patient perspective.

7 Funding

This work was supported by the National Institute for Health Research, Applied Research Collaboration, North West Coast (NIHR ARC NWC). The views expressed are those of the author(s) and not necessarily those of the NHS, the NIHR or the Department of Health and Social Care. For the purpose of Open Access, the author has applied a Creative Commons Attribution (CC-BY) licence to any Author Accepted Manuscript version arising.

8 Conflicts of Interest

MP has received partnership funding for the following: MRC Clinical Pharmacology Training Scheme (co-funded by MRC and Roche, UCB, Eli Lilly, and Novartis); Joint PhD funding from EPSRC and Astra-Zeneca, and grant funding from VistaGen Therapeutics. He also has unrestricted educational grant support for the UK Pharmacogenetics and Stratified Medicine Network from Bristol-Myers Squibb. He has developed an HLA genotyping panel with MC Diagnostics, but does not benefit financially from this. MP is also part of the IMI Consortium ARDAT. None of these funding sources were used for the work presented in this paper.

9 References

1. Thomas EE, Taylor ML, Banbury A, Snoswell CL, Haydon HM, Gallegos Rejas VM, et al.Factors influencing the effectiveness of remote patient monitoring interventions: A realist review *BMJ Open* 2021; 11(8):e051844.
2. McLean S, Sheikh A, Cresswell K, Nurmatov U, Mukherjee M, Hemmi A, et al.The impact of telehealthcare on the quality and safety of care: A systematic overview *PLOS ONE* 2013; 8(8):e71238.
3. Al-Naher A, Downing J, Scott KA, Pirmohamed M.Factors affecting patient and physician engagement in remote health care for heart failure: Systematic review *JMIR Cardio* 2022; 6(1):e33366.
4. Thomas J, Harden A.Methods for the thematic synthesis of qualitative research in systematic reviews *BMC medical research methodology* 2008; 8:45.
5. Ryan M, Watson V.Comparing welfare estimates from payment card contingent valuation and discrete choice experiments *Health economics* 2009; 18(4):389-401.
6. Ryan M, Bate A, Eastmond CJ, Ludbrook A.Use of discrete choice experiments to elicit preferences *Quality in health care : QHC* 2001; 10 Suppl 1:i55-60.
7. Coast J, Al-Janabi H, Sutton EJ, Horrocks SA, Vosper AJ, Swancutt DR, et al.Using qualitative methods for attribute development for discrete choice experiments: Issues and recommendations *Health economics* 2012; 21(6):730-741.
8. Penn J. The effect of forced choice with constant choice experiment complexity. In Agricultural & Applied Economics Association's 2014 AAEA Annual Meeting. Minneapolis. 2014.
9. Le A, Han BH, Palamar JJ.When national drug surveys "take too long": An examination of who is at risk for survey fatigue *Drug and Alcohol Dependence* 2021; 225:108769.
10. Kocur G, Adler T, Hyman W, Aunet B Guide to forecasting travel demand with direct utility assessment Transportation USDo 1982.
11. Lancsar E, Fiebig DG, Hole AR.Discrete choice experiments: A guide to model specification, estimation and software *PharmacoEconomics* 2017; 35(7):697-716.
12. Reed Johnson F, Lancsar E, Marshall D, Kilambi V, Muhlbacher A, Regier DA, et al.Constructing experimental designs for discrete-choice experiments: Report of the ispor conjoint analysis experimental design good research practices task force *Value in health : the journal of the International Society for Pharmacoeconomics and Outcomes Research* 2013; 16(1):3-13.
13. de Bekker-Grob EW, Donkers B, Jonker MF, Stolk EA.Sample size requirements for discrete-choice experiments in healthcare: A practical guide *The patient* 2015; 8(5):373-384.
14. HRA Applying a proportionate approach to the process of seeking consent Authority HR 2017.
15. Hauber AB, Gonzalez JM, Groothuis-Oudshoorn CG, Prior T, Marshall DA, Cunningham C, et al.Statistical methods for the analysis of discrete choice experiments: A report of the ispor conjoint analysis good research practices task force *Value in health : the journal of the International Society for Pharmacoeconomics and Outcomes Research* 2016; 19(4):300-315.
16. Tabatabai MA, Li H, Eby WM, Kengwoung-Keumo JJ, Manne U, Bae S, et al.Robust logistic and probit methods for binary and multinomial regression *Journal of biometrics & biostatistics* 2014; 5(4).
17. Berger D. **Introduction to binary logistic regression and propensity score analysis**. In: Claremont Graduate University; 2017.
18. Parzen M, Ghosh S, Lipsitz S, Sinha D, Fitzmaurice GM, Mallick BK, et al.A generalized linear mixed model for longitudinal binary data with a marginal logit link function *The annals of applied statistics* 2011; 5(1):449-467.
19. Sperandei S.Understanding logistic regression analysis *Biochemia medica* 2014; 24(1):12-18.
20. Lindberg MA.The development of attribute dominance in the knowledge base *The Journal of genetic psychology* 1989; 150(3):269-280.

21. Soekhai V, de Bekker-Grob EW, Ellis AR, Vass CM.Discrete choice experiments in health economics: Past, present and future *PharmacoEconomics* 2018.
22. Dobra RA, Boeri M, Elborn S, Kee F, Madge S, Davies JC.Discrete choice experiment (dce) to quantify the influence of trial features on the decision to participate in cystic fibrosis (cf) clinical trials *BMJ Open* 2021; 11(3):e045803.
23. Bansback N, Hole AR, Mulhern B, Tsuchiya A.Testing a discrete choice experiment including duration to value health states for large descriptive systems: Addressing design and sampling issues *Social science & medicine* 2014; 114:38-48.
24. Liljas B, Blumenschein K.On hypothetical bias and calibration in cost-benefit studies *Health policy* 2000; 52(1):53-70.
25. Cravo Oliveira T, Barlow J, Bayer S.The association between general practitioner participation in joint teleconsultations and rates of referral: A discrete choice experiment *BMC family practice* 2015; 16:50.

Table 1 Descriptions of each attribute and level in the discrete choice experiment

Attribute	Description	Level	Level Description
Communication	The ability of the technology to create increased contact and follow up between patients and others, including healthcare staff, family, carers or other patients	0	Reduces or does not improve opportunities for contact and communication
		1	The technology increases opportunities for contacts and communication
Clinical Care	The technology in some way affects the current clinical care given to the patient for their heart failure condition.	0	The technology makes no impact or even worsens current clinical care
		1	Improves clinical care from current practice, or provides more options for medical management, including providing information to make better decisions on care
Education	The impact of the technology on patients' knowledge about their health and self-care	0	There is no improvement in knowledge or ability to self-care
		1	The technology provides details that clarifies and provides useful information to the patient about their condition and aids in their self-care and management
Ease of Use	The intuitiveness and relative ease that the technology can be introduced and used by new users, including technical difficulties and jargon	0	The technology is overly complex, with little technical support and may have a high rate of technical difficulties and complications, or is difficult to access for new users
		1	The technology is easy and intuitive to use, requires relatively little support, or is easy to understand and use by a wide audience
Convenience	The measure of how much time and effort is saved by the use of the technology compared to normal care. Also relates to the level of comfort afforded by the technology in the patient's home.	0	There is no difference in the amount of time and effort required for self-care actions, or the device creates more work for the patient and requires extra time to use, or it creates increased worry or stress
		1	The device functions to save time, such as automating processes or providing relevant information at the right time, and results in less work for self-care actions, or allows the patient to be more comfortable in their own home environment

Table 2 Coefficient values for each theme based on mixed model binary logit

Attribute	Coefficient	95% Confidence Interval		p-value
(Intercept)	-3.357	-3.654	-3.060	p<0.001
Clinical Care	2.022	1.810	2.233	p<0.001
Education	1.252	1.077	1.428	p<0.001
Convenience	1.245	1.053	1.436	p<0.001
Ease of Use	1.155	0.982	1.327	p<0.001
Communication	1.040	0.864	1.216	p<0.001

Table 3 Utility, odds, and percentage probability values for all 32 combinations of attributes

Communication	Clinical care	Education	Ease of use	Convenience	Utility	Odds	% probability
1	1	1	1	1	3.36	28.70	96.63%
0	1	1	1	1	2.32	10.14	91.02%
1	1	1	0	1	2.20	9.05	90.05%
1	1	1	1	0	2.11	8.27	89.21%
1	1	0	1	1	2.10	8.20	89.13%
1	0	1	1	1	1.34	3.80	79.17%
0	1	1	0	1	1.16	3.20	76.17%
0	1	1	1	0	1.07	2.92	74.49%
0	1	0	1	1	1.06	2.90	74.35%
1	1	1	0	0	0.96	2.61	72.26%
1	1	0	0	1	0.95	2.59	72.11%
1	1	0	1	0	0.86	2.36	70.26%
0	0	1	1	1	0.29	1.34	57.32%
1	0	1	0	1	0.18	1.20	54.50%
1	0	1	1	0	0.09	1.09	52.26%
1	0	0	1	1	0.08	1.09	52.07%
0	1	1	0	0	-0.08	0.92	47.93%
0	1	0	0	1	-0.09	0.91	47.74%
0	1	0	1	0	-0.18	0.83	45.50%
1	1	0	0	0	-0.29	0.74	42.68%
0	0	1	0	1	-0.86	0.42	29.74%
0	0	1	1	0	-0.95	0.39	27.89%
0	0	0	1	1	-0.96	0.38	27.74%
1	0	1	0	0	-1.06	0.35	25.65%
1	0	0	0	1	-1.07	0.34	25.51%
1	0	0	1	0	-1.16	0.31	23.83%
0	1	0	0	0	-1.34	0.26	20.83%
0	0	1	0	0	-2.10	0.12	10.87%
0	0	0	0	1	-2.11	0.12	10.79%
0	0	0	1	0	-2.20	0.11	9.95%
1	0	0	0	0	-2.32	0.10	8.98%
0	0	0	0	0	-3.36	0.03	3.37%

Supplementary Files

Multimedia Appendixes

Supplemental Data 1: Participant information sheet for discrete choice experiment.
URL: http://asset.jmir.pub/assets/9eb5c0e8573371885128adbbb957f5b2.docx

Supplemental Data 2: Instructions for answering questionnaire.
URL: http://asset.jmir.pub/assets/16c16ef548693ceeb2dbcabc99c40cdd.docx

Supplemental Data 3: Discrete choice experiment questionnaire.
URL: http://asset.jmir.pub/assets/3063d56d6e31532454c964176609ecfe.docx

Supplemental Data 4: Charities, organisations and social groups approached for distribution of the survey online to heart failure patients.
URL: http://asset.jmir.pub/assets/05d62a58a50a2813abc37464fd5063ce.docx

Supplemental Data 5: Online questionnaire responses.
URL: http://asset.jmir.pub/assets/5a498621a30cadccc25429a2c72cfe79.docx