Feedback preferences in health technology: the influence of health locus of control and educational level

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Abstract

The use and development of personal health technologies provides opportunities for narrowing health disparities due to its great accessibility. However, these technologies often fail to help these vulnerable populations, due to barriers such as educational level, ease of use and low adherence. This survey study investigates the relationship between Health Locus of Control (HLOC, independent variable), educational level (covariate), and feedback style preferences (dependent variable). A total of 72 participants were recruited through simple random sampling in Groningen, the Netherlands. Logistic regression models were conducted to analyze the data on feedback style for each orientation in HLOC respectively. Results showed that Doctor HLOC significantly predicted a preference for complex feedback graphs ($\chi^2 = 6.421$, $p = .040$), while Internal and Chance HLOC, along with education did not significantly influence feedback preferences. The findings of this study suggest that HLOC and educational level do not provide a clear association with feedback style preference. There is a need for better assessment methods for feedback preferences and more studies with large, demographically diverse samples.

Keywords: Locus of Control, Information Seeking, mHealth, Health Gap, Socioeconomic Status, User Needs, Personalization

Feedback preferences in health technology: the influence of health locus of control and educational level.

The development of easily accessible health technologies provides an opportunity for narrowing health disparities and decreasing healthcare costs (Dunn et al., 2018), however, achieving this is not as simple as it seems. Despite the fact that as many as nearly half of smartphone users have a health app on their phone (Pagoto et al., 2025), individuals struggle with using them for prolonged times (Helander et al., 2014; Jacob et al., 2022). Timmermans & Kaufman (2020) highlight the possibility of these technologies to have the opposite effect than intended and widen the health gaps due to lower ease of use and accessibility in certain demographic groups. Health inequities - or the health gap - is a concept that has been widely studied in literature. It shows how disadvantaged populations such as racial or ethnic minorities and low education and income populations tend to get less access to healthcare and lower quality of medical care (Riley, 2012) and have higher mortality rates, even when controlling for risk factors (Stringhini et al., 2017). Moreover, health app usage tends to depend on variables such as health knowledge and health literacy (Jacob et al., 2022), which tend to be lower in people that are part of disadvantaged populations. Thus, health technologies are not as helpful to the populations that could benefit from them most. These aspects point to the existence of factors that prevent technologies from having their desired positive effects, such as helping people gain control of their health, engage more in preventative health behavior, and achieve better health outcomes (Mair et al., 2023; Marcolino et al., 2018). However, if individuals do not believe they can have any influence on their health, this could be a barrier to their usage of those technologies.

Health Locus of Control and Health Outcome

The Health Locus of Control (Wallston, 1978) is a scale based on the construct of locus of control from Rotter's Social Learning Theory (1966). This theory divides the control one feels that they have over their own health into three categories. Those who lean towards an internal orientation feel that their health is within their control. Those with powerful others/ doctor orientation (external) believe that their health is in a doctor's or medical professional's control and those with chance orientation (external) believe that their health is randomly determined. Having an external HLOC is related to worse health outcomes consistently compared to the internal type across research (Berglund et al., 2014). Within the external dimension, those belonging to powerful others have better health outcomes (Burns & Mahalik, 2006) and more engagement with health behaviors (Stephenson-Hunter, 2018) compared to chance. This is because the former group, powerful others, tends to follow doctor's recommendations best, while the latter group dismisses them due to the feeling that nothing they do and none of the doctor recommendations could have a positive effect on their health (Wang et al., 2021).

Health Locus of Control and SES

HLOC varies across socioeconomic groups, populations with high education and income tend to have an internal HLOC, while minorities and low education and income groups tend to have an external HLOC (Rodriguez et al 2023). This link has been hypothesized to be due to the more frequent occurrence of adverse life events, lower access to resources and higher levels of stress amongst these groups (Culpin et al., 2015). Moreover, HLOC has an influence on the relationship between childhood SES and adulthood health behaviors (Pedron et al., 2020) and mediates the relationship between SES and self-rated health (Poortinga et al., 2007). Lifestyle and stressful events have an important role in the way an individual perceives control; these factors can shift LOC over time (Nowicki et al., 2018). Therefore, it seems that the relationship between SES and HLOC forms a feedback loop,

where adverse circumstances and learned helplessness led to increases in external orientation, which in turn leads to less engagement in health behaviors and worse self-rated health. Health technology has the potential of disrupting that feedback loop by providing external users with appropriate feedback that can increase their motivation and perceived control. The feedback can differ based on individual preferences such as preferred amount of information, favored treatment and communication style in the medical setting. These have been found to interact with HLOC in predicting treatment adherence and outcome (Rodriguez et al., 2023; Wallston, 1978).

User preferences

The construct of user preferences is very complex and multifaceted, being influenced by lots of variables, such as culture, social context and past experiences. Personalization and catering to individual user preferences is very important, as it can have a strong impact on users' adherence to health technology, but also on how effective health apps are in aiding people to improve their health (Sun et al., 2021). The research so far on user preferences and HLOC suggests that the desired amount of information a patient expects from their doctor differs, with internals wanting more information, while externals prefer less information from their doctors (Rodriguez et al., 2023). Internals seem to benefit more from interventions that require a high level of personal engagement, while externals may feel overwhelmed by those situations and prefer programs that offer more support and require less personal engagement (Wallston, 1978). It has been shown that a mismatch between patient and provider engagement is harmful towards treatment outcome and adherence (Rodriguez et al., 2023), thus it can be inferred that a similar effect could be happening with health apps. Personal health technology by itself seems to usually require a high level of education and desire for control over one's health, which reflects in the demographics of users, which tend to be on average, younger, more educated, have a higher income (Bol et al., 2018) and have an internal

HLOC (Bennet et al., 2017). By catering to the needs of disadvantaged populations and of those with a more external locus of control, there is potential for narrowing the health gap.

Overall, research on user preferences of disadvantaged populations in health technology is scarce and many articles highlight a need for research with more diverse demographics (McGowan et al., 2022; Rodriguez et al., 2023). This study aims to examine the user preferences of people with different HLOC while accounting for different economic and educational backgrounds, in order to provide a better understanding of their needs. The importance of this lies in the increased vulnerability of the disadvantaged populations to health issues, due to their reduced engagement in preventative health behaviors (Dogonchi et al., 2022). If technology is designed with their needs in mind, this can reduce the influence of barriers to usage and help improve their health outcomes. The main objective is investigating whether users with low education, low income and external HLOC would prefer a simpler interface with a more encouraging message, rather than receiving complex information. The hypotheses for the current study are therefore proposed:

H1a: doctor HLOC and low education are associated with preference for a more positive, simple message

H1b: chance HLOC and low education are associated with preference for a more positive, simple message

H1c: internal HLOC and high education are associated with preference for a more positive, simple message

Methods

Design and Participants

This study employed a cross-sectional correlational design to examine the influence of HLOC and education in determining feedback style preferences. A total of 70 participants were included in the study after screening for incomplete responses. The sample had participants aged between 17 and 87 years (M = 40.78, SD = 20.69), of which 54.3% were male and 44.3% female; 1.4% preferred not to answer. The exclusion criteria concerned people under the age of 16, those who did not speak English or Dutch and lack of consent.

Procedure

Participants for this study were recruited randomly from a pool of individuals approached in public locations in Groningen, including Forum, Vinkhuizen, Paddepoel, and the Groningen Central train station. The researchers approached participants, informed them about the study, and invited them to participate. Data collection lasted for a period of approximately three weeks in November-December 2024. The estimated time for completion is 15-30 minutes. Participants could complete the survey on-site using a tablet provided by the researchers or scan a QR code to participate at their convenience. The tablet was given to the participants with the webpage of the survey pre-loaded in Qualtrics (Version 3, Copyright © 2024 Qualtrics).

Informed consent was obtained at the beginning and end of the questionnaire, where participants were presented with details about the study's purpose, their rights as participants, and data privacy. The last question of the survey asked for a reconfirmation of their consent. Participation was voluntary; incentives were provided in the form of Coffee and Tea, Snacks and participation in a raffle. This raffle was done immediately after the survey in person and required no additional personal information. On the basis of a checklist developed by the EC-

BSS at the University of Groningen, the study was exempt from full ethical review (EC code: PSY-2425-S-0063).

Measurements

The study used a self-designed questionnaire consisting of a combination of published scales and self-developed items collaboratively created by a group of six thesis students. The questionnaire consists of several sections tailored to individual research interests. Shared sections included the general information about the study, informed consent, and demographic questions. Before finalizing the questionnaire, a pilot test was conducted with 22 participants completing the Dutch version. This test was used to evaluate the reliability and validity of the items. Based on the feedback from the participants and the contribution of the items to the reliability of the scale, the questionnaire was refined and reduced from its original 89 items to 69 items. Data was collected digitally to ensure ease of analysis and storage.

Demographics

The first part collected demographic information, which included the variables: age, gender, highest completed degree, education and annual net income. Age was assessed using a dropdown menu with birth years from 1923 up to 2007. Gender was assessed with a multiple-choice question, offering four options: “Male”, “Female”, “Non-binary” and “Prefer not to specify”. The highest completed degree was assessed through a dropdown menu with fourteen possible answer options covering the entire educational system in the Netherlands. Annual net income was assessed using a slider-based item, with a range between 0 and 100 (in thousands). These demographic variables were used to describe the sample.

Health technology use

The second part concerned the participant’s personal health technology usage. The first question assesses whether they use it or not, offering four options: “Yes, through apps”,

"Yes, through wearables", "Yes, but not any of the ones mentioned above" and "No". If the answer was "No", the follow-up questions that assessed which health measurements were tracked ("heart rate", "sleep parameters", "calorie burn" etc.) and frequency ("daily", "weekly", etc.) were automatically skipped.

Health Locus of Control

HLOC was measured using the Multidimensional Health Locus of Control questionnaire (MHLC, Wallston et al., 1978). The Dutch questionnaire that was used in this study shows good internal consistency and has been validated (Halfens RJG., 1985). The MHLC is an 18 item self-report questionnaire. It measures the subject's HLOC using a Likert scale from 1 (strongly agree) to 7 (strongly disagree). The questionnaire measures scores across three dimensions: internal ("If I get sick it is my own behavior that determines how soon I get well again."), external powerful others/doctors ("Medically trained professionals have a lot of influence on whether I stay healthy or not.") and external chance ("Whether or not I stay healthy is a matter of chance."). For this study only the nine most reliable items were kept, based on the item-total correlations (*r.drop* < 0.3) and the reliability if an item was dropped (*raw_alpha* increased when item was dropped). In research, the MHLC has been shown to be moderately reliable with Cronbach alphas of .60 – .75 (Wallston, 2005). The reliability is .746 in the pilot sample and .305 in the study sample.

Feedback style

The user preferences are assessed through two questions with two answer options each. The first question consists of two different answer options which are illustrations depicting two types of feedback texts one could get from a health app. One type is a simple, encouraging message ("Great job! Your BMI dropped by 0.6, enhancing your health. Regular activity helps your heart get stronger and makes your muscles work better. Keep going!"), the other type is more informative and complex ("Your regular exercise and a 0.6 decrease in

BMI promote cardiovascular fitness and optimize muscle performance."). The second question presents the users with two blood pressure graphs. One of them simply shows the current value along with the encouraging message "You are doing great!", while the other one shows a trend of values over a period of time along with the current measurement. (see Image 1A)

Data Analysis

Statistical Analysis

Data was analysed using IBM SPSS Statistics (Version 30). Descriptive statistics were first computed to assess the distributions of the variables and check for any violation of assumptions.

The main analysis consists of three logistic regressions per preferred feedback question. Feedback preference is the dependent variable in all three analyses and with the variable type being binary, the logistic regression analysis was chosen. The answers indicating a preference for simple feedback were coded as "*0"* and the ones indicating preference for complex feedback were coded as '1'. Each HLOC dimension (chance, internal and doctor) will be treated as a continuous, independent variable (IV) in these analyses. The values for each scale were computed according to the test instructions (Halfens RJG., 1985), by adding up the values of the three questions for each scale in order to determine the score of the participants on each facet (internal = q1 + q3 + q7, doctor = q2 + q4 + q6, chance = q5 + q8 + q9). Education was coded as an ordinal variable with three scales: low, medium, high. This was done by coding the values in the dataset as '1' (low) for primary school, Ibo, vbo, homeschool, ihno, vmbo 1-3 and mbo 1-2, '2' (medium) for ulo, mulo, mavo, vmbo-4, mbo 3-4, VWO, atheneum, gymnasium, havo, and '3' (high) for university of applied sciences, university and post-academic. The dependent variables for feedback were coded as follows:

FBtxt for the text feedback style question, and FBimg for the graph feedback style question. In order to test the model fit of the logistic regression models, the Chi square test was used. There will be three logistic regressions performed for each of the two feedback styles (FBimg and FBtxt, see **Image A1 and A2**). Each of the three regression models will test the effect of a HLOC dimension (internal/ doctor/ chance) on feedback preference when accounting for education.

Power Analysis

A priori power analysis was conducted within G*Power 3.1. for a two-tailed analysis at odds ratio of 1.4, desired power of 0.9 and significance level at $\alpha = 0.05$ indicated that a minimal sample size of N = 111 was needed to validly detect the effects for the hypothesized associations.

Results

Sample characteristics

A total of 70 individuals (31 women, 38 men, 1 preferred not to answer) completed the questionnaire. Participants aged between 17 to 87 years (M = 40.79, SD = 20.69), with an overall education level medium to high (5.7% low, 48.6% medium and 45.7% high). The sample had higher scores on the doctor HLOC scale, compared to chance and internal HLOC (See **Table 1, 2**).

Table 1:

Descriptives of continuous variables

Continuous Variable		N	Min	Max	Mean	Std. Deviation
Age		70	17.00	87.00	40.786	20.690
HLOC						
	Internal	70	5.00	18.00	9.843	2.517
	Doctor	70	6.00	16.00	11.700	2.515
	Chance	70	5.00	15.00	9.557	2.529
Income		43	12.00k	100.00k	33.326k	19.706

Table 2:

Descriptives of categorical variables

Categorical Variable		Frequency	Percent
Education	*low*	4	5.7
	medium	34	48.6
	high	32	45.7

Gender	*male*	38	54.3
	female	31	44.3
	prefer not to answer	1	1.4
Tech Use	*yes*	28	40.0
	no	42	60.0
FBtxt	*simple*	49	70.0
	complex	21	30.0
FBimg	*simple*	33	47.1
	complex	37	52.9

Internal HLOC and Feedback Preference

FBtxt (DV) and internal HLOC & education

A binary logistic regression analysis was conducted to assess the effect of Internal HLOC on the likelihood of complex feedback preferences, controlling for education levels. The model was not statistically significant according to the likelihood ratio test ($\chi 2(2) = 1.428$, $p = .490$, *Nagelkerke* $R^2 = .029$), which indicated that the model explained 2.9% of the variance in the likelihood of complex preference. Neither internal HLOC nor education levels were significant predictors of FBtxt (See **Table A1**).

FBimg (DV) and internal HLOC & education

A binary logistic regression analysis was conducted to assess the effect of Internal HLOC on the likelihood of complex feedback preferences, controlling for education levels. The model was not statistically significant according to the likelihood ratio test ($\chi 2(2) = 0.820$, $p = .664$, *Nagelkerke* $R^2 = .016$), which indicated that the model explained 1.6% of the

variance in the likelihood of complex preference. Neither internal HLOC nor education levels were significant predictors of FBimg (See **Table A2**).

Doctor HLOC and Feedback Preference

FBtxt (DV) and doctor HLOC & education

A binary logistic regression analysis was conducted to assess the effect of Doctor HLOC on the likelihood of complex feedback preferences, controlling for education levels. The model was not statistically significant according to the likelihood ratio test ($\chi 2(2) = 2.593$, $p = .273$, *Nagelkerke* $R^2 = .052$), which indicated that the model explained 5.2% of the variance in the likelihood of complex preference. Neither Doctor HLOC nor education levels were significant predictors of FBtxt (See **Table A1**).

FBimg (DV) and doctor HLOC & education

A binary logistic regression analysis was conducted to assess the effect of Doctor HLOC on the likelihood of complex feedback preferences, controlling for education levels. The model was statistically significant according to the likelihood ratio test ($\chi 2(2) = 6.421$, $p = .040$, *Nagelkerke* $R^2 = .117$), which indicated that the model explained 11.7% of the variance in the likelihood of complex preference. Results showed that for every one-unit increase on the score of Doctor HLOC, the odds of preferring the complex feedback increased by 1.271 times (95%CI: 1.032: 1.351). However, the direction of this relationship is reversed to what the study hypothesized, thus not supporting the hypothesis that doctor HLOC would lead to the preference of more simple feedback, but the contrary. Education was not a significant predictor of FBimg (See **Table A2**).

Chance HLOC and Feedback Preference

FBtxt (DV) and education & chance LOC

A binary logistic regression analysis was conducted to assess the effect of Chance HLOC on the likelihood of complex feedback preferences, controlling for education levels. The model was not statistically significant according to the likelihood ratio test ($\chi 2(2) = 2.809$, $p = .246$, *Nagelkerke* $R^2 = .056$) which indicated that the model explained 5.6% of the variance in the likelihood of complex preference. Neither Chance HLOC nor education levels were significant predictors of FBtxt (See **Table A1**).

FBimg (DV) and education & chance LOC

A binary logistic regression analysis was conducted to assess the effect of Internal HLOC on the likelihood of complex feedback preferences, controlling for education levels. The model was not statistically significant according to the likelihood ratio test ($\chi 2(2) = 0.999$, $p = .607$, *Nagelkerke* $R^2 = .019$), which indicated that the model explained 1.9% of the variance in the likelihood of complex preference. Neither Chance HLOC nor education levels were significant predictors of FB1 (See **Table A2**).

Discussion

In this sample of people randomly recruited in the city of Groningen the associations between HLOC, education and feedback preferences were analyzed based on the results of a survey. The study found no significant associations between education, internal and chance HLOC to either of the feedback style questions. The doctor HLOC was significantly associated with a preference for complex feedback graphs.

HLOC and Feedback Preferences

Doctor HLOC had a significant effect on feedback preferences, specifically for more complex health graphs, which is opposite of what had been hypothesized in the current study. It is possible that someone with a doctor's orientation could desire to gather as much information as possible on their health if that is what their doctor has advised them to do. Moreover, the study by Bennet et al. (2017) found that doctor HLOC was the strongest predictor of willingness to use health technology, pointing to a potential desire of people with this HLOC orientation to use medical tools, such as health technology more than internals. This effect could occur due to the fact that those of doctor HLOC might perceive the instructions of a health app in a similar way to the type of feedback they would be getting from a doctor, leading to an increased desire for information.

The dimensions of internal and chance HLOC had no significant effect on feedback preference. This finding is in line with previous research that found no difference in health behaviors (Pourhoseinzadeh et al., 2017) or in medical information seeking (Krantz et al., 1980) between internal and external locus of control. This finding was not in line with previous research, which showed a clear association between internal HLOC and a preference for more information about their health, while chance HLOC was shown to have negative attitudes when presented with an abundance of information. (Rodriguez et al., 2023; Wallston, 1978). Research shows a strong link between internal locus of control and health-related

behavior (Dogonchi et al., 2022), however, that might not extend to technology because they may feel that they are in control enough of their health and perceive technology as an external source of control. Moreover, those who score high on the internal scale may be more interested in using the technology solely for tracking, and prefer to get more detailed information by looking for it themselves online (Roncancio et al., 2012), explaining their lack of preference for the more complex feedback in the current study.

Education and Feedback Preference

Higher education was expected to be significantly associated with a preference for complex, detailed information and it was indeed positively associated with a preference for complex feedback in every logistic regression, however it was not significant in any of them. This result is in line with previous research, which found that education was not a significant predictor of health intervention engagement (Reinwand et al., 2015) or of using wearables for health promotion (Pan et al., 2024), while other predictors, such as age, employment status and quality of life were found to be significant, pointing to other variables of interest that were not accounted for in this paper. On the other hand, the study by Feinberg et al. (2016) found that higher education level was associated with seeking more text-based health information and higher reading literacy scores (capacity to understand complex, dense texts). One possible explanation for the difference is the way the construct of education was defined; in the aforementioned study education was assessed as low vs high based on whether the participants had or had not completed a high school diploma, which is very different from the classification of the current study. Another study found a significant association between education and information preference (Xiao et al., 2021), however their sample consisted of cancer patients, while this study did not screen for health issues, which could explain why the association was significant in their sample, but not in ours.

Implications

This study suggests that, while an individual with a Doctor HLOC may have an aversion toward direct involvement, tools such as digital health technology can fulfill a similar role to a doctor for them, leading to their engagement with their own health and giving them directions they feel motivated to follow. This could be a starting point for designing health technology that caters to the need for external guidance that those with this orientation need, with the potential of improving the health outcomes for them. Thus, it would lead to engagement in preventative health behaviors, rather than going to the doctor for a health issue when it arises.

The non-significant findings for internal HLOC suggest that the information seeking behaviors that those of internal HLOC demonstrate in medical settings may not apply within the context of health technologies, as they may prefer sources where they can control the amount of information they receive directly.

The results of this study suggest that HLOC domains do not behave the same with health technology as they do with health behaviors and health information seeking. An internal orientation is the strongest predictor of engagement with health behaviors and health information seeking, while the doctor and chance orientations predict lack of engagement with them. The current study suggests that when it comes to health technology, doctor HLOC is the strongest predictor of preferences. Therefore, the current theory may need adjustments to account for new developments such as mobile health.

Limitations and Future research

When interpreting the results of the current study, it is crucial to be aware of the following limitations. According to the power analysis conducted, this study needed a minimum of 111 participants in order to have meaningful findings. The sample size had only 70 participants after screening for incomplete responses. The distributions for age, education and income were skewed, with a tendency for high education, high income and younger age,

which may limit the generalizability of the findings. The survey was conducted mostly in the central area of Groningen, at the Forum. This was due to adverse weather conditions and low response rate in the other locations where data collection was conducted. Thus, it could be assumed that the skewness was caused by a sampling selection bias, where the lower SES populations were underrepresented in the data collection locations. Moreover, there could be a participation bias, in which higher education and higher income individuals were more willing to participate in research than those of low socioeconomic position (Brewer, M. B., 2007), potentially due to having more knowledge and trust in researchers (Emery et al., 2023). The questionnaire completion time ranged from approximately 20 minutes to an hour, which was longer than expected. We observed that the elderly portion of the sample took longer, likely due to legibility of the text and lower digital literacy (Eurostat, 2024).

The initial questionnaire had 89 questions and was shortened to the current 69, the construct validity of the HLOC questionnaire might have been affected during this process, causing various issues regarding the scale. The number of individuals in this sample who had their highest score in 2 or 3 categories (n = 26) could have been an unintended consequence of the removal, as 3 questions per scale may not have been enough to accurately differentiate someone's orientation. The removal may have also influenced the reliability of the questionnaire, because in the pilot study the reliability was much higher than that of the sample used in the current study. This could also be due to the fact that the pilot study used convenience sampling, while the current study used simple random sampling. Moreover, the measurement of feedback preference could be improved by a more thorough assessment method of using more questions. The feedback text question we used in the assessment of this construct ended up having a longer text for the simple, encouraging message than for the complex one, potentially leading those with high chance HLOC to avoid it and more internals to choose it. However, this finding could also be explained by the fact that there seemed to be

significant overlaps between our internal and doctor HLOC scales, as 9 participants had the same score on these scales. Research suggests that the internal scale is negatively correlated with doctor and chance (Brosschot et al., 1994), pointing to a potential issue with the questionnaire as we had a non-significant positive correlation between internal and doctor (r = .13), while internal and chance were uncorrelated (r = 0). This could also be due to characteristics of the Dutch population, such as low beliefs in religion, as religious beliefs are associated with chance HLOC (Boyd & Wilcox, 2017), meaning that a lower percentage of the population would have beliefs associated with this orientation than average.

There is an urgent need to develop a validated questionnaire aimed at measuring the feedback preferences in terms of health technology. A better understanding of this construct could help improve adherence rates and facilitate catering to disadvantaged populations, who may not have the same needs as those of medium to high socioeconomic status. A new scale could focus on defining the types of feedback more clearly, in terms of: amount of information, emotional tone, illustration vs no illustration, illustration type, complexity of information, framing of message.

The results of this study point to a need for more research into the components that influence feedback preferences. Future research could focus on conducting similar studies with larger and more demographically diverse samples making use of more thorough assessment methods in order to bring clarity to the associations between education, HLOC and feedback preferences. Moreover, more research should focus on examining which theoretical framework explains the feedback preferences in health technology best.

Conclusion

The findings of this study highlight the importance of understanding the desires and needs of disadvantaged populations when it comes to personal health technologies. It is clear that the factors influencing preferences are complex and the relationship between them and

HLOC is not as straightforward as it seems. More attention should be paid to how doctor HLOC influences the use of health technologies, as the current study finds that this association may provide helpful tools to populations that need them. Sociodemographic factors need to be taken into account along with personal characteristics in order to design personalized digital interventions that demonstrate good patient adherence and positive health outcome results.

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Appendix

Table A1:

Logistic Regressions of HLOC and FBtxt

Model	Factors	B	SE	Wald	df	Sig.	Odds Ratio	95% CI (L,H)
Model 1	*Internal HLOC*	.034	.105	.102	1	.749	1.034	(.841, 1.271)
	Education	-.398	.360	1.222	1	.269	.672	(.332, 1.360)
Model 2	*Doctor HLOC*	.124	.113	1.206	1	.272	1.132	(.907, 1.413)
	Education	-.462	.365	1.605	1	.205	.630	(.308, 1.288)
Model 3	*Chance HLOC*	-.131	.110	1.429	1	.232	.877	(.707, 1.087)
	Education	-.413	.361	1.305	1	.253	.662	(.326, 1.344)

Table A2:

Logistic regressions of HLOC and FBimg

Model	Factors	B	SE	Wald	df	Sig.	Odds Ratio	95% CI (L, H)
Model 1	*Internal HLOC*	-.002	.097	.000	1	.987	.998	(.826, 1.208)
	Education	-.309	.347	.791	1	.371	.734	(.372, 1.451)
Model 2	*Doctor HLOC*	.240	.107	5.073	1	.024	1.271	(1.032, 1.566)
	Education	-.421	.368	1.305	1	.253	.657	(.319, 1.351)
Model 3	*Chance HLOC*	-.041	.096	.179	1	.673	.960	(.795, 1.159)
	Education	-.306	.346	.782	1	.376	.736	(.374, 1.451)

Image A1

Feedback graph (FBimg)

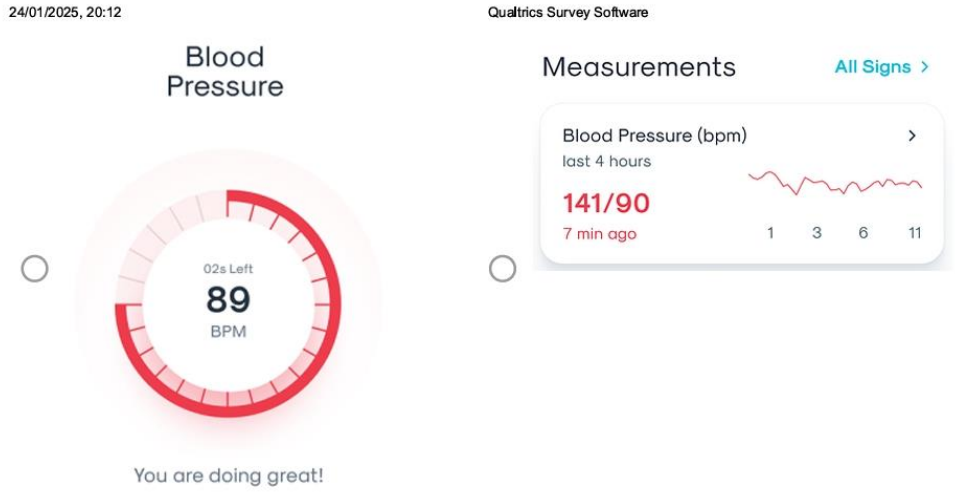

Image A2

Feedback text (FBtxt)