Assessing Health Technology Literacy and Attitudes of Patients in an Urban Outpatient Psychiatry Clinic

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Abstract

Background: Digital health technologies are increasingly being integrated into mental health care. However, the adoption of these technologies can be influenced by patients' digital literacy and attitudes, which may vary based on sociodemographic factors. This variability necessitates a better understanding of patient digital literacy and attitudes to prevent a digital divide, which can worsen existing healthcare disparities.

Objective: This study aimed to assess digital literacy and attitudes toward digital health technologies among a diverse psychiatric outpatient population. Additionally, the study sought to identify clusters of patients based on their digital literacy and attitudes and to compare sociodemographic characteristics among these clusters.

Methods: A survey was distributed to adult psychiatric patients with various diagnoses in an urban outpatient psychiatry program. The survey included a demographic questionnaire, a digital literacy questionnaire, and a digital health attitudes questionnaire. Multiple linear regression analyses were used to identify predictors of digital literacy and attitudes. Cluster analysis was performed to categorize patients based on their responses. Pairwise comparisons and one-way ANOVA were conducted to analyze differences between clusters.

Results: A total of N= 256 patients were included in the analysis. The mean age of participants was 32 years (SD 12.6, range 16-70). The sample was racially/ethnically diverse: White (38.9%), Black (15.2%), Latinx (17.2%), Asian (23.0%), and Other (5.7%). Digital literacy was high for technologies such as smartphones, videoconferencing, and social media (items with >75% of participants reporting at least some use), but lower for health apps, mental health apps, wearables, and virtual reality (items with <42% reporting at least some use). Attitudes toward using technology in clinical care were generally positive (9 out of 10 items received >75% positive score), particularly for communication with providers and health data sharing.

Older age ($P<.001$) and lower educational attainment ($P<.001$) negatively predicted digital literacy scores, but no demographic variables predicted attitude scores.

Cluster analysis identified three patient groups. Relative to the other clusters, Cluster 1 (n=30) had lower digital literacy and intermediate acceptance of digital technology. Cluster 2 (n=50) had higher literacy and lower acceptance. Cluster 3 (n=176) displayed both higher literacy and acceptance. Significant between-cluster differences were observed in mean age and education level between clusters ($P<.001$), with Cluster 1 participants being older and having lower levels of formal education.

Conclusions: High digital literacy and acceptance of digital technologies were observed among our patients, indicating a generally positive outlook for digital health clinics. Our results also found that patients of older age and lower formal levels of educational attainment had lower digital literacy, highlighting the need for targeted interventions to support those who may struggle with adopting digital health tools.

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Keywords: Digital literacy, Attitudes, Mental Health, Digital health technology, Cluster analysis, Psychiatry

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1. Introduction

1.1 The Digital Psychiatry Revolution

The healthcare system is undergoing a digital evolution, driven by rapid technological advancements. “Digital health” is defined as “the use of information and communications technologies in medicine to manage illnesses and health risks and to promote wellness.”[1] Over the past decade, digital health has been met with enthusiasm from both patients and providers due to its potential to revolutionize the delivery of mental health services, making mental health treatment more affordable and accessible.[2–4] The mental health sector has been an early adopter of this technological integration, a trend accelerated by the COVID-19 pandemic. *Digital psychiatry* is a broad term that extends beyond telehealth, encompassing patient/provider information and communication tools (e.g., EMRs, patient portals, telepsychiatry videoconferencing platforms), digital interventions (e.g., therapy delivered through text messaging, smartphone apps, virtual reality headsets, or video games), symptom-monitoring tools (e.g., self-report symptom-tracking, or health data collected through wearable devices), and predictive machine learning tools that seek to use passive data from smartphones and wearable devices to potentially predict major mood episodes and psychotic relapses, offering a glimpse into the future capabilities of digital health.[5–7]

As digital approaches become more common, interest has grown in creating digital mental health clinics—new care delivery models that integrate digital tools into clinical practice.[8,9] Such clinics can potentially ameliorate existing disparities in healthcare accessibility and promote health equity among psychiatric patient populations.

1.2 Health Equity and the Digital Divide

Despite the benefits offered by digital psychiatry tools, an overreliance on digital tools could inadvertently exacerbate pre-existing disparities in healthcare access between those who can use technology and those who cannot. This is a concept known as the digital divide.[10] A variety of documented factors contribute to this inequity in the utilization of health technology, including differences in access (i.e., home wifi/broadband connectivity), proficiency or technological skills required to engage with these tools effectively, and attitudes towards the use of technology in mental healthcare.[10–12] For this paper, we group accessibility and usability broadly under the term "digital literacy,” which UNESCO defines as “the ability to access, manage, understand, integrate, communicate, evaluate and create information safely and appropriately through digital technologies.”[13] Within a healthcare context, digital literacy pertains to an individual’s ability to access digital tools, to understand health information from electronic sources, and to successfully use digital tools—including patient portals, videoconferencing, smartphone apps, wearable devices, and health trackers—both as interventions and for communication purposes.[12]

1.2.1 Digital Access and Literacy

The existing literature highlights notable disparities in digital access that correlate with demographic variables such as age, race, ethnicity, income, and educational attainment. While a high percentage of US adults own smartphones, access is not uniform across all groups. Ownership rates are marginally lower among individuals from low-income households, Black and older adults, and non-college-educated individuals.[14] Moreover, the same groups tend to be affected by the lack of home broadband connectivity among 15% of smartphone owners, further complicating their engagement with digital health services. This uneven access underscores the need for targeted interventions that address the specific barrier these populations face in utilizing digital health tools effectively.

Beyond access issues, differences in the technical/skills abilities required to successfully use digital health tools have been found in certain demographic groups. In particular, older age has been linked to lower digital literacy. A UK study examining digital technology use among psychiatric patients found that older adults reported less familiarity and confidence with using various mobile and computer devices.[15] Further, a US study of adults age 50 and over found that while usage rates of email, text messaging, and health applications were similar across racial/ethnic groups, older Black and Hispanic individuals were less likely to use patient portals and search online for health information compared to White older adults.[16] Language barriers also present significant challenges, as studies have found that a majority of health applications are monolingual, operating solely in English, thereby limiting use by non-English speakers.[17]

1.2.3 Digital Acceptability

Finally, differences in individual’s interest and motivation to use technology for mental healthcare can impact adoption independent of one’s ability. Personal beliefs about technology have been found to impact engagement with digital health tools—patients who are uninterested or have negative attitudes toward digital health tools could become “self-excluders,” thus exacerbating the risk of digital exclusion.[15]

Further, identifying patients who have positive attitudes toward technology is equally important. For example, a study of digital technology use in older adult patients found that while they reported literacy-related barriers to adoption, they had favorable attitudes toward the use of digital mental health tools.[18] Identifying patients with high digital acceptability, but lower literacy levels can help clinics target specific patients with resources, such as digital navigator support.[19] Currently, little is known about the general attitudes of patients toward mental health technology use in outpatient clinics or the patient characteristics that impact digital acceptability.

1.3 No Patient Left Offline: Bridging a Digital Divide

To successfully develop a digital psychiatric clinic without widening healthcare disparities, it is crucial to address the factors that contribute to a digital divide. Clinic leadership must work to identify patient groups that might be marginalized by the shift to digital workflows, screening, and interventions, so that targeted measures, such as enhanced technical support, resources for digital navigation, education about the benefits of digital tools, or even opting to retain traditional methods can be deployed, as appropriate.

Moreover, comprehending the interplay between digital literacy and the willingness to use digital tools is essential. It ensures that these innovations reach those who are open and stand to benefit from them, thereby optimizing patient engagement and outcomes.

1.4 Objectives

Our objective was to identify clusters of patients based on patterns in their expressed digital health literacy and attitudes, and to compare sociodemographic characteristics among the clusters. To accomplish this, we elicited patient responses to survey questions during intake for an outpatient treatment program in an urban, racially, and socioeconomically diverse area.

Our research questions were as follows:

1. What are the current states of digital literacy and attitudes toward digital health in this urban, racially and socioeconomically diverse outpatient psychiatric population?
2. Do patient characteristics such as race/ethnicity, age, gender, level of education, and marital status influence digital attitudes or digital literacy?
3. Are there patterns and/or subgroups among our patients with regard to digital literacy and attitudes? If so, do they differ by patient characteristic?

2. Methods

2.1 Study design

This study utilized an IRB-approved retrospective chart review design to examine the patient characteristics and digital literacy and attitudes outcomes of patients at an urban adult psychiatric outpatient clinic. During a two-year period, a voluntary electronic health care technology survey was administered via REDCap to all new patient intakes at four adult ambulatory psychiatry clinics as part of routine intake paperwork. The survey was administered as part of an initial pilot project to develop a psychiatric digital health program. The response rate was around 40%.

2.2 Study Setting

The outpatient program, located in Queens, New York, consists of multiple clinics, including the Adult Outpatient Psychiatry Department (AOPD), the Bipolar Disorder Clinic, the Behavioral Health College Partnership program, and the Early Treatment Program for first-break psychosis. The clinics offer comprehensive mental health outpatient services for adults with psychiatric conditions, including mood disorders, anxiety disorders, psychotic spectrum illnesses, and substance use issues. The patient population generally consists of patients who reside in Long Island, Queens, and Brooklyn, and as such, reflects the diversity of the surrounding community, which varies greatly by race and ethnicity, socioeconomic status, age, gender identity and orientation, education, and family structure.

2.3 Measures/Questionnaires

The survey contained three self-assessment questionnaires of interest to our team – a demographic questionnaire, a digital literacy survey, and a digital health attitudes questionnaire. The complete questionnaires can be viewed in the appendix.

2.3.1 Demographic Data/Patient Characteristics

The patients' demographic characteristics, including race and ethnicity, education level, employment status, age, sex, gender, and marital status, were ascertained through a self-reported questionnaire. Income level was not included as part of the survey; thus, employment status and education are used as a rough proxy for economic status.

2.3.2 Digital Literacy Scale

Participants were given a 10-item "Digital Literacy" scale created by the team developing the psychiatric digital health program. The scale reported good internal consistency of α= 0.85 (Cronbach's alpha). Participants were asked to rank their familiarity and frequency of use of several different technologies. The items included online shopping, web search, social media, video conferencing, smart speakers, smartphones, wearable devices, health tracking apps, mental health apps, and virtual reality (VR). Items were scored on a 4-point Likert scale, with 1 being no familiarity with and no use of the technology, and 4 being the highest familiarity and use of the technology. A total Digital Literacy score was generated for each participant by calculating the unweighted sum of the ten individual items. The complete questionnaire is provided in the supplementary materials.

2.3.3. Digital Attitudes Scale

Participants were also surveyed on their attitude toward using digital care for mental health using a 10-item questionnaire (or "Attitudes" scale) created by the team developing the psychiatric digital health program. The scale reported good internal consistency of α= 0.85 (Cronbach's alpha). The questions address participants' willingness to use different technologies for aspects of their mental health care. Participants were asked to rank each question on a 5-point Likert scale ranging from strongly disagree (score of 1) to strongly agree (score of 5). The items assessed attitudes toward three types of tools: a) *self-help and self-monitoring tools* (e.g., "Tracking my own symptoms (e.g., mood, anxiety) using a web or mobile app can support my mental health"), b) *tools that assist in communication with providers* ("e.g., Ability to communicate with my care team via text messages or mobile app can improve my care"), and c) *tools that share health data with providers* (e.g., "Automatically sharing info about my daily activities (e.g. sleep, physical activity) with my care team can improve my mental health" or "Sharing information about my online activity (e.g., Google searches, Facebook posts) can improve my care"). A total Attitudes score was generated for each participant by taking the unweighted sum across all 10 items. The complete questionnaire is provided in the supplementary materials.

2.4 Data Extraction/Preparation

Our inclusion criteria consisted of all patients who completed the healthcare technology survey (Attitude and Literacy scales) on intake. The survey was active between 11/21/2020 and 01/17/2022. A total of N=286 charts were extracted. Test entries (n=2) and charts with incomplete Digital Literacy or Attitudes scales (n=28) were removed from the data set. A total of 256 participants were included in the final analysis. For the remaining cases, missing values in the demographics scale were indicated as "Not Reported" and excluded from any relevant analyses.

2.5 Statistical analyses

All data analyses were conducted using R (version 4.2.2).

2.5.1 Linear Regressions

Multiple linear regression analyses were conducted to evaluate the relationships between patient characteristics (independent variables) and the total Digital Literacy and Attitudes scores (dependent variables). Standardized β coefficients were reported. Statistical significance was determined using a two-sided alpha level of .05.

2.5.2 Cluster Analysis

A two-step cluster analysis approach was performed to identify subgroups within the patient sample based on their responses to the literacy and attitude scales. First, we used the *NbClust* in R to determine the optimal number of clusters. A Euclidean distance matrix was calculated to measure dissimilarities between participants. K-means clustering was performed to produce 3 clusters, iteratively assigning each participant to one of the clusters to minimize the within-cluster sum of squares.

2.5.3 Pairwise Comparisons

To compare the differences in patient characteristics across cluster groups, group comparisons were conducted using either t-test for continuous variables or chi-squared test for categorical variables. For continuous variables (age, literacy score, attitudes score) significance was tested with ANOVA. For categorical variables (race, education, gender, gender, employment, sex, marital status), significance was tested with chi-squared test. For variables with significant differences across clusters, pairwise comparisons using t-tests with pooled standard deviation were conducted to assess the differences in patient characteristics between clusters. The p-values were adjusted using the false discovery rate (FDR) correction method.[20]

3. Results

3.1 Patient characteristics

Participant characteristics are summarized in Table 1. The mean age was 32 years (SD 12.6, range 16 - 70). Notably, the patient population was diverse and representative of the New York City metropolitan area: White (38.9%), Black (15.2%), Latinx (17.2%), Asian (23.0%), and Other (5.7%). Most patients (179/256, 70.1%) were single. Self-reported gender and sex were roughly equal between males and females. The majority (196/254, 77.2%) of the patients obtained some level of post-secondary education. There was a distribution in education status across those who were retired/on disability, unemployed, employed, or a student. Socioeconomic status was inferred from data on employment status and educational attainment rather than directly solicited from respondents.

Table 1. Participant Characteristics by Total and by Cluster

Characteristic	Cluster 1 (n=30) n(%)	Cluster 2 (n=50) n(%)	Cluster 3 (n=176) n(%)	Total (N=256) n(%)	*P*-Value
Age					< 0.001
Mean (SD)	40.5 (16.3)	33.9 (12.6)	30.3 (11.2)	32.3 (12.6)	
Range	20.0 - 66.0	19.0 - 63.0	16.0 - 70.0	16.0 - 70.0	
Not Reported	0	0	4	4	
Gender					0.32
Female	12 (42.9%)	26 (54.2%)	100 (56.8%)	138 (54.8%)	
Male	16 (57.1%)	22 (45.8%)	71 (40.3%)	109 (43.3%)	
Other*	0 (0.0%)	0 (0.0%)	5 (2.8%)	5 (2.0%)	
Not Reported	2	2	0	4	
Race & Ethnicity					0.32
White	13 (50.0%)	20 (42.6%)	62 (36.3%)	95 (38.9%)	
Black	2 (7.7%)	7 (14.9%)	28 (16.4%)	37 (15.2%)	
Latinx	5 (19.2%)	12 (25.5%)	25 (14.6%)	42 (17.2%)	
Asian	4 (15.4%)	6 (12.8%)	46 (26.9%)	56 (23.0%)	
Other	2 (7.7%)	2 (4.3%)	10 (5.8%)	14 (5.7%)	
Not Reported	4	3	5	12	
Education					< 0.001
Some High School	9 (30.0%)	2 (4.1%)	10 (5.7%)	21 (8.3%)	
High School	6 (20.0%)	4 (8.2%)	27 (15.4%)	37 (14.6%)	
Some College	10 (33.3%)	26 (53.1%)	70 (40.0%)	106 (41.7%)	
College	3 (10.0%)	10 (20.4%)	33 (18.9%)	46 (18.1%)	
Graduate School	2 (6.7%)	7 (14.3%)	35 (20.0%)	44 (17.3%)	
Not Reported	0	1	1	2	
Employment Status					0.06
Retired	1 (3.3%)	2 (4.1%)	3 (1.7%)	6 (2.4%)	
Disability	5 (16.7%)	1 (2.0%)	14 (8.0%)	20 (7.8%)	
Unemployed	11 (36.7%)	22 (44.9%)	48 (27.3%)	81 (31.8%)	
Employed Part-Time	6 (20.0%)	5 (10.2%)	22 (12.5%)	33 (12.9%)	
Employed Full-Time	4 (13.3%)	12 (24.5%)	43 (24.4%)	59 (23.1%)	
Student	3 (10.0%)	7 (14.3%)	46 (26.1%)	56 (22.0%)	
Not Reported	0	1	0	1	
Marital Status					0.19
Single	17 (58.6%)	31 (66.0%)	128 (73.1%)	176 (70.1%)	

Divorced/Widowed	2 (6.9%)	5 (10.6%)	6 (3.4%)	13 (5.2%)
Married	10 (34.5%)	11 (23.4%)	41 (23.4%)	62 (24.7%)
Not Reported	1	3	1	5

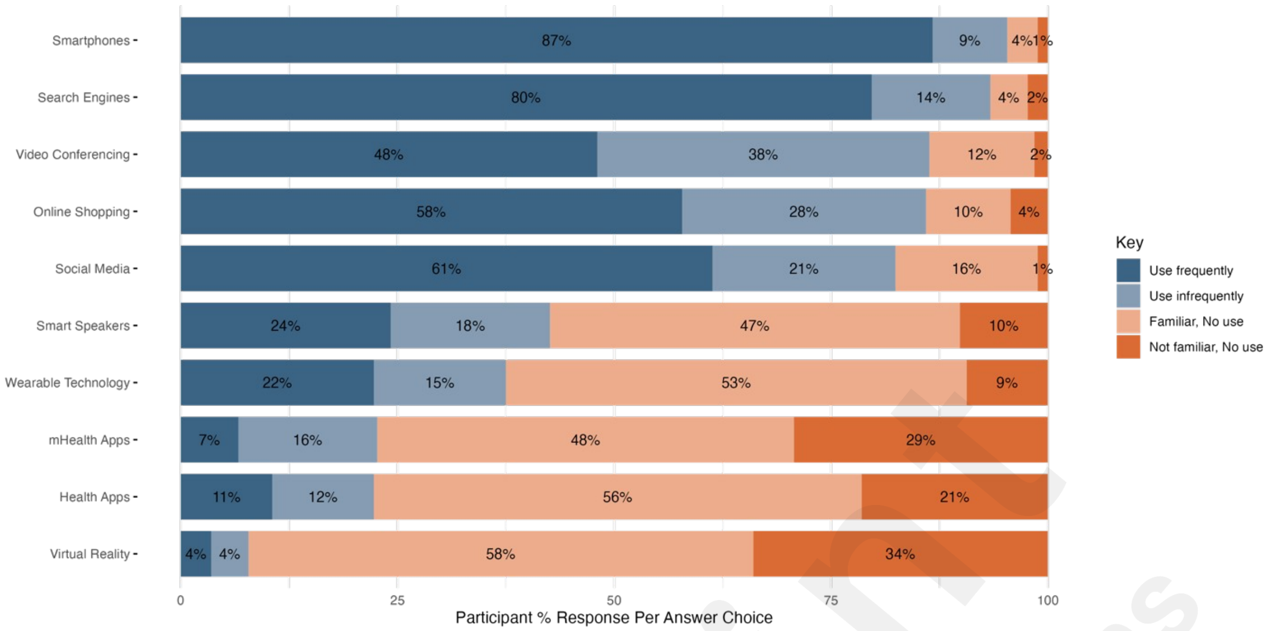
Note:
Ages are reported as mean (standard deviation) and ranges.
P-value shown for group comparisons using either *t*-test for continuous variables or chi-squared test for categorical variables.
P-values less than 0.005 are considered statistically significant and are bolded.
"Latin-x" includes all participants who indicated their ethnicity as Latino or Hispanic, including Black Hispanic or Latino and White Hispanic or Latino.
"Other" includes participants who indicated "Other" or whose race/ethnicity was not reported.
"Not Employed" includes Unemployed and Retired.
"Employed" includes both full-time and part-time employment.
"Completed high school" includes High School and GED.
"Some College" includes completed two-year college or technical program.
"Graduate School" includes completed graduate degree or some graduate school.

3.2 Digital Literacy and Attitudes scales results

Findings from the Digital Literacy and Attitudes scales are displayed in **Figure 1**, which shows the total responses for each individual item. Overall, participants reported a fair level of digital literacy, as indicated by high levels of familiarity and use of digital tools (**see Figure 1a**). For 5 out of the 10 items (social media, video conferencing, online shopping, search, and smartphone use), over 75% of participants reported at least some use of the technology. The most frequently used technologies by patients were smartphones, search engines, video conferencing, online shopping, and social media, respectively. Patients reported the least familiarity and use of virtual reality tools, health apps, mental health apps, wearable technology, and smart speakers.

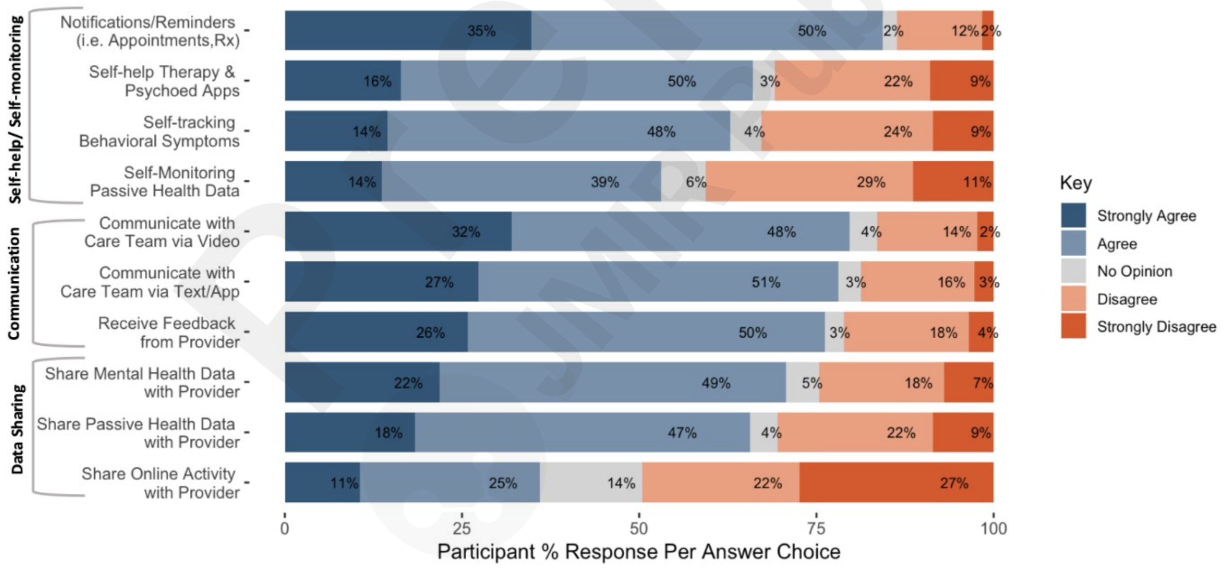
Participants also demonstrated positive attitudes toward using technology in their mental health care, with over 50% favorable responses (agree or strongly agree) in 9 out of the 10 items (**see Figure 1b**). Notifications and reminders and communication with the treatment team were found to be the most acceptable uses of technology, followed by self-help and self-monitoring. Sharing online activity with providers (e.g., social media, search activity) was the least favorable, with 49% of participants disagreeing that this would be helpful to their care. Attitudes toward self-monitoring one's own passive data were similarly divided, with 53% reporting positive attitudes and 40% reporting negative attitudes.

Figure 1a. Digital Literacy Scale Response % by Individual Item



Note: (a) Figure 1a illustrates the distribution of technological literacy among study participants, segmented by their frequency of technology use and familiarity. (b) Each category represents the percentage of participants (N=256) who regularly use, occasionally use, are familiar with but do not use, or are not familiar with various digital technologies. (c) Data is presented in descending order based on the combined percentages of participants who either use the technology frequently and infrequently.

Figure 1b. Digital Attitudes Scale Response % by Individual Item



Note: (a) Figure 1b illustrates the percentage distribution of responses across various digital health communication preferences (N=256). (b) Responses were grouped and ordered based on predefined categories reflecting different aspects of digital health communication.

3.3 Relationship between patient characteristics and Digital Literacy and Attitude total scores

To determine the relationship between patient characteristics and digital literacy and attitudes scale scores, multiple linear regression analyses were conducted. The results are summarized in **Table 2**. Age was negatively associated with digital literacy (*P*<.001). Higher educational attainment was associated with higher literacy total scores (*P*<.03 to *P*<.001).

There were no statistically significant associations between patient characteristics and attitude scores. When adding total literacy score into the model, Literacy Total was found to positively correlate with Attitude Total scores (estimate 0.33, std. Error 0.12, t-value 2.68, P= 0.001).

Table 2. Multiple Linear Regression Analysis – Impact of Patient Characteristics on Literacy and Attitude Total Score

Literacy Total Score Predicted by Patient Characteristics.						**Attitude Total Score Predicted by Patient Characteristics.**					
Variable	Coefficient	Std. Error	t value	Pr(>|t|)	Sig	Variable	Coefficient	Std. Error	t value	Pr(>|t|)	Sig
(Intercept)	31.73	3.24	9.80	<0.001	***	(Intercept)	33.38	5.85	5.71	<0.001	***
Age	-0.11	0.03	-3.5	<0.001	***	Age	-0.04	0.06	-0.62	0.54	
Gender						**Gender**					
Female	1.0					Female	1.0				
Male	-0.91	0.63	-1.44	0.15		Male	0.82	1.14	-0.72	0.47	
Other	2.14	2.31	0.93	0.36		Other	1.14	4.17	0.27	0.78	
Race						**Race**					
White	1.0					White	1.0				
Black	-0.15	0.94	-0.17	0.87		Black	0.32	1.69	0.19	0.849	
Latinx	0.05	0.89	0.06	0.96		Latinx	2.00	1.61	1.25	0.21	
Asian	-0.53	0.80	-0.66	0.51		Asian	1.13	1.45	0.78	0.44	
Other	-3.46	1.30	-2.66	**0.008**	**	Other	1.47	2.35	0.63	0.53	
Education						**Education**					
Some High School	1.0					Some High School	1.0				
High School	2.43	1.31	1.85	**0.07**	**.**	High School	3.62	2.37	1.52	0.13	
Some College	2.50	1.16	2.16	**0.03**	*	Some College	1.97	2.09	0.95	0.35	
College	2.60	1.30	2.00	**0.05**	*	College	1.76	2.34	0.75	0.45	
Graduate School	4.46	1.29	3.47	**<0.001**	***	Graduate School	3.31	2.32	1.43	0.16	
Employment						**Employment**					
Not Employed	1.0					Not Employed	1.0				
Disability	-3.08	2.38	-1.24	0.20		Disability	-1.72	4.30	-0.40	0.69	
Unemployed	-2.34	2.28	-1.03	0.31		Unemployed	-0.92	4.12	-0.22	0.82	
Employed Part-Time	-1.98	2.37	-0.83	0.41		Employed Part-Time	0.93	4.29	0.22	0.83	
Student	-0.91	2.42	-0.38	0.71		Student	1.15	4.38	0.26	0.80	
Employed	-0.64	2.22	-0.29	0.78		Employed	1.27	4.02	0.32	0.75	
Marital Status						**Marital Status**					
Divorced/Widowed	1.0					Divorced/Widowed	1.0				
Single	0.12	1.44	0.09	0.93		Single	0.58	2.60	0.22	0.82	
Married	0.73	1.48	0.49	0.63		Married	-0.12	2.67	-0.05	0.96	

Note: Table 2 illustrates the coefficients from multiple linear regression analyses assessing the impact of patient demographics on literacy and attitude total scores. Coefficients represent the estimated change in the total score for a one-unit increase in the predictor variable, holding other variables constant. Standard errors (Std. Error), t-values, and associated p-values are provided for each coefficient. Significant levels are denoted as: '***'for $P< .001$, '**'for $P < .01$, '*'for $P < .05$, and '.' for $P <.1$. The reference category for each categorical variable is denoted by a coefficient of 1.00.

The literacy model for total scores yielded a residual standard error of 4.373 on 214 df, with 23 observations omitted for missingness. Multiple R-squared value of 0.209 and an adjusted R-squared of 0.1423. The F-statistic is 3.141 on 18 and 214 df, with a highly significant p-value of 3.747e-05.

The attitude model for total scores yielded a residual standard error of 7.902 on 214 df, with 23 observations omitted for missingness. Multiple R-squared of 0.05458 and an adjusted R-squared of –0.0249. The F-statistic is 0.6863 on 18 and 214 df, with a p-value of 0.8229. Observations with missing values were excluded from the analysis.

3.4 Cluster analysis findings

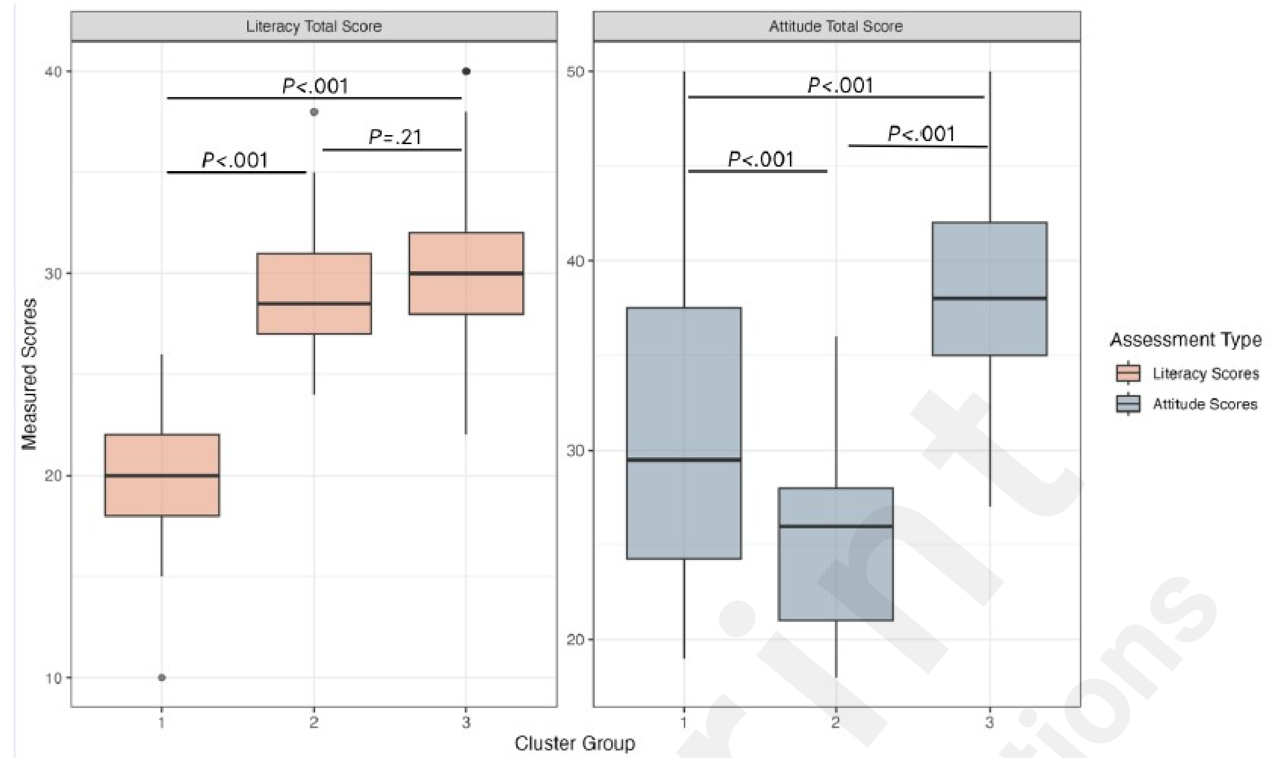
A cluster analysis was conducted to group participants based on similarities in their responses to the Attitude and Literacy scales using the previously described method. Three distinct participant clusters were identified (**see Table 1**). Cluster 1 had 30 participants, Cluster 2 had 50 participants, and Cluster 3 had 176 participants.

Using pairwise comparisons conducted using t-tests and pooled standard deviation, we examined the relative differences in Literacy Total scores between the participant clusters **(see Figure 2)**. There was a significant difference in Literacy Total scores between Cluster 1 and the other two clusters (*P*<.001 vs. Cluster 2, and *P*<.001 vs. Cluster 3), indicating that Cluster 1 had relatively lower total literacy scores than Clusters 2 and 3. The median item-level score was 2, “Familiar but no use.” There was no significant difference in Literacy Total scores between Clusters 2 and 3 (*P*=0.07). Median item-level scores were 3, and 3 respectively, corresponding to “Use infrequently.”

The results of the pairwise comparisons of the Attitude Total Scores across the different clusters revealed significant differences in attitudes among all three clusters. Cluster 1 Attitude Total scores were significantly higher than Cluster 2 (*P*<.001) and lower than Cluster 3 (*P*<.001), with a median item-level score of 3, corresponding to “No opinion.” Cluster 2 Attitude Total was significantly lower than both Clusters 1 and 3 (*P*<.001), with a median item-level score of 2, corresponding to “disagree.” Cluster 3 Attitude scores were significantly higher than both Clusters 1 and 2 (*P*<.001), with a median item-level score of 4, corresponding to “Agree.” The results after adjusting for multiple comparisons using the false discovery rate (FDR) method demonstrated consistent findings, reinforcing the significant differences in attitudes across all pairs of clusters.

Taken together, the clusters were characterized based on their relative Attitude Total and Literacy Total scores. Cluster 1 demonstrated lower literacy levels and intermediate acceptance of digital technology relative to the other two clusters. Cluster 2 exhibited higher literacy levels and lower acceptance. Cluster 3 displayed both high literacy and acceptance.

Figure 2. Cluster Analysis – Comparative Distribution of Attitude and Literacy Scores Across Clusters



Note: Box plots illustrate the total scores for attitude and literacy compared across the three clusters.
Pairwise comparisons were conducted using t-tests with pooled standard deviation.
An initial one-way ANOVA was performed for each variable, indicating significant differences among the clusters for both attitude ($F(2,253)=99.16$, *P*<.001 and literacy ($F(2,253)=112.6$, *P* <.001).
Subsequent pairwise t-tests corrected for multiple comparisons using the Benjamini-Hochberg method identified specific clusters between which significant differences exist; these are denoted on the plots with horizontal lines and labeled with exact p-values.

3.4.1 Cluster differences by patient characteristics

Clusters were then compared based on key patient characteristics, as summarized in **Table 1**. There were statistically significant group differences across the three clusters for mean age (*P*<.001) and education level (*P*<.001). Employment status reached near significance (*P*=.06). No statistically significant differences between clusters were observed for race/ethnicity (*P*=.32), sex (*P*=.39), gender (*P*=.32) and marital status (*P*=.19).

Additional pairwise comparisons between clusters were completed for patient characteristic variables that exhibited statistically significant group differences (**See Table 2**). Regarding age, Cluster 1 participants were significantly older than Clusters 2 and 3 participants (*P*=.02, *P*=.03 after adjustment and *P*<.001, *P*<.001 after adjustment, respectively). There were no significant differences in age between Clusters 2 and 3 (*P*=.07, .07 after adjustment).

Statistically significant differences in formal educational attainment were observed between Cluster 1 and Clusters 2 and 3. Specifically, Cluster 1 had a higher ratio of participants who only completed some high school versus those who completed some high school or higher when compared to Cluster

3 (P-values range *P*=.02 to *P*<.001) and versus those who completed some college or higher when compared to Cluster 2 (*P*-values range *P*=0.05 to *P*<.001). There were no significant differences in education level between Clusters 2 and 3. After adjusting for multiple comparisons, group differences between Clusters 1 and 3 remained statistically significant. Taken together, these findings indicate Cluster 1 participants had less formal education than Clusters 2 and 3.

Overall, the largest differences were found between clusters 1 and 3; on average, Cluster 1 participants had lower levels of formal education and were older.

While employment did not reach statistically significant group differences, comparison of data in Table 1 demonstrates a trend of higher percentage of students and employed individuals in Clusters 2 and 3 compared to Cluster 1.

Table 2. Pairwise Comparisons for patient characteristics that were significantly different in the cluster analysis (Age and Education)

A) Mean Age Comparison between Clusters

	1	2
2	**0.02**	-
3	**<.001**	0.07

P-Value Adjustment Method: None

	1	2
2	**0.03**	-
3	**<.001**	0.07

P-Value Adjustment Method: FDR

Note: Table A illustrates the p-values for pairwise comparisons of mean age differences between clusters, assessed using pairwise t-tests with pooled SD. The p-values are shown both without adjustment and with adjustment for multiple comparisons using the False Discovery Rate (FDR) method, with bold numbers indicating statistical significance at the p < .05 level. '-' used to show non-significance.

B) Education Level Comparison between Clusters

Comparison	1:2	1:3	2:3
some hs:hs	0.36	**0.05**	1.00
some hs:some col	**0.00**	**0.00**	0.73
some hs:col	**0.01**	**0.00**	1.00
some hs:grad	**0.02**	**0.00**	1.00
hs:some col	0.07	0.55	0.14
hs:col	0.10	0.29	0.37
hs:grad	0.17	0.14	0.75
some col:col	1.00	0.75	0.68
some col:grad	1.00	0.33	0.28

Comparison	1:2	1:3	2:3
some hs:hs	0.65	0.23	1.00
some hs:some col	**0.03**	**0.02**	0.94
some hs:col	0.07	**0.02**	1.00
some hs:grad	0.11	**0.01**	1.00
hs:some col	0.28	0.92	0.40
hs:col	0.34	0.63	0.65
hs:grad	0.42	0.40	0.94
some col:col	1.00	0.94	0.94
some col:grad	1.00	0.65	0.63

P-Value Adjustment Method: None		P-Value Adjustment Method: FDR
Note: Table B illustrates the p-values for pairwise comparisons of employment status among clusters, calculated using Fisher's exact test. The p-values are shown both without adjustment and with adjustment for multiple comparisons using the False Discovery Rate (FDR) method, with bold numbers indicating statistical significance at the P<.05 level. Abbreviations: some hs= some high school, hs= completed high school, some col = completed some college, col = completed college, grad = some graduate school or completed graduate school.		

4. Discussion

4.1 Discussion

Our study captured a demographically and socioeconomically diverse psychiatric outpatient population. Overall responses to the Digital Literacy scale suggest patients have high literacy for certain types of digital technology, particularly smartphone use, search, videoconferencing, and social media. These tools are important for healthcare activities such as attending telemedicine appointments and communicating with providers. Furthermore, they support the potential of using digital phenotyping tools, which utilize data from social media use, internet search data, and cell phones to predict psychiatric episodes. However, patients reported less familiarity with health apps, mental health apps, wearables, and virtual reality, suggesting that there may need to be more education or support should such tools be introduced into care.

Overall responses to Attitude scale demonstrated that our patients found the use of technology in clinical care to be highly acceptable, which aligns with prior literature highlighting favorable patient attitudes toward using telepsychiatry and mobile interventions in mental health care.[18,21–23] In our study, the most acceptable uses of technology in health care were for communication with one's provider and both monitoring and sharing health data with providers. Patients were divided on the perceived usefulness of sharing their online activity with providers, suggesting that not all patients may be open to sharing this data with providers for digital phenotyping. More psychoeducation may be needed to explain the utility of digital phenotyping to patients.

Our study highlighted several demographic factors associated with digital literacy in our patient population. Predictably, digital literacy scores were directly correlated with level of formal education and indirectly correlated with age. However, surprisingly, none of the patient characteristics we identified predicted total attitude scores. Notably, there were no significant differences in total digital Literacy or Attitude scores by race/ethnicity. This contradicts prior literature that found racial differences and supports the idea that digital interventions could help improve access to care and bridge health disparities. Attitude was, however, directly correlated with digital literacy scores, indicating that patients with higher familiarity and comfortability with digital tools have higher likelihood of finding their use in clinical practice acceptable.

Our cluster analysis revealed that there are three primary groups or clusters of patients based on their relative levels of digital literacy and acceptability: those with lower digital literacy and intermediate acceptance (Cluster 1), those with higher literacy but lower acceptance (Cluster 2), and those that are high in both literacy and acceptance (Cluster 3). Promisingly, Cluster 3 was the largest cluster, representing 69% of the participants, suggesting that a majority of patients have both the literacy levels and interest necessary to embrace technology into clinical care. Participants with lower digital literacy levels and higher acceptance of digital technology were more likely to be older and have less formal educational attainment (Cluster 1). In contrast, the other two groups (Clusters 2 and 3) both demonstrated higher literacy levels but vary with respect to digital health acceptance. Our study did not find meaningful demographic differences between the higher literacy groups (Cluster 2 and Cluster 3), suggesting that there are likely additional factors outside of the patient characteristics examined in this study.

While age and educational status correlated positively with digital literacy levels, our negative findings that these same characteristics did not correlate with Attitude scores is promising, as it suggests that diverse groups of patients are interested in using such technologies. We propose that patient characteristics should be considered when building out programming to determine the level of support needed to appropriately train and educate patients on how to use technologies. Special attention should be paid to providing additional resources such as digital health navigators who can help people who are older in age and have lower formal levels of education. There remains a risk that if health systems do not incorporate extra support to those with lower digital literacy levels—whether due to lack of awareness or funding for additional resources—that these groups will be digitally excluded, thus exacerbating existing healthcare disparities. In such cases, health systems should consider whether adoption of digital tools would be beneficial over traditional means of care.

4.2 Limitations

This study focused on evaluating the demographic factors that may contribute to digital literacy and attitudes. Clinical factors such as diagnoses and illness severity may also play a role and should be explored as a future direction. One limitation of this study is the classification of race. The classification of race and ethnicity presents inherent challenges due to the intricacies of identity, cultural nuances, and intersectionality. Despite our efforts to meaningfully categorize individuals, distinctions such as Black Latino versus White Latino and individuals of mixed race pose complexities that cannot always be fully disentangled or accurately represented. While we have tried to employ the most appropriate methodologies available, it is important to acknowledge that this process remains imperfect, constituting a notable limitation in our study's scope. Another limitation of our study is that our survey was only available in English and likely did not capture non-English speakers. Language is a notable barrier for digital literacy, and additional studies should be conducted to examine the impact of native language on digital literacy and attitudes.

4.3 Conclusions

In conclusion, our study found that there were high overall rates of digital literacy and digital acceptability among patients in a diverse, urban outpatient psychiatric clinic. This has general overall positive implications in the likelihood that patients could successfully adopt digital tools into clinical care. Our cluster analysis results also highlight the importance of identifying patients with lower digital literacy levels with generally favorable attitudes toward using technology in health care, paying special attention to those with lower formal levels of educational attainment and those of older age.

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Conflicts of Interest

SXT owns equity and serves as a consultant for North Shore Therapeutics, received research funding and serves as a consultant for Winterlight Labs, is on the advisory board and owns equity for Psyrin, and serves as a consultant for Catholic Charities Neighborhood Services.

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Appendix

5.1 Scales

“Digital Technology Literacy Scale”
The question prompt was: “How familiar are you with the following technologies?”
Participants could choose from the following answer choices*: I use this technology frequently I use this technology but not so frequently I am familiar with this technology but do not use it myself I am not familiar with this technology
Questions: 1. Online shopping (Amazon, Seamless, etc.) 2. Web search (Google, Bing etc.) 3. Social media (Facebook, Twitter, Instagram, Reddit etc.) 4. Wearable devices and activity trackers (Apple watch, Fitbit, Oura ring etc. 5. Smartphones (iPhone, Google Pixel, Samsung Galaxy etc.) 6. Video conferencing (e.g. Skype, Zoom etc.) 7. Smart speakers (Amazon Echo (Alexa), Google Home etc.) 8. Virtual reality (Oculus, Google Daydream etc.) 9. Health tracking apps (MyFitnessPal, Sleep Cycle etc.) 10. Mental health apps (Headspace, Calm etc.)
Notes: *Scoring: Answer choices were scored as follows: I use this technology frequently = 4 points, I use this technology but not so frequently = 3 points, I am familiar with this technology but do not use it myself = 2 points, I am not familiar with this technology = 1 point

“Digital Care for Mental Health” Attitudes Scale

The question prompt was: “How much do you agree or disagree with these statements?”

Participants could choose from the following answer choices:

Strongly agree, Agree, Disagree, Strongly disagree, No Opinion*

Questions:

1. Monitoring my own behavior (e.g. sleep, physical activity) using a mobile app or wearable device can help support my mental health.
2. Using mobile apps for therapy and learning new knowledge can improve my mental health.
3. Automatically sharing info about my daily activities (e.g. sleep, physical activity) with my care team can improve my mental health.
4. Sharing info about my online activity (e.g. Google searches, Facebook posts) can improve my care.
5. Tracking my own symptoms (e.g. mood, anxiety) using a web or mobile app can help support my mental health.
6. Automatically sharing info about my own symptoms (e.g. mood, anxiety) with my care team can improve my mental health.
7. Ability to communicate with my care team via text messages or mobile app can improve my care.
8. Access to my care team via video conferencing (e.g. Skype, Zoom) can improve my mental health.
9. Feedback via notifications or email about my progress from my care team can improve my mental health.
10. Reminders to follow my team's recommendations (e.g. medications, therapy) can improve my mental health.

Notes:

*Scoring: Answer choices were scored as follows: Strongly agree = 5 points, Agree = 4 points, Disagree = 2 points, Strongly disagree= 1 point, No Opinion= 3 points

The question items were grouped into the following categories:

A) Self-help and self-monitoring: items 1, 2, 5, and 10

B) Communication with providers: items 7, 8, and 9

C) Data sharing with treatment team: items 3, 4, and 6

Bibliography

1. Ronquillo Y, Meyers A, Korvek SJ. Digital Health. In: *StatPearls*. StatPearls Publishing; 2024. Accessed March 28, 2024. http://www.ncbi.nlm.nih.gov/books/NBK470260/
2. Sterling WA, Sobolev M, Van Meter A, et al. Digital Technology in Psychiatry: Survey Study of Clinicians. *JMIR Form Res*. 2022;6(11):e33676. doi:10.2196/33676
3. Pokhrel P, Karmacharya R, Taylor Salisbury T, et al. Perception of healthcare workers on mobile app-based clinical guideline for the detection and treatment of mental health problems in primary care: a qualitative study in Nepal. *BMC Med Inform Decis Mak*. 2021;21(1):21. doi:10.1186/s12911-021-01386-0
4. Cortelyou-Ward K, Rotarius T, Honrado JC. Using Technology to Improve Access to Mental Health Services. *Health Care Manag*. 2018;37(2):101-108. doi:10.1097/HCM.0000000000000211
5. Currey D, Torous J. Digital phenotyping correlations in larger mental health samples: analysis and replication. *BJPsych Open*. 2022;8(4):e106. doi:10.1192/bjo.2022.507
6. Tang SX, Kriz R, Cho S, et al. Natural language processing methods are sensitive to sub-clinical linguistic differences in schizophrenia spectrum disorders. *NPJ Schizophr*. 2021;7(1):25. doi:10.1038/s41537-021-00154-3
7. Torous J, Bucci S, Bell IH, et al. The growing field of digital psychiatry: current evidence and the future of apps, social media, chatbots, and virtual reality. *World Psychiatry*. 2021;20(3):318. doi:10.1002/wps.20883
8. Connolly SL, Kuhn E, Possemato K, Torous J. Digital Clinics and Mobile Technology Implementation for Mental Health Care. *Curr Psychiatry Rep*. 2021;23(7):38. doi:10.1007/s11920-021-01254-8
9. Macrynikola N, Nguyen N, Lane E, Yen S, Torous J. The Digital Clinic: An Innovative Mental Health Care Delivery Model Utilizing Hybrid Synchronous and Asynchronous Treatment. *NEJM Catal*. 2023;4(9). doi:10.1056/CAT.23.0100
10. Van Dijk JAGM. Digital divide research, achievements and shortcomings. *Poetics*. 2006;34(4-5):221-235. doi:10.1016/j.poetic.2006.05.004
11. Alvarez-Galvez J, Salinas-Perez JA, Montagni I, Salvador-Carulla L. The persistence of digital divides in the use of health information: a comparative study in 28 European countries. *Int J Public Health*. 2020;65(3):325-333. doi:10.1007/s00038-020-01363-w
12. Faux-Nightingale A, Philp F, Chadwick D, Singh B, Pandyan A. Available tools to evaluate digital health literacy and engagement with eHealth resources: A scoping review. *Heliyon*. 2022;8(8):e10380. doi:10.1016/j.heliyon.2022.e10380
13. Law, Nancy, Woo, David (second), Torre, Jimmy de la (third), Wong, Gary (last). A global framework of reference on digital literacy skills for indicator 4.4.2 - UNESCO Digital Library. Published June 2018. Accessed March 28, 2024. https://unesdoc.unesco.org/ark:/48223/pf0000265403.locale=en
14. NW 1615 L. St, Washington S 800, Inquiries D 20036 U 419 4300 | M 857 8562 | F 419 4372 | M. Internet, Broadband Fact Sheet. Pew Research Center: Internet, Science & Tech. Accessed February 27, 2024. https://www.pewresearch.org/internet/fact-sheet/internet-broadband/
15. Ennis L, Rose D, Denis M, Pandit N, Wykes T. Can't surf, won't surf: The digital divide in mental health. *J Ment Health*. 2012;21(4):395-403. doi:10.3109/09638237.2012.689437
16. Mitchell UA, Chebli PG, Ruggiero L, Muramatsu N. The Digital Divide in Health-Related Technology Use: The Significance of Race/Ethnicity. *The Gerontologist*. 2019;59(1):6-14. doi:10.1093/geront/gny138
17. Muñoz AO, Camacho E, Torous J. Marketplace and Literature Review of Spanish Language Mental Health Apps. *Front Digit Health*. 2021;3:615366. doi:10.3389/fdgth.2021.615366
18. Andrews JA, Brown LJ, Hawley MS, Astell AJ. Older Adults' Perspectives on Using Digital Technology to Maintain Good Mental Health: Interactive Group Study. *J Med Internet Res*. 2019;21(2):e11694. doi:10.2196/11694
19. Wisniewski H, Gorrindo T, Rauseo-Ricupero N, Hilty D, Torous J. The Role of Digital Navigators in Promoting Clinical Care and Technology Integration into Practice. *Digit Biomark*. 2020;4(Suppl 1):119-135. doi:10.1159/000510144
20. Benjamini Y, Hochberg Y. Controlling the False Discovery Rate: A Practical and Powerful Approach to Multiple Testing. *J R Stat Soc Ser B Methodol*. 1995;57(1):289-300.
21. Ben-Zeev D, Brenner CJ, Begale M, Duffecy J, Mohr DC, Mueser KT. Feasibility, acceptability, and preliminary efficacy of a smartphone intervention for schizophrenia. *Schizophr Bull*. 2014;40(6):1244-1253. doi:10.1093/schbul/sbu033
22. Berry N, Lobban F, Bucci S. A qualitative exploration of service user views about using digital health interventions for self-management in severe mental health problems. *BMC Psychiatry*. 2019;19(1):35. doi:10.1186/s12888-018-1979-1
23. Guinart D, Marcy P, Hauser M, Dwyer M, Kane JM. Patient Attitudes Toward Telepsychiatry During the COVID-19 Pandemic: A Nationwide, Multisite Survey. *JMIR Ment Health*. 2020;7(12):e24761. doi:10.2196/24761

Abbreviations

None