Internet Interventions 31 (2023) 100599

Contents lists available at ScienceDirect

Internet Interventions

journal homepage: www.elsevier.com/locate/invent

Development and usage of a health recommendation web tool (HeaRT) designed to inform women of personalized preventive health recommendations

Keren L. Greenberg [a,*], Tamar Poupko [a], Devorah Sorotzkin [a], Osnat Keidar [a,b], Donna R. Zwas [a]

[a] The Linda Joy Pollin Cardiovascular Wellness Center for Women, Hadassah University Medical Center, P.O.B 12000, Jerusalem, Israel
[b] The Braun School of Public Health and Community Medicine, Hebrew University and Hadassah University Medical Center, P.O.B 12272, Jerusalem, Israel

A R T I C L E I N F O

Keywords:
Decision aid
Screening
Gender-medicine
Ehealth
Web-tool
Ehealth literacy

A B S T R A C T

Background: Implementation of guidelines for evidence-based screening and disease prevention remains a core challenge in health care. The lack of access to accurate and personalized health recommendations may contribute to sub-optimal performance of medical screening, and ultimately increased risk for communicable and non-communicable disease. Many women do not monitor their cardiovascular disease (CVD) risk or receive regular medical screenings. A health recommendation tool (HeaRT) that provides women with profiled, individually tailored information about recommended tests and screening was designed to improve women's engagement in preventive health. This study characterized utilization of the tool in a real world setting.

Objective: To describe the development and usage patterns of HeaRT, a novel health web-tool that provides personalized health recommendations for women.

Methods: Extracted web-tool data including user input (age, BMI, smoking status and family history of CVD) and time spent in the results screen were analysed. Engagement was assessed by time spent in each results category, number of clicks and whether the user emailed/printed the recommendations. Usage patterns were analysed using multivariate analyses, logistic regression and cluster analyses.

Results: HeaRT was used 13,749 times in the years between its launch and data extraction three years later. Web-tool analysis found that 68.6 % of users accessed results and approximately 15 % printed or emailed the list of recommendations. Further analysis found that almost all the users entered the nutrition category (78 %), followed by the risk-factor category (69.5 %) and Physical activity category (61.9 %). Three usage patterns were identified by cluster analysis, including a nutrition/physical activity cluster, a risk-factor cluster and an all-categories cluster. Cluster affiliation analysis found BMI and smoking status were not predictors of cluster affiliation, whereas users over the age of 65 were more likely to solely enter the risk-factor tab ($P < .001$) and users with family history of CVD were more likely to either enter only the risk-factor tab or to enter all tabs ($P < .01$).

Conclusions: HeaRT users looked at health recommendations on a variety of health topics, and 15 % printed or emailed the recommendations. A tailored health recommendation web-tool may empower women to seek preventive-care and health maintenance, and help them interact with health care providers from a position of shared responsibility. This tool and similar programs may enable health care consumers to actively participate in directing their own health maintenance by providing consumers with personalized health recommendations. Additionally, user characteristics may inform future web-tool designers on target population profile and usage patterns.

1. Introduction

Implementation of guidelines for evidence-based screening and disease prevention remains a core challenge in health care (Matheson et al., 2015). Despite health agency recommendations and insurance coverage of screening tests and disease prevention interventions,

* Corresponding author at: The Linda Joy Pollin Cardiovascular Wellness Center for Women, Hadassah University Medical Center, P.O.B 12000, Jerusalem, Israel.
E-mail address: kereng@hadassah.org.il (K.L. Greenberg).

https://doi.org/10.1016/j.invent.2022.100599
Received 20 March 2022; Received in revised form 15 November 2022; Accepted 23 December 2022
Available online 24 December 2022

preventive services are considerably underused (Carey et al., 2020). Individuals without active health issues often do not visit their physicians, and appointments for acute issues may not allow time for preventive medicine. Social determinants of health including health literacy, ethnicity and socio-economic status affect utilization of screening, risk factor assessment and preventive interventions (Department of Health and Human Services, 2008). Both opportunistic and organized screening efforts require dissemination of information, reduction of barriers to participation, and tools to encourage compliance (Lynge et al., 2012).

Current research indicates that health care consumers may be more likely to engage in preventive behaviours through technology-facilitated self-care (Sarasohn-Kahn, 2013; King et al., 2021; Gordon et al., 2020). The number of people turning to the web to search for heath information and recommendations increases each year (Zhao and Zhang, 2017). However, as the amount of online health information increases, so do the difficulties in locating credible and relevant health information (Fergie et al., 2013; Kitchens et al., 2014; Chu et al., 2017). The lack of access to accurate and personalized health recommendations may contribute to sub-optimal performance of relevant medical screening (Sivaram et al., 2018), and ultimately increased risk for communicable and non-communicable disease (Fernandez et al., 2016). If used correctly, available online health information can lead to health behaviour change and reduced health risks (Bujnowska-Fedak and Węgierek, 2020). The challenge remains, however, in finding a credible source that offers personalized health recommendations, tailored to individual characteristics and health risks (Metzger and Flanagin, 2013; Sbaffi and Rowley, 2017).

Gender is particularly relevant to online health information seeking, as studies suggest that women use the internet more frequently for health purposes (Bujnowska-Fedak and Węgierek, 2020), and are more likely to search for active health-related information than men (Bidmon and Terlutter, 2015; Ek, 2015). Focus groups conducted with women from different backgrounds, ages, and sectors indicate a common need: women report being unaware of certain risk factors and the health agency recommended screenings and medical consultations, perceive that they lack the ability to obtain this information, want to obtain this information in order to actively participate in their own health care, and report knowledge deficits in health behaviours and preventive measures (Greenberg et al., 2017; Baird et al., 2021). Other studies similarly indicate that women engage in less cardiovascular disease (CVD) screenings and tests than men (Woodward, 2019) and tend to neglect their own health (while caring for others) (Vogel et al., 2021).

A user-friendly web tool that provides personalized, gender-specific health recommendations may facilitate increased risk factor assessments and screenings in women, reducing the risk of communicable and non-communicable disease.

This study describes the development and usage patterns of the Health Recommendation Tool (HeaRT), a novel ehealth web tool that provides personalized health recommendations for women. This is the first stage of a two-phase study. The second phase will evaluate end-user behaviour change in the setting of usage of HeaRT.

2. Methods

2.1. Development of HeaRT

The designing of HeaRT stemmed from the needs exposed in focus groups conducted with various populations of women in Jerusalem throughout 2013–2015 (Greenberg et al., 2017). The development was there for target population-centred (O'Cathain et al., 2019), based on needs that surfaced from the target population and designed to accommodate their various levels of skills and ehealth literacy.

The creation of this ehealth tool aimed to provide clear, accessible, personalized, evidence-based gender-specific recommendations for health maintenance and health screening to women who seek that information, and to increase utilization of preventive health screening and testing. This tool seeks to reduce health inequalities by making health information available and accessible to a low health literate population.

The design process was carried out by a team of health and public health professionals, as well as programmers, web designers and marketing experts. The models and principles used in the development of HeaRT included the Patient Health Engagement Model (Graffigna et al., 2017), which is considered a critical factor in enhancing the quality of care and increases patient activation and adherence. The principles of health literacy were used to inform the output development, which was targeted to a low health literacy population.

The design of HeaRT included creating a system in which women answer five simple questions and receive personalized age, risk and gender tailored evidence-based recommendations for preventive testing and screening (e.g bone density test, Pap smear), vaccines, nutrition (e.g iron and fiber consumption), physical activity (PA), medical risk factor assessment (e.g. levels of cholesterol, glucose), and general health recommendations (e.g. eye exam, sleep habits, baseline EKG). Users can print the information or email it to themselves, and subsequently bring it to doctor visits to facilitate reception of appropriate care (example of output printout is presented in supplement 1). The recommendations presented in HeaRT are based on the official recommendations of the Israeli Ministry of Health, the World Health Organization and specialist consultants. All recommended tests and screenings are based on the national health recommendations and are provided by government-funded health maintenance organizations (HMOs). As the official recommendations of the Ministry of Health were establish according to BMI and age, they are presented in the tool in such a manner. In addition, smoking was chosen as an additional profiling risk factor as it constitutes one of the risk behaviours that most negatively affects health, and family history of heart disease was chosen as well, CVD being the leading cause of death for women worldwide. Although many additional risk factors (including gender-specific risk factors) exist, we opted to avoid an overload of input questions that can deter usage, and thus keep the tool simple and user-friendly. HeaRT provides personalized health recommendations to women (over the age of 20) who are generally heathy and do not suffer from chronic conditions that demand more specific care.

Outputs are composed of several layers of data in accordance to ehealth literacy principles, including informative pop-ups with additional information and tips, and active links which lead to detailed articles on our website about the highlighted term. By layering content and using simple language the tool caters to populations with different levels of health and ehealth literacy.

HeaRT was piloted by target populations, their input being incorporated into the design and content presented in the tool. The development process is summarized in the GUIDED checklist, presented in Supplement 2.

To date, HeaRT is available exclusively in Hebrew; a culturally adapted Arabic version is currently in mid-stage of development.

2.2. Feature description

2.2.1. Input section

The users are prompted to answer five questions regarding their age, height, weight, smoking status, and family history of heart disease. Once this profile is completed, a personalized recommendations screen appears.

2.2.2. Individually-tailored output

HeaRT provides 64 different output options, based on the various input combinations that include eight age groups, two BMI groups, two smoking status options and two family history options (unknown family history is coded as no family history). Output options are presented in Fig. 1.

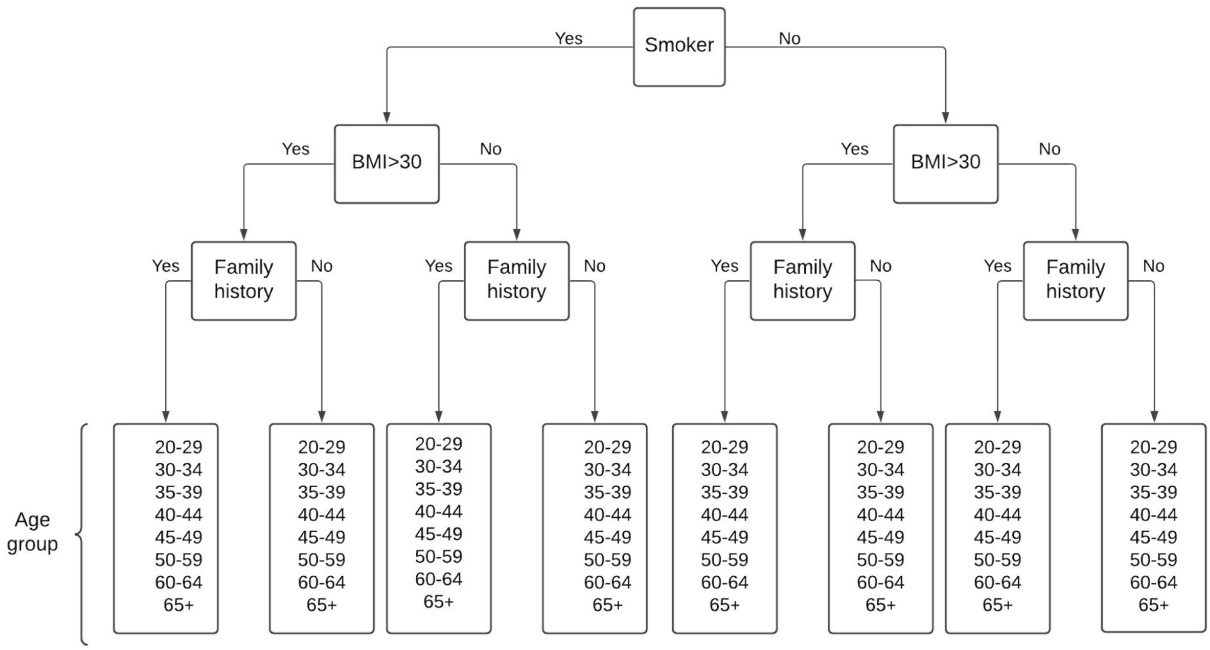

Fig. 1. Output combinations.

2.2.3. *Personalized recommendations screen*

This screen includes health recommendations in six categories, as specified in Table 1. All recommendations are tailored for women.

Each category appears as a separate tab and when clicked, a checklist appears with tailored recommendations according to age, BMI, smoking status and family history of heart disease. The recommendations include screening and test frequency when relevant. Personalized output can be printed or emailed for later reference. The output is worded in simple language in accordance with health literacy guidelines, and is composed of several layers of data, including informative pop-ups and active links which lead to more detailed information. There is also an option to share HeaRT with friends and family via social media.

2.2.4. *Visual features (interface)*

HeaRT features a well-known local celebrity who actively advocates for women. The HeaRT graphics were piloted with users, who described them as clear and user-friendly. The output recommendations are presented in a clean simple manner, so as to avoid content overload. Additional information can be obtained by using the pop-ups or live links (Fig. 2). The visited vs non-visited categories appear in different colours, to help users identify content they have not yet accessed. HeaRT is adapted for viewing on tablets and smartphones as well as computer desktops.

2.2.5. *Administrative features*

Administrative features include user analytics (number of users, IP address, entry date and time, characteristics collected by input screens, completion of profile, number of clicks, time spent in each tab, and use of printing/emailing buttons).

2.3. *Beta testing and incorporation of user feedback*

HeaRT was launched in 2017 for beta testing. It was promoted via a social media campaign that included a video starring a local celebrity who introduced the web tool and emphasized its importance. A group of seven representatives of the target population (ages 32–75) were asked to fill out an online questionnaire to assess their user experience. All respondents stated that navigating HeaRT was simple and that recommendations were clear and tangible. When questioned, six thought that the information obtained was important, some of it new. Of the participants, all seven reported a positive experience and indicated that they would forward it to their friends. When asked if they printed the results to discuss with their doctor, four responded that they had not thought of this option. In light of that feedback, a ‘call for action’ element was added to the tool, suggesting users print their list of recommendations and take them to their next doctor's visit. Additional feedback was obtained that enabled further fine-tuning of the tool (i.e. colour, font size, terminology, etc.). In 2018, HeaRT was relaunched via social media campaign. In 2021 Additional changes were made to adapt HeaRT to updated health recommendations in Israel, including Covid-19 vaccines, CT scans for long term smokers, and BRCA screenings for Ashkenazi women.

Table 1
Web tool input, output, and features.

Input by user (range)	Output categories	Extra features
• Age (20–120) • Height (120–210 cm) • Weight (30–250 kg) • Smoking status (Yes/No) • Family history of heart disease (Yes/No/I don't know)	• Risk factor identification and medical consultation recommendations • General health recommendations • Cancer screening recommendations • Vaccine recommendations • Nutrition recommendations • Physical activity recommendations	• Print recommendations • Email recommendations • Share on social media • Active links • Additional information pop-ups

Fig. 2. HeaRT screenshots.
HeaRT screenshots, translated to English, displaying (A) one of the input screens where patients fill in their personal information: age, height and weight, smoking status, and family history of CVD status, (B) recommendations screen, divided into six category tabs, including printing/emailing buttons, (C) personalized recommendations in the 'Risk factor identification' category, including live links, as well as a call for action and (D) recommendations in the 'Nutrition Recommendations' category showing pop-ups (appear when link clicked).

2.4. Usage analysis

Documentation was made of whether users reached the results screen (i.e., time in results screen equal to or greater than 0) and of time spent in each category tab of the results screen. Some users reached the results screen, but did not enter any tabs. For this analysis, users who spent over 30 minutes (average time + 3 SD) in the tool were removed, as this is unlikely to represent active usage.

Engagement of users was assessed by time spent in each results category, number of clicks (the recommendations contain live links with additional information, pop-ups activated by clicks, and additional action buttons such as social media sharing, Facebook "like" button, and print/email buttons) and whether the user emailed or printed the recommendations.

2.5. Data analysis

Data was analysed using SPSS version 27 (SPSS, Inc. Chicago Illinois).

Frequencies were used to describe descriptive variables. Anova tests were used to identify correlations between personal risk and entry variables. Pearson test was used to assess correlations between continuous variables. Logistic regressions were conducted to assess the effect of risk factors on the probability of entering the various tabs. A cluster analysis was preformed using the k-means ($k = 3$) cluster analysis procedure in SPSS and based on the case distance from the cluster centroids

(Everitt et al., 2011), to detect different usage patterns. Statistical significance was defined at the level of $P < .05$.

For the analyses, time (in seconds) was transformed into log form, due to asymmetry in the time allocation distribution, providing a better fit to the normal distribution. However, tables show the actual mean time in seconds to simplify the presentation of results.

2.6. User data collection

HeaRT does not require users to fill in personal information such as names, addresses, or emails. IP addresses were coded into random user numbers to identify multiple users, at which point original IP addresses were deleted. No personalized health information was stored. Data was examined anonymously, and users were unidentifiable. The retrospective analysis was approved by the Helsinki Ethics Committee of Hadassah University Medical Center (HMO-0036-22).

3. Results

HeaRT was used 13,749 times by 12,547 users in the years between the launch in May 2018 and July 2021, when data was extracted for analysis. Of the users, 11,735 were one-time users and 812 were multiple users (entering the tool 2–42 times; 98.5 % of these entered 2–5 times). Thirty-seven users who spent over 30 minutes in the tool were removed from the analysis. Of the remaining entries, 13.8 % did not reach the results screen, 20.6 % reached the results screen but did not check the data and 68.6 % entered the results tabs (Supplement 3).

When we compared one-time users (users who used the tool one time only) who reached and entered category tabs, one-time users who did not reach and/or enter category tabs (filled out profiling questions but either did not submit and move on to results screen or did get to results screen but did not enter any tabs), and users who used the web tool multiple times (2–5 times, longest entry used for analysis), significant differences between user profiles were found. The average age of one-time users who did not enter category tabs was older, they had more risk factors, were more likely to be smokers, and were more likely to print or email themselves the list of recommendations (Table 2). Multiple entry users and one-time users who entered category tabs had similar profile data.

For the in-depth usage analysis, we examined data from the one-time users only, as an analysis of the multiple log-ins showed significant variance in time spent in the tool, tabs visited in each log-in, and profile data. From the 11,705 one-time log-ins (log-in<30 minutes), we removed the data of users who did not reach the results screen or who reached the results screen but did not enter any category. The in-depth usage analysis was performed on the remaining sample of 7708 (Fig. 3).

Of the 7708 users in the in-depth usage analysis, mean age of users was 52.2 (SD 10.6), of whom 75.2 % were over the age of 45. Mean BMI was 27.2. Nearly half of the users had a family history of heart disease, while only 13.4 % were smokers (Table 2). Out of the four risk factors taken into account (smoking, family history of heart disease, BMI $\geq$ 30, age $\geq$ 65), 29.9 % of users had no risk factors, 43.8 % had at least one risk factor, 22.6 % had two risk factors, and 3.7 % had three or four risk factors. Of all the one-time users, 15.1 % (1714 users), printed or emailed their personalized recommendations.

3.1. In-depth usage analysis

3.1.1. Category tabs

The most popular category in the results section was nutrition, visited by 78.1 % of users. The Second most popular category was risk factor identification (69.5 %), followed by PA, cancer screenings, general health and vaccines (Fig. 4).

3.1.2. Predictors of engagement

A set of univariate ANOVA models factored by user characteristics showed that an increase in age was significantly correlated with an increase in time engaged with the tool ($P < .001$). Family history of heart disease was also a predictor of time engaged with the tool ($P < .001$). BMI and smoking status were not correlated with engagement. The number of risk factors was positively correlated with overall time engaged with the tool ($P < .001$), and time spent in each category ($P < .001$) other than PA.

Logistic regression modelling framework was used to assess the effect of user characteristics on the probability of visiting different categories. For this analysis, the Generalized Linear Model was applied, allowing an estimate of expected marginal probability of a visit to one of the categories and a comparison of these marginal probabilities to each other, generating between category probability differences. Table 4 shows the modelling results. Users in the age group 65+ had a significantly higher probability of entering the risk factor, general health, vaccines and cancer screening categories. Users with a family history of heart disease had a higher probability of entering all categories, compared to those without a family history. Users with higher BMI had higher probability of entering the risk factor and vaccine categories than lower BMI users. The users who reported being active smokers entered the risk factor, general health and PA categories more than non-smoking users.

Analysis of the number of clicks paralleled time spent in the tool. Number of clicks per user login was significantly inversely associated with age ($P < .001$).

Users with family history of heart disease had a significantly higher number of clicks compared to those with no history ($P < .001$), non-

Table 2
User profile.

Characteristics	One-time users, did not enter results tabs (n = 3646)	One-time users, entered results tabs (n = 7708)	Multiple entry users, entered 2–5 times (n = 765)	Test statistic	P value
Age, mean (SD)	55.13[b] (10.47)	52.17[a] (10.63)	52.76[a] (10.68)	F = 97.60	$P <$ .001
BMI, mean (SD)	27.19 (5.21)	27.20 (5.23)	27.47 (5.53)	F = 0.94	0.39
BMI ≥ 30, % (n)	25.7 % (937)	24.8 % (1912)	26.9 % (206)	X^2 = 2.33	0.31
Currently smoke, % (n)	22.5 % (821)	13.4 % (1035)	13.1 % (100)	X^2 = 156.79	$P <$ .001
Have family history of CVD, % (n)	49.5 % (1805)	48.4 % (3728)	50.8 % (389)	X^2 = 2.58	0.27
Number of risk factors, % (n)				X^2 = 108.29	$P <$ .001
No risk factors	23.1 % (843)	29.9 % (2302)	25.6 % (196)		
One risk factor	43.1 % (1573)	43.8 % (3375)	46.8 % (358)		
Two risk factors	27.2 % (992)	22.6 % (1744)	23.4 % (179)		
Three or four risk factors	6.5 % (238)	3.7 % (287)	4.2 % (32)		
Minutes spent in web tool, mean (SD)	0[a] (0)	1.75[c] (1.99)	2.18 (2.55)	F = 1408.12	$P <$ .001
Number of clicks, mean (SD)	7.19[a] (3.28)	12.05[b] (5.12)	12.08[b] (5.64)	F = 1373.78	$P <$ .001
Printed and/or emailed results, % (n)	17.2 % (626)	14.1 % (1088)	14.0 % (107)	X^2 = 18.77	$P <$ .001

The Latin letters reflect the post-hoc marginal probability ranking based on multiple pairwise comparisons with the Bonferroni correction. Letters represent grouping of results that are significantly different, i.e. results marked ‘a’ are significantly different from results marked ‘b’ or ‘c’. Results marked ‘ab’ are not different from results marked ‘a’ or ‘b’, but are different from those marked ‘c’, etc.

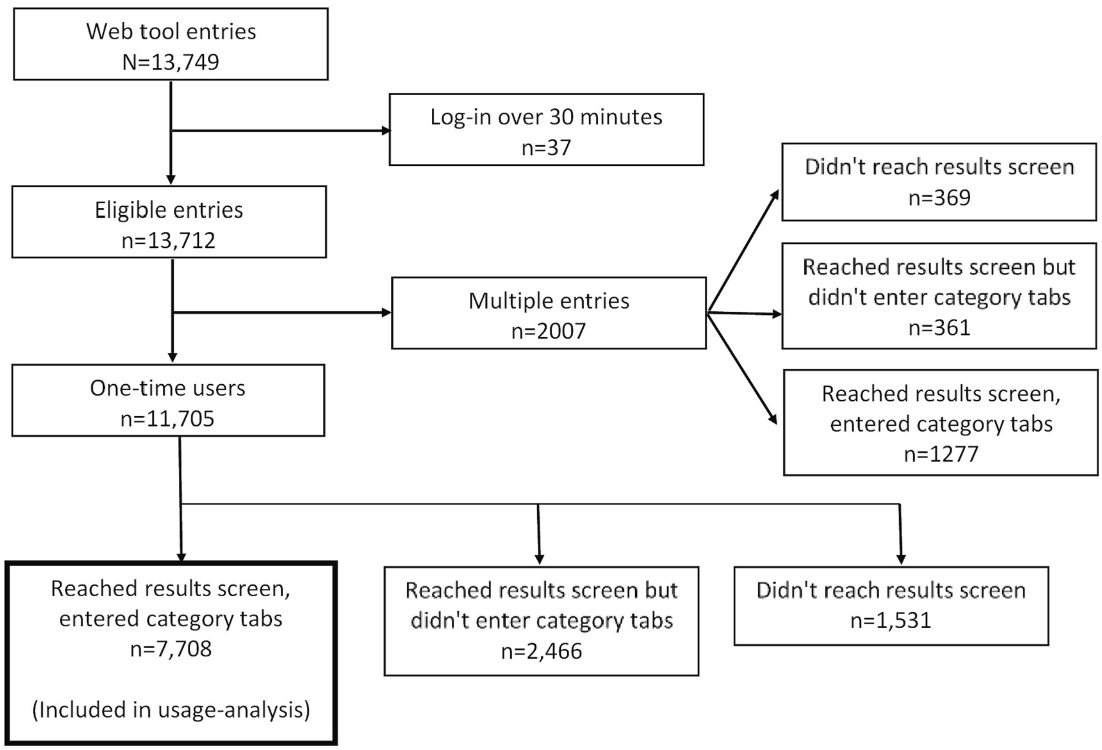

Fig. 3. Flowchart of users included in usage-analysis.

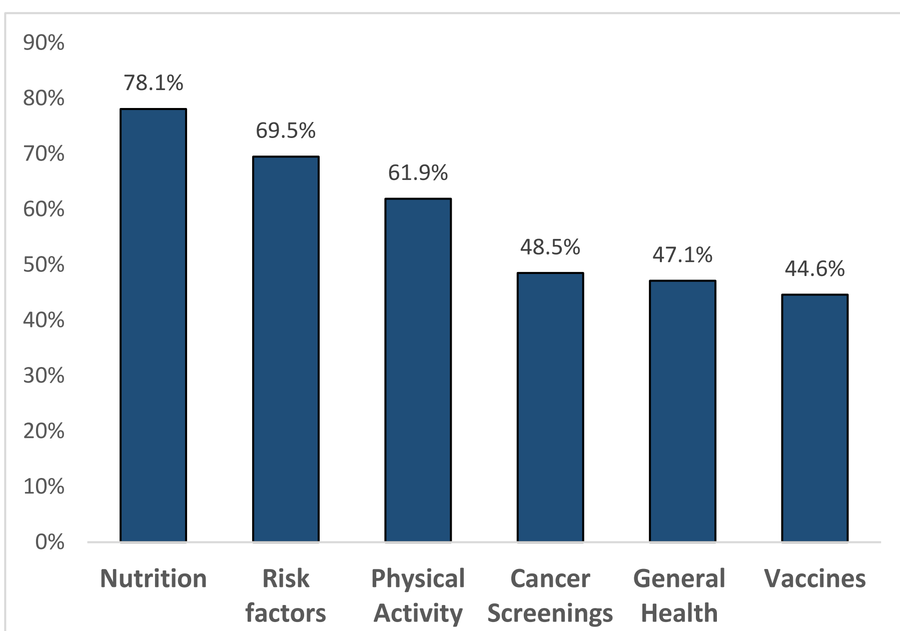

Fig. 4. Entry percentage in each category, N = 7, 708.

smoking users clicked more than smoking users ($P < .001$), and users who printed or emailed the results had a significantly higher number of clicks ($P < .001$). BMI did not predict the number of clicks.

3.1.3. User profiles

A cluster analysis was performed using the k-means (k = 3) cluster analysis procedure in SPSS (Everitt et al., 2011). Binary entries to the six categories were classified into three independent clusters (Fig. 5). Out of the full sample, 2778 users were defined as a distinct cluster that entered the nutrition and PA categories but were less likely to enter other categories (cluster 1). The second cluster included 1957 users who entered the risk factor category, but had lower entry probabilities to other categories (cluster 2). The third cluster included 2973 users who had high probability to enter all categories (cluster 3). Cluster affiliation was based on individuals' highest probability to enter one of the six categories.

Cluster affiliation was tested in response to user characteristics, including user's age (younger or older than 65), BMI (under or over 30),

Table 4
Factors affecting the probability of visiting the various result categories.

Category	N	Risk Factors	General Health	PA	Nutrition	Vaccines	Cancer Screening
		5356	3631	4769	6021	3434	3742
Age group							
20–29	48	0.60^{ab} (0.07)	0.48^{abc} (0.07)	0.56^{a} (0.07)	0.71 (0.07)	0.40^{abcd} (0.07)	0.38^{ab} (0.07)
30–34	311	0.66^{a} (0.03)	0.50^{abc} (0.03)	0.62^{a} (0.03)	0.79 (0.02)	0.41^{abc} (0.03)	0.46^{ab} (0.03)
35–39	536	0.71^{ab} (0.02)	0.44^{ab} (0.02)	0.56^{a} (0.02)	0.78 (0.02)	0.44^{abc} (0.02)	0.55^{b} (0.02)
40–44	1010	0.66^{a} (0.02)	0.42^{a} (0.02)	0.60^{a} (0.02)	0.79 (0.01)	0.40^{ab} (0.02)	0.51^{ab} (0.02)
45–49	1303	0.68^{a} (0.01)	0.43^{a} (0.01)	0.61^{a} (0.01)	0.79 (0.01)	0.39^{a} (0.01)	0.47^{a} (0.01)
50–59	2469	0.69^{a} (0.01)	0.47^{ab} (0.01)	0.63^{a} (0.01)	0.78 (0.01)	0.45^{bc} (0.01)	0.47^{a} (0.01)
60–64	975	0.70^{ab} (0.02)	0.51^{bc} (0.02)	0.63^{a} (0.02)	0.78 (0.01)	0.47^{c} (0.02)	0.48^{ab} (0.02)
65+	1056	0.76^{b} (0.01)	0.53^{c} (0.02)	0.64^{a} (0.02)	0.76 (0.01)	0.54^{d} (0.02)	0.50^{ab} (0.02)
Wald X^2		32.57	48.38	15.23	4.87	64.66	19.50
P value		$P < .001$	$P < .001$	0.03	0.68	$P < .001$	0.007
Family history							
No	3980	0.67^{a} (0.01)	0.44^{a} (0.01)	0.60^{a} (0.01)	0.77^{a} (0.01)	0.41^{a} (0.01)	0.45^{a} (0.01)
Yes	3728	0.72^{b} (0.01)	0.50^{b} (0.01)	0.63^{b} (0.01)	0.79^{b} (0.01)	0.48^{b} (0.01)	0.53^{b} (0.01)
F		27.75	23.78	7.27	4.60	36.10	48.06
P value		$P < .001$	$P < .001$	0.007	0.03	$P < .001$	$P < .001$
BMI							
<30	5796	0.69^{a} (0.01)	0.47 (0.01)	0.62 (0.01)	0.78 (0.01)	0.44^{a} (0.01)	0.49 (0.01)
30+	1912	0.71^{b} (0.01)	0.47 (0.01)	0.61 (0.01)	0.79 (0.01)	0.47^{b} (0.01)	0.48 (0.01)
F		4.84	0.00	1.06	1.54	7.96	0.73
P value		0.03	0.99	0.30	0.21	0.005	0.39
Smoker							
No	6673	0.71^{b} (0.01)	0.48^{b} (0.01)	0.63^{b} (0.01)	0.78 (0.01)	0.45 (0.01)	0.49 (0.01)
Yes	1035	0.61^{a} (0.02)	0.43^{a} (0.02)	0.55^{a} (0.02)	0.77 (0.01)	0.44 (0.02)	0.49 (0.02)
F		42.32	8.10	20.73	0.47	0.04	0.001
P value		$P < .001$	0.004	$P < .001$	0.49	0.83	0.97

The Latin letters reflect the post-hoc marginal probability ranking based on multiple pairwise comparisons with the Bonferroni correction. Letters represent grouping of results that are significantly different, i.e. results marked 'a' are significantly different from results marked 'b' or 'c'. Results marked 'ab' are not different from results marked 'a' or 'b', but are different from those marked 'c', etc.

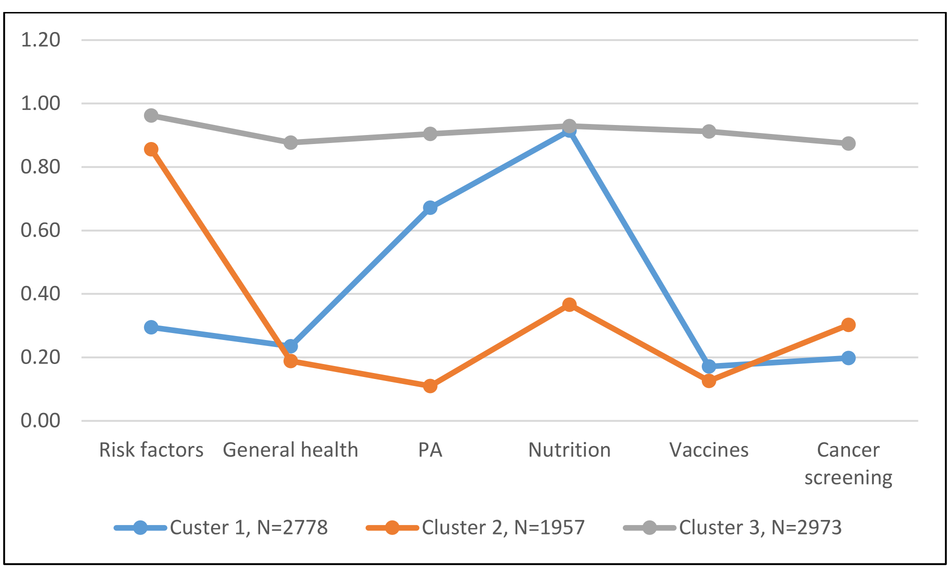

Fig. 5. Cluster analysis results for three clusters by probability to enter categories.

smoking status, and family history of heart disease, as well as time spent in HeaRT and number of clicks (Table 5). A multinomial logit model was applied to test the difference in response to the independent variables, in which we compared the probability of users to affiliate with one cluster versus another. As only one reference cluster is allowed in multinomial logit modelling, we reran the model with a different reference cluster to complete this comparison. The model results showed that visit duration (time) was found to affect cluster affiliation probability: longer visits indicated higher probability to be affiliated with cluster 3 versus cluster 1 and 2 ($P < .001$), and with cluster 1 versus cluster 2 ($P < .001$), that is, the probability to affiliate with clusters that were characterized by higher levels of entry was higher in response to longer visits, and similarly in response to number of clicks.

Additionally, we found that risk factors were not uniform in their contribution to cluster affiliation. While BMI and smoking status had no effect on belonging to a certain cluster, that is, having a specific "visiting

Table 5
Multinomial regression.

	X^2	Cluster 1 vs Cluster 3 B (SE)	Exp(B)	Cluster 2 vs Cluster 3 B (SE)	Exp(B)	Cluster 2 vs Cluster 1 B (SE)	Exp(B)
Time	1239.32***	−0.01 (0.001)***	0.99	−0.02 (0.001)***	0.98	−0.0 (0.001)***	0.99
Clicks	561.00***	−0.18 (0.01)***	0.84	−0.22 (0.01)***	0.80	−0.05 (0.01)***	0.95
Age	34.98***	−0.04 (0.10)	0.96	0.48 (0.10)***	1.62	0.52 (0.10)***	1.69
BMI	0.925	−0.07 (0.07)	0.94	−0.06 (0.08)	0.94	0.01 (0.07)	1.01
Smoking status	4.45	0.18 (0.09)	1.19	−0.05 (0.11)	1.05	−0.13 (0.09)	0.88
Family history	9.16**	−0.17 (0.06)**	0.84	−0.05 (0.07)	0.95	0.12 (0.06)**	1.13

Cluster 1: High Nutrition and PA, Cluster 2: High risk factors, Cluster 3: All categories.
$X^2 = 3382.67$, $P < .001$; Pseudo-R square: Cox = 0.36, Nag = 0.40, McFadden = 0.20.
** $P < .01$.
*** $P < .001$.

pattern", having family history of heart disease increased the probability of belonging to cluster 3 versus 1 ($P < .01$) and to cluster 2 versus 1 ($P < .01$). In other words, users with a family history of heart disease were more likely to enter all categories or focus on the risk factor category (both clusters have a high probability of entering the risk factors tab). Older users (age > 65) were more likely to be affiliated with cluster 2 (entered mainly the risk factors tab) versus clusters 3 and 1 ($P < .001$).

4. Discussion

4.1. Principle results

This study described the development and initial usage of HeaRT- a web tool designed to provide users with personalized preventive and health promotion recommendations, including various disease screening (e.g. cancer, CVD, diabetes, etc.), vaccines, and nutrition and PA recommendations. Each recommendation was tailored to user's age, BMI, family history of heart disease and smoking status. In our web tool analysis, we found that 68.6 % of users accessed results and almost 15 % of users responded to the call to action to print or email themselves the list of recommendations.

4.2. Comparison with prior work

The role of ehealth and its potential to improve health outcomes has been well established (Gordon et al., 2020). Research shows that online health seeking can lead to behaviour change and increased adherence to health recommendations: in their study from 2007, Ayers and Kronenfeld suggest that using the internet increases patients' participation in management of their own health problems and increases their ability to make informed decisions about health (Ayers and Kronenfeld, 2007). Regarding preventive ehealth tools, although automated messaging or reminders have been less effective in promoting screening (Carey et al., 2020), interactive tools that promote patient engagement may be more successful (Timmermans, 2020). A systematic review from 2018 showed that mobile health application usage has a positive impact on health-related behaviours and clinical health outcomes (Han and Lee, 2018). Several studies have shown the benefits of specific health apps, such as an app aimed to improve self-care quality in heart failure (Bakogiannis et al., 2021), an app to counsel women who use an intrauterine system (Karakoyun et al., 2021), and an app to improve health outcomes of diabetics (Ghose et al., 2022); however, there are fewer holistic web tools that offer a comprehensive preventive health approach. One such tool, the Wellness-Portal, is a novel web-based patient portal focused on wellness, prevention, and longitude health. A 2012 study (Nagykaldi et al., 2012) investigating the impact of this tool on patient-centred preventative care found that a patient portal integrated into the process of primary care could improve patient activation and enhance the delivery of age and risk factor-appropriate preventive services.

A systematic review performed by De Croon et al. in 2021 (De Croon et al., 2021) found that web-based health recommender systems operated in four non-mutually exclusive categories: nutrition, lifestyle, general health information and specific health condition-related recommendations. The review found a clear trend toward health recommender systems that provide general and wellbeing recommendations but do not directly intervene in the user's medical status. The authors recommended designing and developing richer applications that offer tailored and specific recommendations over general information, are based on trusted sources, and are actionable.

HeaRT integrates a call to action, encouraging users to print the recommendations and advocate for specific preventive health screenings with their primary care doctor. Additionally, HeaRT provides comprehensive tailored gender-specific recommendations in multiple health topics. Personalized comprehensive knowledge that enables women to perform preventive and screening tests may lower the incidence of CVD, and reduce the risk of mortality from cancer and other diseases (Birtwhistle et al., 2017).

4.3. eHealth and eHealth literacy

As the "digital divide" narrows with increased proliferation of internet access, in particular via mobile phones, attention is shifting from disparities in connectivity toward interventions that address a 'knowledge divide' and an 'agency divide' (McAuley, 2014). eHealth literacy (eHL) is defined as the ability to seek, find, understand, and appraise health information from electronic sources and apply the knowledge gained to address or solve a health problem (Norman and Skinner, 2006). While research shows that many adults face challenges finding and understanding online health information (Fergie et al., 2013; Kitchens et al., 2014; Chu et al., 2017), eHealth can play a critical role in reducing health disparities, by providing content appropriate to various eHL levels. Inclusion of several layers of content to fit the needs of users with different levels of eHL, and using simple navigational elements, and nonmedical language can lead to reduced usage disparities (MacKert et al., 2009). Similarly, tailoring of the health technology to a specific cultural or underserved population will increase the likelihood of uptake and effectiveness (Montague and Perchonok, 2012), as does active participation of future users from at risk populations in the development of eHealth tools (Latulippe et al., 2017). This tool was specifically tailored to women of limited health literacy, and was piloted and revised in response to this testing.

The accessibility of clear, tailored, layered health recommendations by a reliable source addresses the eHL challenge of understanding and locating credible health information, and, according to user feedback, enables women to easily access it. eHealth tools and mHealth can reduce disparities by offering clear, credible, and vital preventative health recommendations (Anderson-Lewis et al., 2018).

4.4. User analysis

Although this study does not present data regarding user behaviour change, it does provide valuable data describing usage patterns. As health care becomes more patient-centred, it is important to understand what health care consumers are interested in, and how those interests, priorities and values vary across different age and risk groups (Hirpai et al., 2020). Knowing more about patients' preferences and interests can enable more efficient and effective care (Brennan and Strombom, 1998).

Most of the HeaRT users who completed their profile and entered the recommendation pages were over 50 years old, with an average BMI of 27.2. Nearly one quarter of these users had a BMI over 30 and approximately half of them reported having a family history of heart disease. Those who did not view the recommendations reported more risk factors than those who did (primarily smoking) and were slightly, but significantly older. Even though they did not enter the recommendation tabs, these users were more likely to print or email themselves the list of recommendations. These users may have not entered the tabs due to lack of time and instead printed or emailed themselves the recommendations for later reference. The BMI and family history status were similar in both groups.

Understandably, users with more risk factors spent more time in the tool, visited more tabs, and had a higher average number of clicks.

The cluster affiliation analysis found three distinct subtypes of users: those primarily interested in risk factors, those primarily interested in nutrition and physical activity, and those who were interested in all the categories. While BMI and smoking status were not predictors of cluster affiliation (usage pattern), age and family history of heart disease were. Users over the age of 65 were more likely to solely enter the risk factor tab. Users with a family history of heart disease were more likely to either enter only the risk factor tab or to enter all tabs.

This is consistent with research showing individuals with reported chronic conditions and older individuals are more likely to search for health information online (Ayers and Kronenfeld, 2007; Faith et al., 2016; Bundorf et al., 2006) while BMI is not correlated with surfing the web for health information (Faith et al., 2016). More so, research shows that the frequency of internet use to retrieve health information is correlated with the number of chronic conditions (Ayers and Kronenfeld, 2007). Our study shows that not only chronic conditions impact online surfing patterns, but also chronic disease risk, such as family history.

In our study, users who reported smoking were less likely to enter the recommendation tabs, and smoking was not identified as a cluster predictor. This may be due to lower levels of engagement and trust in medical sources of health information among smokers compared to non-smokers (Calixte et al., 2020).

The user pattern analysis may assist future ehealth intervention designers in the adaptation and design of tools that use patient preferences to increase and support patient engagement with targeted behaviours, and guide marketing and messaging strategies to target populations. It can also be used to advise community health care providers as to the information different age groups and individuals with various risk factors are searching for, i.e. what their interests and perhaps their knowledge gaps are, and what information they are more or less likely to pursue. For example, we see that smokers are less likely to enter the health recommendations tab. Further research can further explore patient preferences to determine causes and outcomes of these preferences. Future research examining the described search patterns in this study may elucidate the causes and implications of these patterns- whether it is for lack of interest, reluctance to be told to quit smoking or skewed perceptions.

A qualitative study preformed in 2017 showed that the main type of information sought by web health-information seekers includes healthy lifestyle advice (nutrition and PA) and prevention of chronic or infectious disease (Chu et al., 2017). Similarly, analysis of usage of our web tool found that almost all the users entered the nutrition category (78 %), followed by the risk factor table (69.5 %) that presents the recommended risk factor screening tests (preventive medicine), and the PA table (61.9 %). The popularity of the nutrition tab suggests a common interest among HeaRT users that can possibly be used as a hook for future apps, by incorporating additional health information with nutrition information.

4.5. Limitations

This study is limited by the absence of socio-economic data on the users, including education level, employment status, and health status. This data was not collected to avoid an overload of profiling questions, and keep the input stage short and simple, leaving out questions that can cause a feeling of invasion of privacy. This decision does however prevent a full descriptive analysis of the sample population.

This study is also limited by the inability to track user behaviours in response to usage of this tool. It did, however, find that 15 % emailed or printed the recommendations, presumably with intent to review at another time or take it to the doctor. The study is also limited in that it targets only women and evaluated only female users; the focus on women, however, may have assisted personalization and accessibility of information. HeaRT is easily adaptable to men as well, although this would require adjustment of images as well as content.

Additionally, the large sample size carries a higher risk of type II errors.

Surfing patterns that were analysed in the usage section may have been influenced by the images selected for promotion on social media, i.e. images containing nutrition themes may have increased web tool entrances of nutrition information seekers.

4.6. Conclusions

This women's health recommendations web tool was created based on a need identified by women in different communities. The development process incorporated the patient health engagement model to create a user-friendly tool that provides age, risk, gender tailored, evidence-based health recommendations to enable the user to seek appropriate medical care. HeaRT was designed acknowledging the different levels of eHL in society, and provides health recommendations in simple language, including a single call for action and avoiding content overload. Users looked at health recommendations on a variety of health topics, and 15 % printed or emailed the recommendations to themselves. The three usage profiles identified can help inform future eHealth tool designers on target population profile and usage patterns. This in turn can contribute to marketing strategies and personalization of messages to target population and their interests.

Although the recommended tests and screenings may be covered by health insurance, women have reported that they do not get these tests unless they advocate for themselves, due to the limited time available for the doctor-patient encounter (Greenberg et al., 2017). A tailored health recommendation web tool may empower women to seek the preventive care and health maintenance that they deserve, and help them interact with health care providers from a position of shared responsibility (Sarasohn-Kahn, 2013; Bujnowska-Fedak and Węgierek, 2020). This tool and similar programs may enable health care consumers to actively participate in directing their own health maintenance.

Supplementary data to this article can be found online at https://doi.org/10.1016/j.invent.2022.100599.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sector.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The authors would like to thank Mr. Dror Gliksman and Mr. Gil Slovik for their assistance, creativity and insight, Ms. Chani Nachmias for her generous participation in this project, Dr. Elisheva Leiter for editorial support and insight, Drs. Gabi Liberman and Amir Hefetz for statistical assistance, and the Pollin Center staff for their ongoing support.

References

Anderson-Lewis, C., Darville, G., Mercado, R.E., Howell, S., Di Maggio, S., 2018. mHealth technology use and implications in historically underserved and minority populations in the United States: systematic literature review. JMIR mHealth uHealth 6 (6), e128. PMID:29914860.

Ayers, S.L., Kronenfeld, J.J., 2007. Chronic illness and health-seeking information on the internet. Health (Irvine Calif) 11 (3), 327–347. PMID:17606698.

Baird, J., Yogeswaran, G., Oni, G., Wilson, E.E., 2021. What can be done to encourage women from black, asian and minority ethnic backgrounds to attend breast screening? A qualitative synthesis of barriers and facilitators. Public Health 190, 152–159. PMID:33419526.

Bakogiannis, C., Tsarouchas, Anastasios, Mouselimis, D., Lazaridis, C., Theofillogianakos, E.K., Billis, A., Tzikas, S., Fragakis, N., Bamidis, P.D., Papadopoulos, C.E., Vassilikos, V.P., 2021. A patient-oriented app (ThessHF) to improve self-care quality in heart failure: from evidence-based design to pilot study. JMIR mHealth uHealth 9 (4), e24271. PMID:33847599.

Bidmon, S., Terlutter, R., 2015. Gender differences in searching for health information on the internet and the virtual patient-physician relationship in Germany: exploratory results on how men and women differ and why. J. Med. Internet Res. 17 (6), e156. PMID:26099325.

Birtwhistle, R., Grad, R., Bell, N.R., Thombs, B.D., Dickinson, J.A., 2017. Periodic preventive health visits: a more appropriate approach to delivering preventive services: from the Canadian task force on preventive health care. Can. Fam. Physician 63 (11), 824–826. PMID:29138150.

Brennan, P.F., Strombom, I., 1998. Improving health care by understanding patient preferences: the role of computer technology. J. Am. Med. Inform. Assoc. 5 (3), 257–262. PMID:9609495.

Bujnowska-Fedak, M.M., Węgierek, P., 2020. The impact of online health information on patient health behaviours and making decisions concerning health. Int. J. Environ. Res. Public Health 17 (3), 880. PMID:32023828.

Bundorf, M.K., Wagner, T.H., Singer, S.J., Baker, L.C., 2006. Who searches the internet for health information? Health Serv. Res. 41, 819–836. PMID:16704514.

Calixte, R., Rivera, A., Oridota, O., Beauchamp, W., Camacho-Rivera, M., 2020. Social and demographic patterns of health-related internet use among adults in the United States: a secondary data analysis of the health information national trends survey. Int. J. Environ. Res. Public Health 17 (18), 6856. PMID:32961766.

Carey, T.S., Bekemeier, B., Campos-Outcalt, D., Koch-Weser, S., Millon-Underwood, S., Teutsch, S., 2020. National Institutes of Health pathways to prevention workshop: achieving health equity in preventive services. Ann. Intern. Med. 172 (4), 272–278. PMID:31931530.

Chu, J.T., Wang, M.P., Shen, C., Viswanath, K., Lam, T.H., Chan, S.S.C., 2017. How, when and why people seek health information online: qualitative study in Hong Kong. Interact J. Med. Res. 6 (2), e24. PMID:29233802.

De Croon, R., Van Houdt, L., Htun, N.N., Štiglic, G., Vanden Abeele, V., Verbert, K., 2021. Health recommender systems: systematic review. J. Med. Internet Res. 23 (6), e18035. PMID:34185014.

Department of Health and Human Services, 2008. The Secretary's Advisory Committee on National Health Promotion and Disease Prevention Objectives for 2020. Phase I Report: Recommendations for the Framework and Format of Healthy People 2020. October. Washington, DC.

Ek, S., 2015. Gender differences in health information behaviour: a finnish population-based survey. Health Promot. Int. 30 (3), 736–745. PMID:23985248.

Everitt, B., Landau, S., Morven, L., Stahl, D., 2011. Cluster Analysis, 5th edition. John Wiley & Sons, Ltd, Chichester, UK. https://doi.org/10.1002/9780470977811. ISBN: 9780470977811.

Faith, J., Thorburn, S., Smit, E., 2016. Body mass index and the use of the internet for health information. Health Educ. J. 75 (1), 94–104. https://doi.org/10.1177/0017896914568435.

Fergie, G., Hunt, K., Hilton, S., 2013. What young people want from health-related online resources: a focus group study. J. Youth Stud. 16 (5), 579–596. PMID:24748849.

Fernandez, D.M., Larson, J.L., Zikmund-Fisher, B.J., 2016. Associations between health literacy and preventive health behaviors among older adults: findings from the health and retirement study. BMC Public Health 16, 596. PMID:27430477.

Ghose, A., Guo, X., Li, B., Dang, Y., 2022. Empowering patients using smart Mobile health platforms: evidence from a randomized field experiment. MIS Q. 46, 151–192.

Gordon, W.J., Landman, A., Zhang, H., Bates, D.W., 2020. Beyond validation: getting health apps into clinical practice. npj Digit. Med. 3 (14). PMID:32047860.

Graffigna, G., Barello, S., Bonanomi, A., 2017. The role of patient health engagement model (PHE-model) in affecting patient activation and medication adherence: a structural equation model. PLoS One 12 (6), e0179865. PMID:28654686.

Greenberg, K., Leiter, E., Donchin, M., Littman, I., Nubani, M., Lotan, C., Keidar, O., Zwas, D.R., 2017. Health Literacy and Cardiovascualr Knowledge Workshop in Women from Disadvantaged Communities. 15th World Congr Public Heal Melbourne.

Han, M., Lee, E., 2018. Effectiveness of mobile health application use to improve health behavior changes: a systematic review of randomized controlled trials. Healthc. Inform. Res. 24 (3), 207–226. PMID:30109154.

Hirpai, M., Woreta, T., Addis, H., Kebede, S., 2020. What matters to patients? A timely question for value-based care. PLoS One 15 (7), e0227845. PMID:32644993.

Karakoyun, T., Podhaisky, H.-P., Frenz, A.-K., Schuhmann-Giampieri, G., Ushikusa, T., Daniel, S., Zvolanek, M., Lopes Da Silva Filho, A., 2021. Digital Medical Device Companion (MyIUS) for new users of intrauterine systems: app development study. JMIR Med. Inform. 9 (7), e24633. PMID:34255688.

King, E.L., Spencer, C.M., Meeks, C.A., 2021. How the COVID-19 pandemic can and must expand social worker e-interventions for mental health, family wellness, and beyond. Soc. Work, swab043. https://doi.org/10.1093/sw/swab043.

Kitchens, B., Harle, C.A., Li, S., 2014. Quality of health-related online search results. Decis. Support. Syst. 57, 454–462. https://doi.org/10.1016/j.dss.2012.10.050.

Latulippe, K., Hamel, C., Giroux, D., 2017. Social health inequalities and eHealth: a literature review with qualitative synthesis of theoretical and empirical studies. J. Med. Internet Res. 19 (4), e136. PMID:28450271.

Lynge, E., Törnberg, S., Von Karsa, L., Segnan, N., Van Delden, J.J.M., 2012. Determinants of successful implementation of population-based cancer screening programmes. Eur. J. Cancer 48, 743–748. PMID:21788130.

MacKert, M., Kahlor, L., Tyler, D., Gustafson, J., 2009. Designing e-health interventions for low-health-literate culturally diverse parents: addressing the obesity epidemic. Telemed e-Health 15 (7), 672–677. PMID:19694596.

Matheson, G.O., Pacione, C., Shultz, R.K., Klügl, M., 2015. Leveraging human-centered design in chronic disease prevention. Am. J. Prev. Med. 48 (4), 472–479. PMID:25700655.

McAuley, A., 2014. Digital health interventions: widening access or widening inequalities? Public Health 128 (12), 1118–1120. PMID:25458115.

Metzger, M.J., Flanagin, A.J., 2013. Credibility and trust of information in online environments: the use of cognitive heuristics. J. Pragmat. 59, 210–220. https://doi.org/10.1016/j.pragma.2013.07.012.

Montague, E., Perchonok, J., 2012. Health and wellness technology use by historically underserved health consumers: systematic review. J. Med. Internet Res. 14 (3), e78. PMID:22652979.

Nagykaldi, Z., Aspy, C.B., Chou, A., Mold, J.W., 2012. Impact of a wellness portal on the delivery of patient-centered preventive care. J Am Board Fam Med 25 (2), 158–167. PMID:22403196.

Norman, C.D., Skinner, H.S., 2006. eHealth literacy: essential skills for consumer health in a networked world. J. Med. Internet Res. 8 (2), e9. PMID:16867972.

O'Cathain, A., Croot, L., Sworn, K., Duncan, E., Rousseau, N., Turner, K., Yardley, L., Hoddinott, P., 2019. Taxonomy of approaches to developing interventions to improve health: a systematic methods overview. Pilot Feasibility Stud. 5 (41) https://doi.org/10.1186/s40814-019-0425-6.

Sarasohn-Kahn, J., 2013. A role for patients: the argument for self-care. Am. J. Prev. Med. 44 (1), S16–S18. PMID:23195159.

Sbaffi, L., Rowley, J., 2017. Trust and credibility in web-based health information: a review and agenda for future research. J. Med. Internet Res. 19 (6), e218. PMID:28630033.

Sivaram, S., Majumdar, G., Perin, D., Nessa, A., Broeders, M., Lynge, E., Saraiya, M., Segnan, N., Sankaranarayanan, R., Rajaraman, P., Trimble, E., Taplin, S., Rath, G.K., Mehrotra, R., 2018. Population-based cancer screening programmes in low-income and middle-income countries: regional consultation of the international cancer screening network in India. Lancet Oncol. 19 (2), e113–e122. PMID:29413465.

Timmermans, S., 2020. The engaged patient: the relevance of patient-physician communication for twenty-first-century health. J. Health Soc. Behav. 61 (3), 259–273. PMID:32723112.

Vogel, B., Acevedo, M., Appelman, Y., Bairey Merz, C.N., Chieffo, A., Figtree, G.A., Guerrero, M., Kunadian, V., Lam, C.S.P., Maas, A.H.E.M., Mihailidou, A.S., Olszanecka, A., Poole, J.E., Saldarriaga, C., Saw, J., Zühlke, L., Mehran, R., 2021. The lancet women and cardiovascular disease commission: reducing the global burden by 2030. Lancet 19 (397(10292)), 2385–2438. PMID:34010613.

Woodward, M., 2019. Cardiovascular disease and the female disadvantage. Int. J. Environ. Res. Public Health 16, 1165. PMID:30939754.

Zhao, Y., Zhang, J., 2017. Consumer health information seeking in social media: a literature review. Health Inf. Libr. J. 34 (4), 268–283. PMID:29045011.