Title

Patient characteristics associated with objective measures of digital health tool use in the United States: A literature review.

Journal
Journal of the American Medical Informatics Association : JAMIA, 27(5)

ISSN
1527-974X

Authors
Nouri, Sarah S
Adler-Milstein, Julia
Thao, Crishyashi
et al.

Publication Date
2020-05-01

Peer reviewed

Title: Patient Characteristics Associated with Objective Measures of Digital Health Tool Use in the US: A Literature Review.

Authors and affiliations:

Sarah S. Nouri, MD, MPH[1]
Julia Adler-Milstein, PhD[2]
Crishyashi Thao, MPH[2]
Prasad Acharya, MD, MBA, MPH[3]
Jill Barr-Walker, MS, MPH[4]
Urmimala Sarkar, MD, MPH[1,5]
Courtney Lyles, PhD[1,5]

1. Division of General Internal Medicine, Department of Medicine, University of California, San Francisco, San Francisco, CA, United States
2. Center for Clinical Informatics and Improvement Research, School of Medicine, University of California, San Francisco, San Francisco, CA, United States
3. California Department of Public Health, Center for Healthy Communities, Chronic Disease Control Branch, Sacramento, CA, United States
4. Zuckerberg San Francisco General Hospital Library, University of California, San Francisco, San Francisco, CA, United States
5. UCSF Center for Vulnerable Populations, Zuckerberg San Francisco General Hospital, San Francisco, CA, United States

Corresponding author:
Sarah S. Nouri, MD, MPH
1545 Divisadero Street, Box 0320
San Francisco, California 94143-0320
sarah.nouri@ucsf.edu
office: 415-353-7900

Keywords: population health informatics, digital health, health equity, social determinants of health

Word count: 3105

ABSTRACT

Objective: To determine which patient characteristics are associated with use of patient-facing digital health tools in the US.

Materials and Methods: We conducted a literature review of studies of patient-facing digital health tools that objectively evaluated use (e.g., system/platform data representing frequency of use) by patient characteristics (age, race/ethnicity, income, digital literacy, etc.). We included any type of patient-facing digital health tool except patient portals. We re-ran results using the subset of studies identified as having robust methodology to detect differences in patient characteristics.

Results: We included 29 studies; 13 had robust methodology. Most studies examined smartphone apps and text-messaging programs for chronic disease management and evaluated only 1-3 patient characteristics, primarily age and gender. Overall, the majority of studies found no association between patient characteristics and use. Among the subset with robust methodology, white race and poor health status appeared to be associated with higher use.

Discussion: Given the substantial investment in digital health tools, it is surprising how little is known about the types of patients who use them. Strategies that engage diverse populations in digital health tool use appear to be needed.

Conclusion: Few studies evaluate objective measures of digital health tool use by patient characteristics and those that do include a narrow range of characteristics. Evidence suggests that resources and need drive use.

INTRODUCTION

Background and Significance

Availability of interactive digital health tools that enable patients to access health information and personal health data has increased rapidly over the past decade, alongside growing access to the internet and smartphone ownership.[1-4]. These patient-facing tools, including smartphone apps, text messaging programs, and social media tools, among others, have been associated with improved clinical and behavioral outcomes, such as preventive health behaviors, chronic disease management, and patient-provider communication.[3, 5-8]

Despite both high availability and interest in digital health tools among ethnically, economically, and linguistically diverse patient groups,[9, 10] adoption (or use) of these tools by patients is low [2, 3, 11]. Furthermore, data from national patient surveys and evaluations of patient portals in the United States demonstrate differential adoption of digital health tools by various groups based on sociodemographics.[2, 3, 12-22] Specifically, older adults, racial/ethnic minorities, and those with low socioeconomic status, low educational attainment, limited health literacy, and chronic illness use patient portals less often compared to advantaged populations.[19-22] There is also research demonstrating that patient-facing digital health tools themselves are at risk of exacerbating health disparities,[23] but that little effort has been undertaken to address this. For example, despite lack of uptake by diverse populations, there is little evidence that health systems incorporate approaches to address health disparities in the development, implementation, and use of patient portals.[19, 24]

In a conceptual model for understanding and preventing such disparities, Veinot et al. (2018) propose that differences in access, adoption or use, adherence, and/or effectiveness of digital health tools contribute to their risk of exacerbating health disparities.[23] Moreover, effectiveness of digital health tools depends largely on access, adoption/use, and adherence.[23] As described above, effectiveness of digital health tools on various behavioral and clinical outcomes has been evaluated, and there is a significant body of research examining adoption/use of patient portals linked to electronic health records (EHR).[25-28] However, we lack a review of evidence on adoption/use for the vast array of digital health tools beyond patient portals. [29-33] In particular, there is little understanding of which patient characteristics are associated with use of these digital health tools, which may differ from those associated with patient portal use because they feature greater flexibility in design with respect to patient needs and preferences. In the setting of increasing availability and prioritization of patient-facing digital health tools and the risk of these tools widening existing health disparities, it is critical to better understand factors influencing their uptake.[23, 34, 35]

Objective

We conducted a literature review of studies of patient-facing digital health tools (excluding patient portals) to identify which patient characteristics were associated with adoption/use of these digital health tools in the US. We included only studies with objective (rather than self-reported) measures of use (e.g., system/platform usage data representing frequency or duration of use).

METHODS

We adhered to Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines;[36] however, we did not present data synthesis as this is a literature review rather than a systematic review.

Search strategy

We developed a search strategy in collaboration with a clinical librarian (JBW) that combined two main concepts: health information technology (including search terms reflecting mobile/smartphone, apps, texting, and other mHealth and digital health terminology) and patient engagement (including search terms reflecting uptake and participation; see Appendix A1 for complete details). We intentionally omitted the word "use" from the search strategy, as it was non-specific (given the lack of uniform terminology to describe this construct) and yielded a large number of irrelevant papers. We conducted a search using Boolean operators that combined keywords and MeSH terms in PubMed on July 27, 2018. Because of our specific focus on implementation of digital tools in the health and medical fields, we chose to search within the biomedical literature in PubMed alone. Given the rapid change of technological advancements and our goal of understanding how technology is currently used to inform patient engagement efforts, we limited the search to articles published in the last five years (July 2013 to July 2018).

Exclusion criteria

Papers were reviewed and excluded at two levels using criteria developed by all authors. At the first level, we reviewed titles and abstracts and excluded papers if they were not original research (e.g., review articles, commentaries, study protocols, etc.), did not describe a patient-facing digital health tool, or were not conducted in the United States. We defined patient-facing digital health tools (hereafter also referred to as “digital health tools” or “tools”) as technologies with which patients could directly interact in order to enter/access personal health data, to obtain health or disease-specific information, or to monitor a health behavior or achieve a health goal (e.g., text-messaging app with reminders to take blood pressure medications).[37] At the second screening level, we reviewed the full text of articles and excluded papers that did not evaluate use by patient characteristics (e.g., age, gender, race/ethnicity, health literacy, health status, etc.), were studies of patient portals (as there are existing reviews focused on portals and other digital health tools are becoming increasingly ubiquitous), or included pediatric populations (as these evaluated surrogates’ rather than patients’ characteristics). Using DistillerSR (Evidence Partners, Ottowa, Canada), title and abstract screening were completed by one reviewer (CT), with two additional reviewers (SN and CRL) completing a subset of screening to ensure agreement on the categorization. Two reviewers (SN and CT) completed full text screening, with a subset double-screened to ensure concordance among reviewers. Any discordance (<5% of papers) was discussed in-person between SN, CT, and CRL until agreement was reached.

Data extraction: Outcome and predictor variables

We extracted only use measures that were evaluated by patient characteristics. Use was measured differently across studies, and included: reach, retention over time, frequency of engagement (e.g., number of times app was opened), and duration of engagement (e.g., viewing time per link on a website).

We extracted patient characteristics that were included in the evaluations of use. In other words, we were not interested in the general description of the sample by patient demographics like age and gender, but in whether the study reported on use stratified by patient characteristics. The full list of patient characteristics extracted from each study included age, gender, race, health status, education, digital literacy, income, health literacy or numeracy, and limited English proficiency. We chose these variables based on previous research [2, 3, 15] and a consensus approach of all authors in determining factors likely to influence digital health use. For each digital health tool, we determined which patient characteristics were statistically significantly associated or not associated with use, as well as the direction of the association, if any.

Data extraction: Determination of patient-level variations in use

Due to the tremendous variation in how patient characteristics were measured, they were categorized into relative subgroups that could be applied to all studies (e.g., age was divided into “older” versus “younger” subgroups). We then extracted whether the paper reported a statistically significant ($P<0.05$) versus non-significant association between any patient characteristic and the use outcomes. If there was a statistically significant association reported, we identified which patient sub-group was *favored*. For example, if use of a smartphone app was higher among younger compared to older individuals, the smartphone app was determined to *favor* younger individuals. If there was no statistically significant association between a patient characteristic and a use measure, this was reported as *non-significant*.

Selection of studies to support more robust subgroup analysis

Since not all included studies were designed with the primary objective of evaluating use by patient characteristics, we identified the subset of included studies with a greater likelihood of internal validity in the examination of patient subgroup relationships. We did this to determine if there was a similar or stronger relationship between patient characteristics and use for studies that were more likely to support such inference. More specifically, we adapted criteria from a validated measure of risk of bias [38] to evaluate whether included studies (1) clearly included and reported characteristics of non-users of the digital health solution, (2) included ≥50 participants in analyses of use, and (3) presented multivariable relationships to assess whether a characteristic was predictive of use holding all other characteristics constant. If a study met at least two of these three criteria, it was selected for subgroup analysis. We then replicated the data extraction described above on this subset of studies.

Analyses

We took extracted data and first calculated descriptive statistics to summarize study and patient characteristics. Next, we determined the number of studies in which use outcomes were associated with each patient characteristic (including the direction of the association), as well as the number in which they were not associated with each patient characteristic. We did this analysis for all included studies and repeated it for the subgroup of studies described above.

RESULTS

We identified 3367 studies using our search criteria; 29 studies met our final inclusion criteria (Figure 1, Appendix A2).[36]

Study and Patient Characteristics

Study and patient characteristics are summarized in Table 1, with additional details in Appendix A3.

Table 1. Study characteristics.

	Number of studies (N=29)	
	N	%
Patient characteristics*		
Age	21	72.4
Gender	20	69.0
Race/ethnicity	18	62.1
Health status or comorbidities	15	51.7
Education	9	31.0
Digital literacy	5	17.2
Income	5	17.2
Health literacy or numeracy	4	13.8
Limited English proficiency	1	3.5
Primary type of digital health tool*		
Smartphone or tablet app	11	37.9
Text messaging	11	37.9
Interactive voice response	4	13.8
Internet	3	10.4
Social media	2	6.9
Activity tracker	1	3.5
Health area of focus		
Chronic disease management	11	37.9
Tobacco or substance use	7	24.1
Weight management	5	17.2
Prevention/Promotion	4	13.8
Other°	2	6.9
Study setting*		
Academic Medical Center	26	89.7
Community Medical Center	6	20.7
Government^	5	17.2
Tech company/organization	5	17.2

*Twenty-four studies evaluated >1 patient characteristic. Three studies equally evaluated 2 types of digital health tool. Twelve studies included >1 setting.
°Other includes hospital discharge planning and postoperative care.
^Includes Veterans Health Administration, military bases and US Army, and local departments of public health.

The most commonly included patient characteristics were age (21 studies), gender (20 studies), race (18 studies), and health status (15 studies). Definitions, measurement, and categorization of patient characteristics varied across studies (see Appendix A4).

The digital health tools comprised 6 types of technologies: smartphone or tablet applications (11 studies), text messaging (11 studies), interactive voice response (IVR; 4 studies), Internet (3 studies), social media (2 studies), and activity tracking devices (1 study). Eleven studies focused on chronic disease management. Twenty-six of the 29 studies were conducted at academic medical centers.

Studies Selected for Subgroup Analysis

Appendix A5 lists the studies that were selected for a more robust subgroup analysis and summarizes their appropriateness for subgroup analysis per each criterion and overall.

Thirteen of the 29 studies evaluating use met criteria for subgroup analysis. As an exemplar study of use that met criteria for appropriateness of subgroup analysis, Heminger et al. [39] evaluated use of Text2Quit, an interactive text-messaging program aimed at smoking cessation, among 262 participants, including non-users. They created a multivariable linear regression model that included all sociodemographic data to determine which patient characteristics were associated with use, which was defined as the sum of user-initiated survey responses, keyword usage, and web logins.

Association of Patient Characteristics with Use of Digital Health Tools

Figure 2 summarizes the association between use of digital health tools and patient characteristics, showing the overall number of studies per finding as well as the proportion of those that met criteria for a more robust analysis. Overall among the studies evaluating use of digital health tools, most were not associated with age (14/21), gender (15/21), race (12/20), health status (7/15), education (7/9), digital literacy (4/5), income (4/5), or health literacy or numeracy (3/4). Only one study evaluated use by English proficiency and found that the digital health tool favored those with limited English proficiency (Spanish speakers spent more time per link on a website). However, this same study also found that white participants had more link views compared to racial/ethnic minority participants.[40] The remaining studies of digital literacy, income, and health literacy or numeracy favored those with adequate digital or health literacy or numeracy and those with higher income.

When considering only the thirteen studies of use that met criteria for a more robust analysis, there appears to be a relationship between use and two characteristics: race and health status. Notably, half of digital health tools that examined use by race (6/12) favored those who self-identify as white, while only one favored those who identify as a racial minority. Digital health tools that favored white populations compared to racial minorities included an Internet-based intervention for HIV prevention among men who have sex with men,[41] a text-messaging program for assessing diabetes risk,[42] a text-messaging and IVR program for medication adherence among adults with diabetes,[43] an Internet- and IVR-based program for weight management,[44] a smartphone app for management of schizophrenia after hospital discharge,[45] and an Internet program about nutrition.[40] In these studies, use was measured as any adoption, retention over months, frequency of interactions with the digital health tool, and/or time spent using the digital health tool. Our subgroup analysis also found that half of the studies that examined use by health status (4/8) favored those with poorer health status, while only two favored those with better health status. Digital health tools that favored those with poorer health status included a social media intervention for people living with HIV,[46] smartphone apps and an Internet-based program for mental health management,[47 48] and a text-messaging tool to improve postoperative care.[49] Measures of use in these studies included any use of the tools and frequency of interactions with the tools.

DISCUSSION

In this review of recent evidence, we found only 29 studies evaluating use by patient characteristics. There was almost no uniformity across studies in how use was measured. The majority of studies included only 1-3 patient characteristics, primarily age and gender. For other factors, notably digital literacy and health literacy, the representation was extremely low despite a growing body of work documenting barriers to digital health use by these factors.[12, 13, 15, 17, 28, 50] Moreover, the wide variability in measurement of patient characteristics represents the need for future work in digital health to not only include but also measure these variables in a standardized and validated manner.

For most patient characteristics, the majority of studies found no statistically significant association between the patient characteristic and use. For example, while older age is often assumed to be a barrier to engaging in digital health, our results suggest that for a range of digital health tools age does not predict use. In fact, in some cases use is higher among older adults. Nevertheless, among studies including large enough sample size of diverse subjects and non-users, we did observe differences in digital health use by race and health status. These differences seemed to favor white participants and those with poorer health status more often. Literature evaluating patient portals has similarly found lower use among racial and ethnic minority populations [20, 32, 51-53] but has not found an association between use and health status.[30, 54, 55] Possible reasons for differences by race/ethnicity include cultural differences and patterns of use of digital health tools that may vary between social networks.[23] For example, privacy concerns regarding EHR are expressed more frequently among African-Americans compared to whites, and this may extend to other digital health tools.[23] Additionally, people whose friends/social networks can help learn how to use digital health tools are more likely to use them.[56, 57] Our findings suggest that studies that prioritize inclusion of adequate sample sizes of diverse populations and of those with lived experiences with the health conditions of interest [58] might be better positioned to provide greater generalizability about uptake of patient-facing digital health tools in real-world dissemination.[59]

Furthermore, despite the known high digital literacy, health literacy, numeracy, and language demands of many digital health tools, there were few studies examining use by these characteristics.[60-63] It is imperative that these characteristics be included in evaluation studies of digital health tools in order to inform the real-world usefulness and likely uptake of such tools.

Studies of usability of digital health tools, though few in number, have overwhelmingly found that adequate digital literacy, health literacy or numeracy, and English proficiency are associated with higher usability.[31, 64-66] This underscores the need not only to evaluate use by these patient characteristics but also to dedicate research to understanding usability by key patient characteristics, as usability predicts adherence to digital health tool use.[23]

Despite the large investment in an increasing number of digital health tools available to patients, few are using them, and this number has not grown appreciably over the past several years.[67] Furthermore, while research has demonstrated the potential of these tools in widening existing health disparities,[23] there has been little attention paid thus far to *who* users versus non-users are. Our review underscores this and highlights that even among the studies that consider the relationship between patient characteristics and use, a wider range of patient characteristics and greater attention to robust methodology is needed. Some studies included in this review had robust methodology and did include a wide range of patient characteristics, demonstrating that it is possible to design and conduct such studies well. In fact, those studies that included digital literacy, health literacy, and English proficiency also tended to have more robust methodology. In order to understand why adoption of digital health tools remains so low, it is essential to consistently and deliberately assess their use. It is particularly necessary to do so among diverse populations that more accurately reflect the US population, rather than among self-selecting, homogeneous, advantaged populations. Regardless of whether a digital health tool has been shown in a study to be effective in improving a behavioral or clinical outcome, these upstream factors of use and usability will ultimately determine whether it will be successful in improving health and ensuring health equity.[23] As digital health tools continue to be rapidly developed and promoted, and patients are increasingly empowered to manage their personal health data,[3, 68] this becomes even more necessary.

This study has several limitations. Because of the wide variation in the definitions, measurements, and reporting of our outcome measures, we used terms capturing patient engagement in our search strategy for studies evaluating use—it is possible that we have not captured all relevant studies, particularly if they used different terminology for these measures. For the same reasons, we were unable to perform a meta-analysis of effect size or use a single validated tool to assess risk of bias or quality. However, we developed a set of proxy criteria to decide which of our included studies were methodologically appropriate for a subgroup analysis. We were similarly unable to assess publication bias; however, a large number of the included studies had negative (non-significant) findings. We limited our search to PubMed given our specific focus on biomedical literature and may therefore have missed studies available only in other databases. Finally, due to the significant contribution of social factors (including patient characteristics highlighted in this study) to poor health outcomes in the US compared to other high-income countries,[69] we limited inclusion to US studies, which could limit generalizability of results.

In conclusion, by specifically examining studies with objective measures of use, our results offer a substantially better understanding than provided by prior literature of patient adoption of digital health tools within different populations, including those vulnerable populations with high burden of disease and health inequity. Similar to studies of patient portal use, we found lower use of digital health tools among racial and ethnic minority populations. Evaluating use among diverse populations is critical in order to inform strategies to address low adoption of and adherence to patient-facing digital health tools. These efforts are important not only to increase patient uptake and sustained use of digital health tools, but also to identify inequities that may be perpetuated by growing availability of these tools.

FIGURE LEGENDS

Figure 1. PRISMA Flow Diagram.

Figure 2. Patient characteristics associated with use, both among all included studies (entire bar) and within the subgroup of studies with more robust methodology (black). Studies that found no association ($P \geq 0.05$) between use and patient characteristics were labeled "non-significant." There were no tools that favored men or those with lower educational attainment, limited digital literacy, lower income, limited health literacy or numeracy, or English proficiency. Robust methodology was defined as meeting two of the following 3 criteria: (1) clearly included and reported characteristics of non-users of the digital health solution, (2) included ≥50 participants in analyses, and (3) presented multivariable relationships to assess whether a characteristic was predictive of use holding all other characteristics constant. LEP=limited English proficiency.

FUNDING STATEMENT

This work was supported by The Commonwealth Fund (Grant No. 20181504). Dr. Nouri is funded in part by a National Research Service Award fellowship training grant (T32HP19025).

Dr. Lyles and Dr. Sarkar are funded in part by the National Library of Medicine (R01LM013045); Dr. Sarkar is additionally funded in part by the National Cancer Institute (K24 CA212294-01). Dr. Acharya is funded in part by the Centers for Disease Control and Prevention (1 NB01OT009226-01-00) and the Health Resources and Services Administration (Grant # 4 D33HP29250).

COMPETING INTERESTS STATEMENT

The authors have no competing interests to declare.

CONTRIBUTORSHIP STATEMENT

All authors contributed to the 1) conception or design of the work, 2) drafting or critically revising the work, 3) final approval of the version to be published, and 4) the accuracy and integrity of the work. Dr. Nouri, Ms. Thao, Dr. Acharya, and Dr. Lyles also contributed to the acquisition, analysis, and interpretation of the data.

ACKNOWLEDGMENTS

The authors thank Roy Cherian for his contributions to the literature search and development of inclusion and exclusion criteria.

REFERENCES

1. Pew Research Center. Mobile Fact Sheet. Pew Research Center: Internet and Technology 2018

2. Kontos E, Blake KD, Chou WY, Prestin A. Predictors of eHealth usage: insights on the digital divide from the Health Information National Trends Survey 2012. J Med Internet Res 2014;**16**(7):e172 doi: 10.2196/jmir.3117[published Online First: Epub Date]|.

3. Lustria ML SS, Hinnant CC. Exploring digital divides: an examination of eHealth technology use in health information seeking, communication and personal health information management in the USA. Health Informatics 2011;**17**(3):224-43

4. Singh K, Meyer SR, Westfall JM. Consumer-Facing Data, Information, And Tools: Self-Management Of Health In The Digital Age. Health Aff (Millwood) 2019;**38**(3):352-58 doi: 10.1377/hlthaff.2018.05404[published Online First: Epub Date]|.

5. Anglada-Martinez H, Riu-Viladoms G, Martin-Conde M, Rovira-Illamola M, Sotoca-Momblona JM, Codina-Jane C. Does mHealth increase adherence to medication? Results of a systematic review. Int J Clin Pract 2015;**69**(1):9-32 doi: 10.1111/ijcp.12582[published Online First: Epub Date]|.

6. Rathbone AL, Prescott J. The Use of Mobile Apps and SMS Messaging as Physical and Mental Health Interventions: Systematic Review. J Med Internet Res 2017;**19**(8):e295 doi: 10.2196/jmir.7740[published Online First: Epub Date]|.

7. Whitehead L, Seaton P. The Effectiveness of Self-Management Mobile Phone and Tablet Apps in Long-term Condition Management: A Systematic Review. J Med Internet Res 2016;**18**(5):e97 doi: 10.2196/jmir.4883[published Online First: Epub Date]|.

8. Wu Y, Yao X, Vespasiani G, et al. Mobile App-Based Interventions to Support Diabetes Self-Management: A Systematic Review of Randomized Controlled Trials to Identify Functions Associated with Glycemic Efficacy. JMIR Mhealth Uhealth 2017;**5**(3):e35 doi: 10.2196/mhealth.6522[published Online First: Epub Date]|.

9. Cohen AB, Safavi K. The Oversell and Undersell of Digital Health. Health Affairs Blog, 2019.

10. Schickedanz A, Huang D, Lopez A, et al. Access, interest, and attitudes toward electronic communication for health care among patients in the medical safety net. J Gen Intern Med 2013;**28**(7):914-20 doi: 10.1007/s11606-012-2329-5[published Online First: Epub Date]|.

11. Health Information Technology: HHS Should Assess the Effectiveness of Its Efforts to Enhance Patient Access to and Use of Electronic Health Information. In: Office UGA, ed. Washington DC: US Government Accountability Office 2017

12. Broderick JD, T.; Langhans, E.; Lemerise, A.J.; Lier, S.; Harris, L. Designing health literate mobile apps. Discussion Paper. Institute of Medicine, Washington, DC. 2013

13. Chakkalakal RJ, Kripalani S, Schlundt DG, Elasy TA, Osborn CY. Disparities in using technology to access health information: race versus health literacy. Diabetes Care 2014;**37**(3):e53-4 doi: 10.2337/dc13-1984[published Online First: Epub Date]|.

14. Gordon NP, Hornbrook MC. Differences in Access to and Preferences for Using Patient Portals and Other eHealth Technologies Based on Race, Ethnicity, and Age: A Database and Survey Study of Seniors in a Large Health Plan. J Med Internet Res 2016;**18**(3):e50 doi: 10.2196/jmir.5105[published Online First: Epub Date]|.

15. Mackert M, Mabry-Flynn A, Champlin S, Donovan EE, Pounders K. Health Literacy and Health Information Technology Adoption: The Potential for a New Digital Divide. J Med Internet Res 2016;**18**(10):e264 doi: 10.2196/jmir.6349[published Online First: Epub Date]|.

16. Ray R SA, Gilbert KL, Roberts JD. Missed Opportunity? Leveraging Mobile Technology to Reduce Racial Health Disparities. J Health Polit Policy Law 2017;**42**(5):901-24
17. Sarkar U, Karter AJ, Liu JY, et al. The literacy divide: health literacy and the use of an internet-based patient portal in an integrated health system-results from the diabetes study of northern California (DISTANCE). J Health Commun 2010;**15 Suppl 2**:183-96 doi: 10.1080/10810730.2010.499988[published Online First: Epub Date]|.
18. Zhang Y, Lauche R, Sibbritt D, Olaniran B, Cook R, Adams J. Comparison of Health Information Technology Use Between American Adults With and Without Chronic Health Conditions: Findings From The National Health Interview Survey 2012. J Med Internet Res 2017;**19**(10):e335 doi: 10.2196/jmir.6989[published Online First: Epub Date]|.
19. Grossman LV, Masterson Creber RM, Benda NC, Wright D, Vawdrey DK, Ancker JS. Interventions to increase patient portal use in vulnerable populations: a systematic review. J Am Med Inform Assoc 2019 doi: 10.1093/jamia/ocz023[published Online First: Epub Date]|.
20. Ancker JS, Hafeez B, Kaushal R. Socioeconomic Disparities in Adoption of Personal Health Records Over Time. Am J Manag Care 2016;**22**(8):539-40.
21. Anthony DL, Campos-Castillo C, Lim PS. Who Isn’t Using Patient Portals And Why? Evidence And Implications From A National Sample Of US Adults. Health Affairs 2018;**37**(12):1948-54 doi: 10.1377/hlthaff.2018.05117[published Online First: Epub Date]|.
22. Peacock S, Reddy A, Leveille SG, et al. Patient portals and personal health information online: perception, access, and use by US adults. J Am Med Inform Assoc 2017;**24**(e1):e173-e77 doi: 10.1093/jamia/ocw095[published Online First: Epub Date]|.
23. Veinot TC, Mitchell H, Ancker JS. Good intentions are not enough: how informatics interventions can worsen inequality. J Am Med Inform Assoc 2018;**25**(8):1080-88 doi: 10.1093/jamia/ocy052[published Online First: Epub Date]|.
24. Antonio MG, Petrovskaya O, Lau F. Is research on patient portals attuned to health equity? A scoping review. J Am Med Inform Assoc 2019 doi: 10.1093/jamia/ocz054[published Online First: Epub Date]|.
25. Irizarry T, DeVito Dabbs A, Curran CR. Patient Portals and Patient Engagement: A State of the Science Review. J Med Internet Res 2015;**17**(6):e148 doi: 10.2196/jmir.4255[published Online First: Epub Date]|.
26. Wildenbos GA, Peute L, Jaspers M. Facilitators and Barriers of Electronic Health Record Patient Portal Adoption by Older Adults: A Literature Study. Stud Health Technol Inform 2017;**235**:308-12 doi: 10.3233/978-1-61499-753-5-308[published Online First: Epub Date]|.
27. Fraccaro P, Vigo M, Balatsoukas P, Buchan IE, Peek N, van der Veer SN. Patient Portal Adoption Rates: A Systematic Literature Review and Meta-Analysis. Stud Health Technol Inform 2017;**245**:79-83 doi: 10.3233/978-1-61499-830-3-79[published Online First: Epub Date]|.
28. Coughlin SS, Stewart JL, Young L, Heboyan V, De Leo G. Health literacy and patient web portals. Int J Med Inform 2018;**113**:43-48 doi: 10.1016/j.ijmedinf.2018.02.009[published Online First: Epub Date]|.
29. Lyles CR, Nelson EC, Frampton S, Dykes PC, Cemballi AG, Sarkar U. Using Electronic Health Record Portals to Improve Patient Engagement: Research Priorities and Best

Practices. Ann Intern Med 2019;**171**:xxx-xxx doi: doi:10.7326/M19-0876[published Online First: Epub Date]|.

30. Turvey C, Klein D, Fix G, et al. Blue Button use by patients to access and share health record information using the Department of Veterans Affairs' online patient portal. J Am Med Inform Assoc 2014;**21**(4):657-63

31. Taha J, Sharit J, Czaja SJ. The impact of numeracy ability and technology skills on older adults' performance of health management tasks using a patient portal. J Appl Gerontol 2014;**33**(4):416-36 doi: 10.1177/0733464812447283[published Online First: Epub Date]|.

32. Graetz I, Gordon N, Fung V, Hamity C, Reed ME. The Digital Divide and Patient Portals: Internet Access Explained Differences in Patient Portal Use for Secure Messaging by Age, Race, and Income. Med Care 2016;**54**(8):772-9

33. Price-Haywood EG, Harden-Barrios J, Ulep R, Luo Q. eHealth Literacy: Patient Engagement in Identifying Strategies to Encourage Use of Patient Portals Among Older Adults. Popul Health Manag 2017;**20**(6):486-94

34. Hung M, Conrad J, Hon SD, Cheng C, Franklin JD, Tang P. Uncovering patterns of technology use in consumer health informatics. Wiley Interdiscip Rev Comput Stat 2013;**5**(6):432-47 doi: 10.1002/wics.1276[published Online First: Epub Date]|.

35. Yen PY, Walker DM, Smith JMG, Zhou MP, Menser TL, McAlearney AS. Usability evaluation of a commercial inpatient portal. Int J Med Inform 2018;**110**:10-18 doi: 10.1016/j.ijmedinf.2017.11.007[published Online First: Epub Date]|.

36. Moher D, Liberati A, Tetzlaff J, Altman DG, Group atP. Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA StatementThe PRISMA Statement. Annals of Internal Medicine 2009;**151**(4):264-69 doi: 10.7326/0003-4819-151-4-200908180-00135[published Online First: Epub Date]|.

37. Digital Health. Secondary Digital Health 2020. https://www.fda.gov/medical-devices/digital-health.

38. Sterne JA, Hernan MA, Reeves BC, et al. ROBINS-I: a tool for assessing risk of bias in non-randomised studies of interventions. BMJ 2016;**355**:i4919 doi: 10.1136/bmj.i4919[published Online First: Epub Date]|.

39. Heminger CL, Boal AL, Zumer M, Abroms LC. Text2Quit: an analysis of participant engagement in the mobile smoking cessation program. Am J Drug Alcohol Abuse 2016;**42**(4):450-8 doi: 10.3109/00952990.2016.1149591[published Online First: Epub Date]|.

40. Brusk JJ, Bensley RJ. A Comparison of Mobile and Fixed Device Access on User Engagement Associated With Women, Infants, and Children (WIC) Online Nutrition Education. JMIR Res Protoc 2016;**5**(4):e216 doi: 10.2196/resprot.6608[published Online First: Epub Date]|.

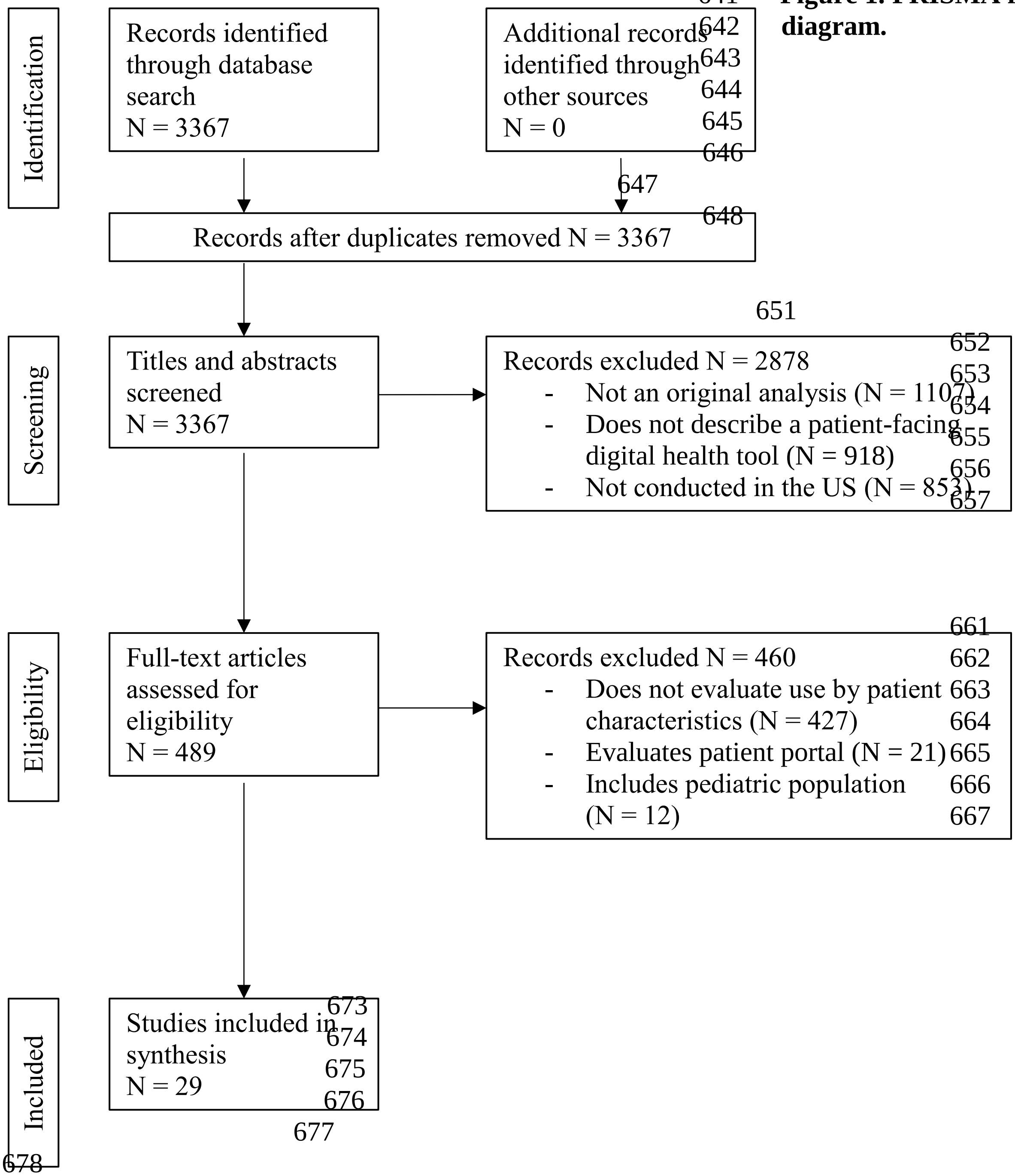
41. Khosropour CM, Johnson BA, Ricca AV, Sullivan PS. Enhancing retention of an Internet-based cohort study of men who have sex with men (MSM) via text messaging: randomized controlled trial. J Med Internet Res 2013;**15**(8):e194 doi: 10.2196/jmir.2756[published Online First: Epub Date]|.

42. Buis LR, Hirzel L, Turske SA, Des Jardins TR, Yarandi H, Bondurant P. Use of a Text Message Program to Raise Type 2 Diabetes Risk Awareness and Promote Health Behavior Change (Part I): Assessment of Participant Reach and Adoption. J Med Internet Res 2013;**15**(12):e281

43. Nelson LA, Mulvaney SA, Gebretsadik T, Ho YX, Johnson KB, Osborn CY. Disparities in the use of a mHealth medication adherence promotion intervention for low-income adults with type 2 diabetes. J Am Med Inform Assoc 2016;**23**(1):12-8 doi: 10.1093/jamia/ocv082[published Online First: Epub Date]|.
44. Wolin KY, Steinberg DM, Lane IB, et al. Engagement with eHealth Self-Monitoring in a Primary Care-Based Weight Management Intervention. PLoS One 2015;**10**(10):e0140455 doi: 10.1371/journal.pone.0140455[published Online First: Epub Date]|.
45. Ben-Zeev D, Scherer EA, Gottlieb JD, et al. mHealth for Schizophrenia: Patient Engagement With a Mobile Phone Intervention Following Hospital Discharge. JMIR Ment Health 2016;**3**(3):e34 doi: 10.2196/mental.6348[published Online First: Epub Date]|.
46. Flickinger TE, DeBolt C, Wispelwey E, et al. Content Analysis and User Characteristics of a Smartphone-Based Online Support Group for People Living with HIV. Telemed J E Health 2016;**22**(9):746-54 doi: 10.1089/tmj.2015.0160[published Online First: Epub Date]|.
47. Frisbee KL. Variations in the Use of mHealth Tools: The VA Mobile Health Study. JMIR Mhealth Uhealth 2016;**4**(3):e89 doi: 10.2196/mhealth.3726[published Online First: Epub Date]|.
48. Toscos T, Carpenter M, Drouin M, Roebuck A, Kerrigan C, Mirro M. College Students' Experiences with, and Willingness to Use, Different Types of Telemental Health Resources: Do Gender, Depression/Anxiety, or Stress Levels Matter? Telemed J E Health 2018 doi: 10.1089/tmj.2017.0243[published Online First: Epub Date]|.
49. Sosa A, Heineman N, Thomas K, et al. Improving patient health engagement with mobile texting: A pilot study in the head and neck postoperative setting. Head Neck 2017;**39**(5):988-95 doi: 10.1002/hed.24718[published Online First: Epub Date]|.
50. O'Connor S, Hanlon P, O'Donnell CA, Garcia S, Glanville J, Mair FS. Understanding factors affecting patient and public engagement and recruitment to digital health interventions: a systematic review of qualitative studies. BMC Med Inform Decis Mak 2016;**16**(1):120 doi: 10.1186/s12911-016-0359-3[published Online First: Epub Date]|.
51. Gerber DE, Laccetti AL, Chen B, et al. Predictors and Intensity of Online Access to Electronic Medical Records Among Patients With Cancer. J Oncol Pract 2014;**10**(5):e307-12
52. Graetz I, Huang J, Brand RJ, Hsu J, Yamin CK, Reed ME. Bridging the Digital Divide: Mobile Access to Personal Health Records Among Patients With Diabetes. Am J Manag Care 2018;**24**(1):43-48
53. Shimada SL, Allison JJ, Rosen AK, Feng H, Houston TK. Sustained Use of Patient Portal Features and Improvements in Diabetes Physiological Measures. J Med Internet Res 2016;**18**(7):e179 doi: 10.2196/jmir.5663[published Online First: Epub Date]|.
54. Griffin A, Skinner A, Thornhill J, Weinberger M. Patient Portals: Who uses them? What features do they use? And do they reduce hospital readmissions? Appl Clin Inform 2016;**7**(2):489-501 doi: 10.4338/ACI-2016-01-RA-0003[published Online First: Epub Date]|.
55. Wallace LS, Angier H, Huguet N, et al. Patterns of Electronic Portal Use among Vulnerable Patients in a Nationwide Practice-based Research Network: From the OCHIN Practice-based Research Network (PBRN). J Am Board Fam Med 2016;**29**(5):592-603 doi: 10.3122/jabfm.2016.05.160046[published Online First: Epub Date]|.

56. Jensen JD, King AJ, Davis LA, Guntzviller LM. Utilization of internet technology by low-income adults: the role of health literacy, health numeracy, and computer assistance. J Aging Health 2010;**22**(6):804–26
57. Rogers EM. *Diffusion of Innovations.* New York, NY: Free Press, 1962.
58. Anthony DL, Campos-Castillo C. Patient Portals And Disparities: The Authors Reply. Health Aff (Millwood) 2019;**38**(3):510 doi: 10.1377/hlthaff.2019.00083[published Online First: Epub Date]|.
59. Toscos T, Drouin M, Pater J, Flanagan M, Pfafman R, Mirro MJ. Selection biases in technology-based intervention research: patients' technology use relates to both demographic and health-related inequities. J Am Med Inform Assoc 2019 doi: 10.1093/jamia/ocz058[published Online First: Epub Date]|.
60. Berland GK EM, Morales LS, Algazy JI, Kravitz RL, Broder MS, Kanouse DE, Munoz JA, Puyol JA, Lara M, Watkins KE, Yang H, McGlynn EA. Health information on the Internet: accessibility, quality, and readability in English and Spanish. JAMA 2001;**285**(20):2612–21
61. Colorafi K, Greenes RA, Kates M. Preferences of older adults and their families for Meaningful Use clinical summaries. Mhealth 2018;**4**:8 doi: 10.21037/mhealth.2018.03.04[published Online First: Epub Date]|.
62. Irizarry T SJ, Nilsen ML, Czaja S, Beach S, DeVito Dabbs A. Patient Portals as a Tool for Health Care Engagement: A Mixed-Method Study of Older Adults With Varying Levels of Health Literacy and Prior Patient Portal Use. JMIR 2017;**19**(3):e99
63. Mishuris RG SM, Fix GM, et al. Barriers to patient portal access among veterans receiving home-based primary care: a qualitative study. Health expectations 2015;**18**(6):2296-305
64. Tieu L, Schillinger D, Sarkar U, et al. Online patient websites for electronic health record access among vulnerable populations: portals to nowhere? J Am Med Inform Assoc 2017;**24**(e1):e47-e54 doi: 10.1093/jamia/ocw098[published Online First: Epub Date]|.
65. Crosier BS, Brian RM, Ben-Zeev D. Using Facebook to Reach People Who Experience Auditory Hallucinations. J Med Internet Res 2016;**18**(6):e160 doi: 10.2196/jmir.5420[published Online First: Epub Date]|.
66. Bravo C, O'Donoghue C, Kaplan C, Luce J, Ozanne E. Can mHealth Improve Risk Assessment in Underserved Populations? Acceptability of a Breast Health Questionnaire App in Ethnically Diverse, Older, Low-Income Women. J Health Dispar Res Pract 2014;**7**(4)
67. Health R, Health SCfD. Digital Health Consumer Adoption Report 2019. Secondary Digital Health Consumer Adoption Report 2019 2019. https://rockhealth.com/reports/digital-health-consumer-adoption-report-2019/.
68. Kreps GL NL. New directions in eHealth communication: opportunities and challenges. Patient Educ Couns 2010;**78**(3):329-36
69. National Research Council (US); Institute of Medicine (US); Woolf SH, Aron L, editors. U.S. Health in International Perspective: Shorter Lives, Poorer Health. Washington (DC): National Academies Press (US); 2013.

Figure 1. PRISMA flow diagram.



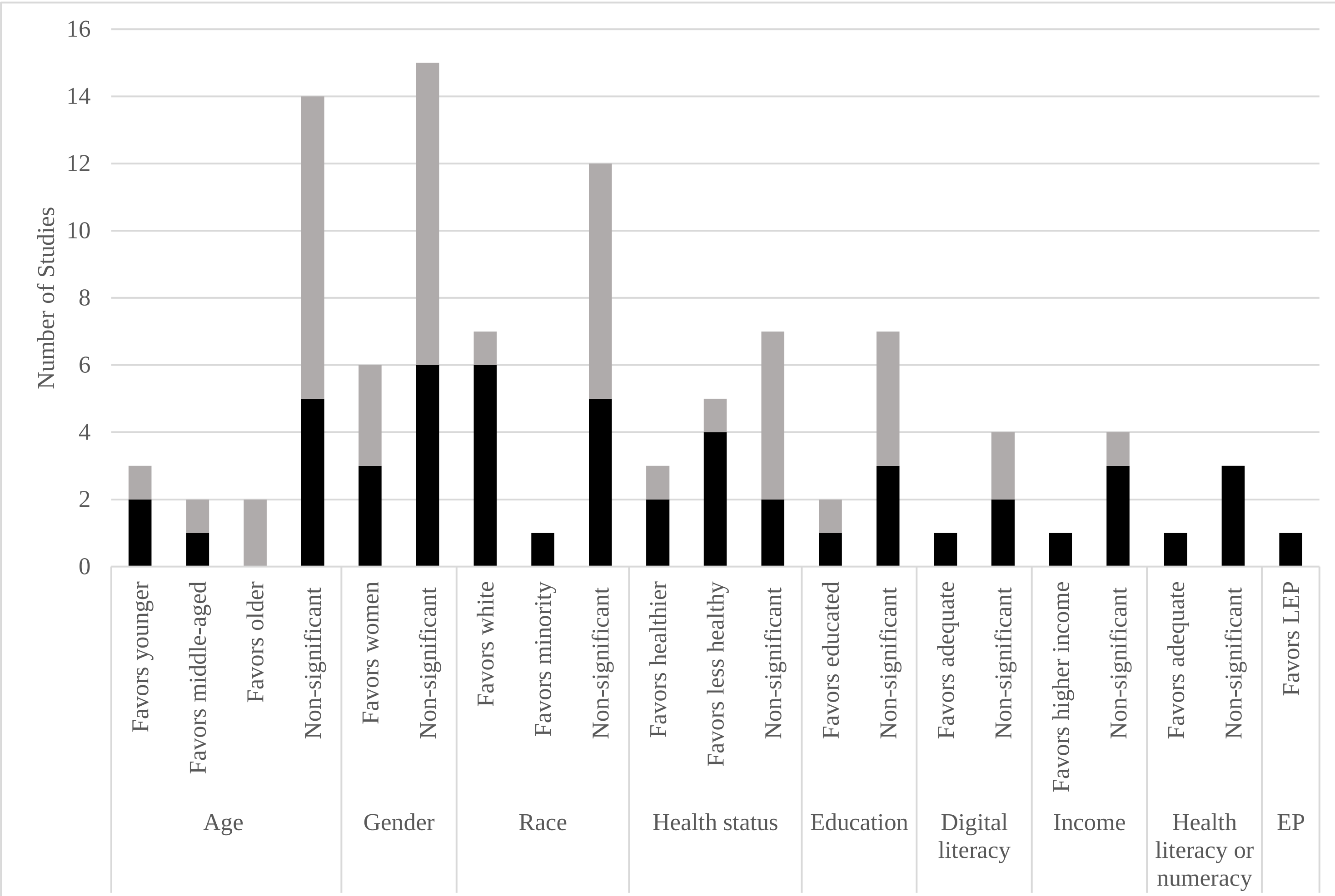


Figure 2. Patient characteristics associated with use, both among all included studies (entire bar) and within the subgroup of studies with more robust methodology (black).

Appendix A1. Search strategy details.

We conducted term harvesting, the identification of keywords and controlled vocabulary used in key articles, followed by an iterative process of testing individual search terms to develop our final search strategy. Boolean logic was applied by combining similar terms with OR and using AND between the two concepts: for example, (“Patient Participation”[Mesh] OR “self management”) AND (“health information technology” OR “patient portals”). The database search was conducted in PubMed on July 27, 2018.

Date	Database searched	Search strategy	Number of results
7/27/18	PubMed (1966-)	("self management"[tiab] OR engaged[tiab] OR engagement[tiab] OR engages[tiab] OR engage[tiab] OR engaging[tiab] OR "user uptake"[tiab] OR "self help"[tiab] OR "Patient Participation"[Mesh]) AND ("health information technology"[tiab] OR "health information technologies"[tiab] OR "health technology"[tiab] OR "health technologies"[tiab] OR "patient portal"[tiab] OR "patient portals"[tiab] OR "portal use"[tiab] OR "online portal"[tiab] OR "online portals"[tiab] OR apps[tiab] OR app[tiab] OR "cell phone"[tiab] OR "cell phones"[tiab] OR smartphone[tiab] OR smartphones[tiab] OR "smart phone"[tiab] OR "smart phones"[tiab] OR "mobile phone"[tiab] OR "mobile phones"[tiab] OR "mobile device"[tiab] OR "mobile devices"[tiab] OR "mobile applications"[tiab] OR "mobile health"[tiab] OR mhealth[tiab] OR "m-health"[tiab] OR	3367

		ehealth[tiab] OR "digital health"[tiab] OR "text messaging"[tiab] OR "text message"[tiab] OR "text messages"[tiab] OR texting[tiab]) AND ("2013/07/29"[PDat] : "2018/07/27"[PDat])	

Appendix A2. Complete reference list of included studies.

1. Almodovar AS, Surve S, Axon DR, Cooper D, Nahata MC. Self-Directed Engagement with a Mobile App (Sinasprite) and Its Effects on Confidence in Coping Skills, Depression, and Anxiety: Retrospective Longitudinal Study. JMIR Mhealth Uhealth. 2018 Mar 16;6(3):e64.
2. Ben-Zeev D, Scherer EA, Gottlieb JD, Rotondi AJ, Brunette MF, Achtyes ED, et al. mHealth for Schizophrenia: Patient Engagement With a Mobile Phone Intervention Following Hospital Discharge. JMIR Ment Health. 2016 Jul 27;3(3):e34.
3. Bergner EM, Nelson LA, Rothman RL, Mayberry L. Text Messaging May Engage and Benefit Adults with Type 2 Diabetes Regardless of Health Literacy Status. Health Lit Res Pract. 2017 Oct;1(4):e192-e202.
4. Brusk JJ, Bensley RJ. A Comparison of Mobile and Fixed Device Access on User Engagement Associated With Women, Infants, and Children (WIC) Online Nutrition Education. JMIR Res Protoc. 2016 Nov 15;5(4):e216.
5. Buis LR, Hirzel L, Turske SA, Des Jardins TR, Yarandi H, Bondurant P. Use of a Text Message Program to Raise Type 2 Diabetes Risk Awareness and Promote Health Behavior Change (Part I): Assessment of Participant Reach and Adoption. J Med Internet Res. 2013;15(12):e281.
6. Christofferson DE, Hertzberg JS, Beckham JC, Dennis PA, Hamlett-Berry K. Engagement and abstinence among users of a smoking cessation text message program for veterans. Addict Behav. 2016 Nov;62:47-53.
7. Dean DAL, Griffith DM, McKissic SA, Cornish EK, Johnson-Lawrence V. Men on the Move-Nashville: Feasibility and Acceptability of a Technology-Enhanced Physical Activity Pilot Intervention for Overweight and Obese Middle and Older Age African American Men. Am J Mens Health. 2018 Jul;12(4):798-811.
8. Flickinger TE, DeBolt C, Wispelwey E, Laurence C, Plews-Ogan E, Waldman AL, et al. Content Analysis and User Characteristics of a Smartphone-Based Online Support Group for People Living with HIV. Telemed J E Health. 2016 Sep;22(9):746-54.
9. Frisbee KL. Variations in the Use of mHealth Tools: The VA Mobile Health Study. JMIR Mhealth Uhealth. 2016 Jul 19;4(3):e89.
10. Greysen SR, Khanna RR, Jacolbia R, Lee HM, Auerbach AD. Tablet computers for hospitalized patients: a pilot study to improve inpatient engagement. J Hosp Med. 2014 Jun;9(6):396-9.
11. Hales S, Turner-McGrievy GM, Wilcox S, Davis RE, Fahim A, Huhns M, et al. Trading pounds for points: Engagement and weight loss in a mobile health intervention. Digit Health. 2017 Jan-Dec;3:2055207617702252.
12. Heminger CL, Boal AL, Zumer M, Abroms LC. Text2Quit: an analysis of participant engagement in the mobile smoking cessation program. Am J Drug Alcohol Abuse. 2016 Jul;42(4):450-8.
13. Iacoviello BM, Steinerman JR, Klein DB, Silver TL, Berger AG, Luo SX, et al. Clickotine, A Personalized Smartphone App for Smoking Cessation: Initial Evaluation. JMIR Mhealth Uhealth. 2017 Apr 25;5(4):e56.
14. Irizarry T, Allen M, Suffoletto BP, Einhorn J, Burke LE, Kamarck TW, et al. Development and Preliminary Feasibility of an Automated Hypertension Self-Management System. Am J Med. 2018 Sep;131(9):1125 e1- e8.

15. Khosropour CM, Johnson BA, Ricca AV, Sullivan PS. Enhancing retention of an Internet-based cohort study of men who have sex with men (MSM) via text messaging: randomized controlled trial. J Med Internet Res. 2013 Aug 27;15(8):e194.
16. Lanpher MG, Askew S, Bennett GG. Health Literacy and Weight Change in a Digital Health Intervention for Women: A Randomized Controlled Trial in Primary Care Practice. J Health Commun. 2016;21 Suppl 1:34-42.
17. Mohr DC, Tomasino KN, Lattie EG, Palac HL, Kwasny MJ, Weingardt K, et al. IntelliCare: An Eclectic, Skills-Based App Suite for the Treatment of Depression and Anxiety. J Med Internet Res. 2017 Jan 5;19(1):e10.
18. Moitra E, Gaudiano BA, Davis CH, Ben-Zeev D. Feasibility and acceptability of post-hospitalization ecological momentary assessment in patients with psychotic-spectrum disorders. Compr Psychiatry. 2017 Apr;74:204-13.
19. Moore BA, Buono FD, Printz DMB, Lloyd DP, Fiellin DA, Cutter CJ, et al. Customized recommendations and reminder text messages for automated, computer-based treatment during methadone. Exp Clin Psychopharmacol. 2017 Dec;25(6):485-95.
20. Nelson LA, Mulvaney SA, Gebretsadik T, Ho YX, Johnson KB, Osborn CY. Disparities in the use of a mHealth medication adherence promotion intervention for low-income adults with type 2 diabetes. J Am Med Inform Assoc. 2016 Jan;23(1):12-8.
21. Pavliscsak H, Little JR, Poropatich RK, McVeigh FL, Tong J, Tillman JS, et al. Assessment of patient engagement with a mobile application among service members in transition. J Am Med Inform Assoc. 2016 Jan;23(1):110-8.
22. Santa Maria D, Padhye N, Yang Y, Gallardo K, Businelle M. Predicting Sexual Behaviors Among Homeless Young Adults: Ecological Momentary Assessment Study. JMIR Public Health Surveill. 2018 Apr 10;4(2):e39.
23. Schmidt CA, Romine JK, Bell ML, Armin J, Gordon JS. User Participation and Engagement With the See Me Smoke-Free mHealth App: Prospective Feasibility Trial. JMIR Mhealth Uhealth. 2017 Oct 9;5(10):e142.
24. Sosa A, Heineman N, Thomas K, Tang K, Feinstein M, Martin MY, et al. Improving patient health engagement with mobile texting: A pilot study in the head and neck postoperative setting. Head Neck. 2017 May;39(5):988-95.
25. Toscos T, Carpenter M, Drouin M, Roebuck A, Kerrigan C, Mirro M. College Students' Experiences with, and Willingness to Use, Different Types of Telemental Health Resources: Do Gender, Depression/Anxiety, or Stress Levels Matter? Telemed J E Health. 2018 Apr 16.
26. Turner CM, Coffin P, Santos D, Huffaker S, Matheson T, Euren J, et al. Race/ethnicity, education, and age are associated with engagement in ecological momentary assessment text messaging among substance-using MSM in San Francisco. J Subst Abuse Treat. 2017 Apr;75:43-8.
27. Turner-McGrievy GM, Tate DF. Weight loss social support in 140 characters or less: use of an online social network in a remotely delivered weight loss intervention. Transl Behav Med. 2013;3(3):287-94.
28. Wolin KY, Steinberg DM, Lane IB, Askew S, Greaney ML, Colditz GA, et al. Engagement with eHealth Self-Monitoring in a Primary Care-Based Weight Management Intervention. PLoS One. 2015;10(10):e0140455.

29. Zeng EY, Vilardaga R, Heffner JL, Mull KE, Bricker JB. Predictors of Utilization of a Novel Smoking Cessation Smartphone App. Telemed J E Health. 2015 Dec;21(12):998-1004.

Appendix A3. Detailed study characteristics by type of digital health tool.

	Author (year of publication)	Health Area of Focus	Study Design	Size (N)	Study Objective	Use Outcome Measure(s)	Demographics Assessed
Smartphone or Tablet Apps							
	Almodovar, A (2018)	Chronic disease management	Observational (Retrospective analysis of dataset)	34	Evaluate use of Sinasprite (mobile app for mental health) and association between use and depression/anxiety outcomes	Length of time spent in app, completion of activities in app, and answering vs not answering self-assessment questions	Age Gender Race Education Income Health status
	Ben-Zeev, D (2016)	Chronic disease management	Observational (Implementation)	342	Evaluate feasibility and examine association between patient characteristics and engagement with mHealth program	Number of days of app use (overall, per week, and daily on-demand), number of days participants responded to prompts	Age Gender Race Health status
	Frisbee, K (2016)	Chronic disease management	Observational (Pilot)	882	Examine patient and family characteristics associated with app use	Use vs non-use of app	Age Digital literacy Health status
	Greysen, S (2014)	No focus	Observational (Implementation)	30	Pilot study to examine use of tablets to access patient portal in hospitalized patients	Completing vs not completing an online health model and/or of 1 function on tablet	Age Digital literacy

	Hales, H (2017)	Weight management	Observational (Implementation)	24	Examine use of the Social Pounds Off Digitally (weight management app) and predictors of weight loss	Frequency of use of various app features	Age Gender Race Education
	Iacoviello, B (2017)	Tobacco or substance use	Observational (Implementation)	416	Assess engagement, efficacy, and safety of Clickotine (a smoking cessation app)	Number of times app opened, number of weeks actively engaging in app	Age Gender Race Health status
	Mohr, D (2017)	Chronic disease management	Observational (Pilot)	99	Pilot study of IntelliCare (suite of apps for depression and anxiety)	Number of app sessions and length of time spent in app	Age Gender Race Education Health status
	Moitra, E (2017)	Chronic disease management	Observational (Feasibility)	65	Feasibility of ecologic momentary assessment via mobile devices	Completer vs non-completer of EMA	Gender Health status
	Pavliscsak, H (2016)*	Chronic disease management	Secondary analysis of intervention arm of a randomized controlled trial	95	Secondary analysis examining engagement with mCare (an app for rehabilitating wounded Service Members) among those randomized to receive mCare in a randomized controlled trial	Exposure and response to mCare questionnaires	Age Gender

	Schmidt, C (2017)	Tobacco or substance use	Observational (Feasibility)	247	Examine use and outcomes of See Me Smoke-Free (a smoking cessation app)	Number of times participants answered daily questions	Age Race
	Zeng, E (2015)	Tobacco or substance use	Secondary analysis of intervention arm of a randomized controlled trial	98	Secondary analysis examining association between patient characteristics and use of SmartQuit (a smoking cessation app) among those randomized in a pilot trial to receive SmartQuit	Number of times participants opened app over 8 weeks	Age Gender Education Health status
Text Messaging							
	Bergner, E (2017)	Chronic disease management	Observational (Mixed methods usability evaluation)	55	Explore association between health literacy and Rapid Education/Encouragement and Communications for Health (a text messaging intervention to suppor self-care in type 2 diabetes)	Number of times participants answered daily messages	Health literacy or numeracy

	Buis, R (2013)	Prevention/ Promotion	Observational (Retrospective analysis of dataset)	5570	Use RE-AIM framework to evaluate reach and adoption of Txt4health (text messaging program for diabetes risk assessment)	Reach, adoption, and number of times participants responded to weekly requests to log weights	Age Gender Race
	Christofferson, D (2016)	Tobacco or substance use	Observational (Retrospective analysis of dataset)	1470	Examine use and effectiveness of SmokefreeVET (a smoking cessation program)	Number of text messages sent by participants to the SmokeFreeVET program over 6 weeks	Age Gender Health status
	Heminger, C (2016)	Tobacco or substance use	Observational (Retrospective analysis of dataset)	262	Secondary analysis of a randomized controlled trial examining the association between use of Text2Quit (a smoking cessation program) and smoking cessation	Aggregate count of keyword and survey responses and of web logins	Age Gender Race Education Digital literacy Health status
	Irizarry, T (2018)	Chronic disease management	Observational (Implementation)	43	Pilot study of MyBP (text messaging program to support blood pressure self-monitoring and management)	Frequency of responding to prompts about blood pressure	Age Gender Race Education Health status

	Khosropour, C (2013)	Prevention/ Promotion	Observational (Implementation)	710	Compare retention in a 12-month prospective study of HIV-negative MSM receiving surveys via text messages versus Internet	Retention in text-messaging program at 12 months	Race
	Nelson, L (2015)*	Chronic disease management	Observational (Pilot)	80	Examine association between patient factors and engagement in a medication adherence program consisting of text messages and interactive automated calls	Number of responses to daily text messages, and participation in weekly IVR calls over 11 weeks	Age Gender Race Income Health literacy or numeracy Health status
	Santa Maria, D (2018)	Prevention/ Promotion	Observational (Implementation)	66	Use ecologic momentary assessment to determine predictors of sexual activity among homeless youth	Number of responses to EMA	Age Gender Race
	Sosa, A (2017)	Surgery/Post -operative Care	Observational (Pilot)	23	Pilot study evaluating an automated text-message based intervention for post-operative needs	Frequency of text messages sent, dichotomized as high vs low by median split	Age Gender Race Education Income Health status

	Turner, C (2017)	Tobacco or substance use	Observational (Pilot)	30	Examine associations between patient characteristics and engagement in ecologic momentary assessment text messages	Frequency of responding to EMA texts	Age Race
Interactive Voice Response							
	Lanpher, M (2016)	Weight management	Randomized controlled trial	175	Determine the association between health literacy and 12-month weight change and engagement in a weight management intervention	Completion of IVR calls	Health literacy or numeracy
	Moore, B (2017)	Tobacco or substance use	Randomized controlled trial	127	Two randomized controlled trials evaluating features of the Recovery Line (automated real-time assistance by phone for patients in methadone maintenance)	Number of calls and total minutes of call time	Gender
	Wolin, K (2015)	Weight management	Secondary analysis of intervention arm of a randomized controlled trial	180	Examine the effects of intervention modality choice (Internet vs interactive voice response) on engagement in a	Frequency of weekly self-monitoring over 24 months	Gender Race Education Income Health literacy or numeracy Digital literacy

					weight-loss intervention		Health status
Internet							
	Brusk, J (2016)	Prevention/ Promotion	Observational (Retrospective analysis of dataset)	305735	Compare impact of mobile vs fixed devices on user engagement with the website for the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC)	Number of links viewed and link view time	Race Limited English proficiency
	Toscos, T (2018)	Chronic disease management	Observational (Survey)	662	Examine use and willingness of use tele-mental health	Use vs non-use of anonymous chats and online therapy	Gender Health status
Social Media							
	Flickinger, T (2016)	Chronic disease management	Observational (Implementation)	38	Examine patient characteristics associated with posting on a community message board of a program for people living with HIV	Posting vs not posting on a community message board	Age Gender Race Education Income Health status

	Turner-McGrievy, G (2013)	Weight management	Secondary analysis of intervention arm of a randomized controlled trial	47	Secondary analysis to examine content and number of Twitter posts among those randomized to a mobile, social network arm of randomized controlled trial	Number of Twitter posts	Age Gender Race Digital literacy
Fitness Tracker							
	Dean, D (2018)	Weight management	Observational (Implementation)	40	Pilot study to assess feasibility and acceptability of a physical activity intervention including a Fitbit	Use vs non-use of Fitbit	Age

*The following studies are listed only once in the table but evaluated more than 1 type of digital health tool: Pavliscsak = Smart-phone or Tablet App AND Text Messaging; Nelson = Text Messaging AND Interactive Voice Response; Wolin = Internet AND Interactive Voice Response.

Appendix A4. Comment on patient characteristic definitions, measurement, and categorization.

For all included patient characteristics, studies varied in their definitions, measurement, and categorization. Age was most often measured continuously in years, though in 4 studies was divided into 2 or more categories. Gender was defined as “male” or “female” in nearly all studies; 2 studies included “other” and 2 studies included “transgender.” Eight of 18 studies dichotomized race/ethnicity as white versus non-white; the remainder included more than 2 categories for race/ethnicity. (For our data synthesis, we dichotomized race as white versus non-white.) Health status was included as self-reported health status, number of hospitalizations or chronic medical conditions, or various disease markers (e.g., HIV viral load); none of the studies measured health status using validated comorbidity indices. There was significant variation in the categorization of education; we therefore synthesized the data into the following groups: $<$ high school versus $\geq$ high school, and $<$ Bachelors versus $\geq$ Bachelors. Only 5 studies specified including participants with post-graduate education. We defined digital literacy broadly as any assessment of patients’ technology use, including both frequency and competence, as none of the studies used validated measures of digital literacy. Examples include number of text messages sent per day, baseline social media use frequency, or self-reported Internet use skills. Income measurements included both categories of annual incomes and incomes relative to the Federal Poverty Level. Health literacy and/or numeracy were included in analyses as limited versus adequate in 2/4 studies but were measured using different scales. Limited English proficiency was defined in the single study that included it as having a non-English preferred language.

Appendix A5. Appropriateness (“yes” if met criteria and “no” if did not meet criteria) for subgroup analysis by domain and overall for each study.

Author (year)	Sampling strategy*	Sample size**	Measurement or analytic methods^	Overall°
Almodovar, A (2018)	No	No	No	No
Ben-Zeev, D (2016)	No	Yes	Yes	Yes
Bergner, E (2017)	No	Yes	No	No
Brusk, J (2016)	No	Yes	Yes	Yes
Buis, R (2013)	Yes	Yes	Yes	Yes
Christofferson, D (2016)	No	Yes	No	No
Dean, D (2018)	Yes	No	No	No
Flickinger, T (2016)	Yes	No	Yes	Yes
Frisbee, K (2016)	Yes	Yes	Yes	Yes
Greysen, S (2014)	No	No	No	No
Hales, H (2017)	No	No	No	No
Heminger, C (2016)	Yes	Yes	Yes	Yes
Iacoviello, B (2017)	No	Yes	No	No
Irizarry, T (2018)	No	No	No	No
Khosropour, C (2013)	Yes	Yes	No	Yes
Lanpher, M (2016)	Yes	Yes	Yes	Yes
Mohr, D (2017)	No	Yes	No	No
Moitra, E (2017)	No	No	No	No
Moore, B (2017)	No	Yes	No	No
Nelson, L (2016)	No	Yes	Yes	Yes
Pavliscsak, H (2016)	No	Yes	No	No
Santa Maria, D (2018)	No	Yes	No	No
Schmidt, C (2017)	No	Yes	Yes	Yes
Sosa, A (2017)	Yes	No	Yes	Yes
Toscos, T (2018)	Yes	Yes	No	Yes
Turner-McGrievy, G (2013)	Yes	No	No	No
Turner, C (2017)	No	No	Yes	No
Wolin, K (2015)	Yes	Yes	No	Yes

Zeng, E (2015)	No	Yes	No	No

*"Yes" if the study clearly included and reported characteristics of non-users of the digital health solution.

**"Yes" if the study included ≥50 participants in analyses.

^"Yes" if the study presented multivariable relationships to assess whether a characteristic was predictive of use holding all other characteristics constant.

°"Yes" if the study met 2 out of the 3 above criteria.