Original Research

DIGITAL HEALTH

Digital Health
Volume 3: 1–11
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DOI: 10.1177/2055207617713827
journals.sagepub.com/home/dhj
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What might get in the way: Barriers to the use of apps for depression

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Abstract

Objective: Smartphones are being used with increasing frequency to deliver behavioral interventions for depression via apps. However, barriers specific to using an app for depression are poorly defined. The purpose of the current study is to identify barriers to the use of a mobile app to deliver treatment for depression. Secondarily, design implications will be provided based upon identified barriers.

Method: A card sorting task that ranked and grouped barriers to the use of apps for depression was completed. Participants first completed a card sorting task identifying barriers to face-to-face treatment, as a primer to identification of treatment barriers. The sample consisted of those above ($n = 9$) and below ($n = 11$) the threshold for a referral to psychotherapy, to capture anticipated barriers for likely end users. Cluster analyses were conducted to analyze the card sorting data. Multiple analyses were conducted to identify: 1) the most important barriers, and 2) how consistently barriers were ranked as important.

Result: The card sorting task identified a number of primary barriers to the use of apps for depression treatment, including concerns over intervention efficacy, app functioning, privacy, cost, and lack of guidance and tailored feedback. The top face-to-face treatment barrier was cost, overlapping with mobile barriers.

Conclusion: This study identified perceived barriers to the use of mobile treatment apps. Identification of barriers implicates design recommendations for apps for depression.

Keywords

Access barriers, mobile treatment, depression, intervention delivery, apps

Submission date: 8 August 2016; Acceptance date: 9 May 2017

Introduction

Depressive disorders are the leading cause of disability worldwide.[1] While efficacious treatments for depression exist,[2] multiple barriers interfere with the initiation and maintenance of face-to-face (i.e. traditionally delivered) treatments.[3] Therefore, to address this mental health epidemic, significant changes must be made in the strategy with which interventions are delivered. To extend care capacity, technologies are being integrated into multiple health care systems as a mechanism for delivering behavioral health interventions.[4–6] The use of web-based delivery platforms has demonstrated efficacy across a broad range of mental health outcomes,[7,8] however, barriers to this delivery method, such as

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needing to be in front of a computer, impact uptake and usage.[9] Consequently, a small, but growing body of research is examining the efficacy of smartphone apps to deliver behavioral interventions,[10–14] as they offer the potential to provide a nearly continuous connection between a care system and patients.

As smartphones grow in popularity, their ability to serve as a delivery mechanism for behavioral health interventions with the potential to reach increasingly broad communities increases. Indeed, a growing number of people are becoming smartphone-dependent.[15,16] Smartphone-dependency is defined as owning a smartphone, not having broadband internet access at home, and having limited abilities to access the internet outside of a smartphone.[15] Through their instantiation in smartphones, apps are ideally suited to be accessed by users in real-time and in real-world conditions,[17] likely overcoming many previously identified barriers to interventions delivered via face-to-face and computers.[3,9] However, multiple issues exist. First, while there are some initial, promising mental health app outcomes,[10–14] the efficacy of such apps remains primarily unknown.[18] Second, while apps may address many barriers to more traditional delivery mechanisms, they likely have unique barriers of their own. While barrier identification is secondary to the primary issue of efficacy, the quick turnover of technology and the ubiquity of mental health apps make this an issue worth exploring concurrent with ongoing efficacy trials.[18–20] Indeed, identifying these barriers is critical to the success of future iterations of apps in delivering care to those with depression, particularly for those likely to face substantial known barriers to accessing traditionally delivered care.

Identifying barriers will allow us to make changes in the design of mental health treatment apps. For example, if concerns regarding efficacy of an app in addressing psychological symptoms is a barrier, design could shift to include providing specific psychoeducation at download, related to currently established and/or theoretical efficacy. However, without identification of such barriers, app designers must primarily rely on intuition.[21] This promotes a risk that design choices will create a mismatch with the needs or perceptions of the user for this delivery mechanism. Identification of barriers may therefore improve the information available for those who design and develop apps.

The means to identify barriers to the use of apps for depression may include a number of strategies, ranging from self-report questionnaires to moderated focus groups. However, a methodology that has been commonly used to inform multiple design processes and decisions is a card sorting task.[22] Card sorting tasks are designed as a means to categorize and organize variables and ideas.[23] Card sorting therefore enables the identification of potential end users' perception of barriers to the use and uptake of apps for depression. To our knowledge, card sorting tasks have not been used previously as a means to identify barriers to use of mental health apps.

The purpose of the current study is to identify user perceived barriers to the initiation and maintenance of apps for depression. The aims of completing the card sorting tasks therefore are to: 1) identify perceived barriers to depression interventions delivered via apps and 2) identify overlap in primary barriers for intervention delivery via apps with traditional delivery methods (i.e. face-to-face) barriers. Implications for design changes and improvements that better align with the identified needs of the users will also be noted.

Method

Procedure

Recruitment of participants occurred from July to August 2015 from online postings in Chicago and nearby areas, resulting in the participation of 20 adults. Current recommendations for a card sorting task sample size is 15,[23] making the sample of 20 sufficient for the present study. Inclusion criteria were: being at least 18 years of age, the ability to attend an in-lab session, and ability to speak and read in English. Equal numbers of participants currently above and below the criteria for a referral for psychotherapy were recruited.[24] This sampling ensured that perceived barriers were being measured with likely end users, ranging from those with no or mild depressive symptoms to those with moderate or severe depressive symptoms.[25] Participants who completed the card sorting task, as well as an in-lab usability testing session were compensated $20 in petty cash for their time and participation. In compliance with the University's Institutional Review Board (IRB), participants completed an online screening consent prior to the collection of any data and were consented in-person for the card sorting and usability testing session.

Card Sorting. To identify barriers to use and engagement with apps that are specific to users with depression, two separate card sorting tasks using open sort methods were employed. Open card sorting refers to providing participants topics and asking them to sort them into groups that make sense to them, as opposed to a closed card sorting in which the topics would be organized into predefined groups.[22] The first card sort was related to barriers to face-to-face delivery of interventions for depression, and the second was related to barriers to app delivery of interventions for depression. This order was chosen, as a concern was that if participants were asked to consider barriers to an app, they might not be familiar with the concept of an intervention app. If so, participants might identify barriers solely related to phone functionality (e.g. battery) or commonly used apps (e.g. Facebook). However, people are generally able to identify barriers to face-to-face interventions, and having participants first consider these barriers promotes consideration of intervention barriers. Barriers listed for both tasks were informed by findings from the literature and polls from content experts at the Center for Behavioral Intervention Technologies (CBITs).[3,26] Barriers included issues related to typical depression intervention (e.g. concerns about stigma), technology-mediated delivery of care (e.g. data privacy), and app-specific (e.g. data plan) issues.

Prior to each card sorting task, participants were read the following prompt:

> I'm providing you with a stack of cards that have reasons that people might not want to or be able to (card sort 1: attend face-to-face therapy/card sort 2: use a mobile app for treatment) when feeling down. I would like you to go through the cards and choose the ones you think are barriers to (card sort 1: attending face-to-face therapy/card sort 2: using a mobile app for treatment). Once you choose them, please decide which ones are the biggest barriers. As you can see, the table is labeled to help you put ideas down from biggest barriers to smallest. You might notice that some overlap into groups in your mind; feel free to put them into groups. If there are cards you think do not apply, feel free to put them over here to be discarded. If there are cards with reasons missing, we can add more (indicate blank cards and marker). Please feel free to think aloud as you go through the cards.

The card sorting tasks were timed and audio recorded, and photographs of the completed tasks were taken to ensure the moderator recorded the groupings correctly. Participants were provided time to supply a rationale for their choices following the tasks. This qualitative data was intended to enrich the findings and aid in the interpretation of groupings. The stacks of cards were shuffled between participants to remove any possible bias from rankings of other participants.

Measures

Study data were collected and managed using Research Electronic Data Capture (REDCap) electronic data capture tools hosted at Northwestern University.[27] REDCap is a secure, web-based application designed to support data capture for research studies, providing 1) an intuitive interface for validated data entry; 2) audit trails for tracking data manipulation and export procedures; 3) automated export procedures for seamless data downloads to common statistical packages; and 4) procedures for importing data from external sources.

At screening, participants were asked to provide demographic information (i.e. gender, race/ethnicity, age, education and employment status). Further, they completed the Patient Health Questionnaire-9 (PHQ-9), a 9-item self-report instrument measuring depressive symptomology with scores ranging from 0–27.[25] Participants below the criteria for a referral to psychotherapy were defined as having a PHQ-9 score as below 10 (i.e. with no to mild depressive symptoms), whereas those meeting criteria for a referral to psychotherapy were defined as having a score of 10 or greater (i.e. with moderate to severe depressive symptoms). This criterion reflects the MacArthur recommendations for referrals to psychotherapy at the cutoff for mild depressive symptoms.[24]

Data analysis

The card sorting task was analyzed via quantitative data; each card was assigned a number and then the mean rank for each card was determined for each participant. Consistent with past card sorting methodology, cluster analyses, a commonly used statistical method for grouping complex data, were conducted to analyze the card sorting data.[28,29] For both the face-to-face and the app barrier cards, a hierarchical cluster analysis was conducted to determine the number of clusters appearing in the data set. This number was used to then conduct K-means cluster analysis to determine membership of cards within the different clusters. These analyses were conducted for the ranked means of the cards for both groups, as well as for the ranked means with the standard deviations for both card sets. Two analyses were conducted to: 1) identify the most important barriers (ranked means only to provide an indication of the average ranking of barriers); and 2) how consistently barriers were ranked as important (ranked means and standard deviations to provide an indication in the variance of ranked barriers).

Result

Participants

Table 1 displays the sample characteristics for the card sorting tasks. While equal numbers of participants above and below the threshold for a referral for therapy were anticipated, one extra person below the threshold was enrolled. Thus, nine participants were above the threshold for a referral (PHQ-9 $\geq$ 10) and 11 were

Table 1. Card sorting sample characteristics.

	PHQ-9 < 10 ($n = 11$)	PHQ-9 ≥ 10 ($n = 9$)	Total ($n = 20$)
Female, n(%)	7 (63.6)	8 (88.9)	15 (75)
Age, M(SD)	34.5 (10.3)	40.6 (14.0)	37.2 (12.2)
Race/Ethnicity			
African American, n(%)	4 (36.4)	1 (16.7)	5 (25)
Asian, n(%)	2 (18.1)	0 (0)	2 (10)
Hispanic Caucasian, n(%)	1 (9.1)	0 (0)	1 (5)
Non-Hispanic Caucasian, n(%)	5 (45.5)	8 (88.9)	13 (65)
PHQ-9, M(SD)	3.8 (3.2)	14.4 (5.8)	8.6 (7.0)
History of Depression, n(%)	2 (18.2)	7 (77.8)	9 (45)
History of Anxiety, n(%)	2 (18.2)	5 (55.6)	7 (35)

Note. M = mean, SD = standard deviation, PHQ-9 = Patient Health Questionnaire-9.

below the threshold for a referral (PHQ-9 < 10). The sample was comprised primarily of females (75%) and non-Hispanic Caucasians (65%), with a mean age of 37.2 (Standard Deviation = 12.2). Those meeting criteria for a referral to psychotherapy had significantly higher depressive symptom severity (14.4 *versus* 3.8, $p < .001$) and a significantly higher prevalence of past depressive episode(s) (77.8% *versus* 18.2%, $p = .008$).

Face-to-face delivery barriers

Hierarchical cluster analysis indicated four clusters for the face-to-face barrier task. Table 2 displays the four groups, as determined via K-means cluster analyses. The groups are listed in order of strength of the barrier, with Group 1 being the greatest barriers and Group 4 being the smallest barriers. Variance represents the clusters created by mean ranks only and Consistency represents the clusters created by including both the mean ranks and standard deviations. Differences between the rows therefore indicate variance in how highly a certain barrier was ranked. Cost was identified as the single most important barrier to face-to-face treatment. Cost was consistently followed by lack of insurance coverage and motivation, stigma, concerns about effectiveness and being seen while emotional, time for session travel and attendance, and talking with someone unknown about private topics. Barriers identified as being smaller or not as cumbersome (e.g. childcare, distance, etc. in Groups 3 and 4) were identified less consistently, as evidenced by discrepancies between the Variance and Consistency analyses. While all of the barriers included are consistent with past descriptions of barriers to face-to-face treatment for adults with depression,[3] the importance of some barriers appears to have decreased in the current evaluation (i.e. those included in Groups 3 and 4).

App delivery barriers

Hierarchical cluster analysis indicated four clusters for the mobile barrier task. Table 3 displays the four groups, as determined via K-means cluster analyses. Similar to Table 2, the groups are listed by strength of the barriers, with Group 1 being the greatest barriers and Group 4 being the smallest barriers. Concerns about effectiveness, data access and privacy, cost of data package, bugs in the system, availability of Wifi, and misfit of features to needs were consistently rated as the top barriers to mobile treatments. Greater discrepancies occurred in the next highest groupings of barriers, however, concerns over not receiving enough feedback and lack of guidance were the next greatest barriers, on average.

Discussion

The present study identified user perceived barriers to face-to-face and app-based delivery of depression interventions via two card sorting tasks. Cost was consistently rated as the top barrier to face-to-face delivery, and top app barriers included concerns over intervention efficacy, app functioning, privacy, cost, and lack of guidance and tailored feedback. The common top barrier between the two delivery methods was cost, suggesting that this is a cumbersome barrier for users with depression, regardless of delivery mechanism.

Cost was identified as a top barrier for both delivery mechanisms, but it is unclear if the same meaning was associated with both mechanisms. Cost of therapy (i.e. cost of service) has previously been detailed as a primary barrier to initiation and maintenance of face-to-face delivered treatment.[3] Ancillary costs, such as paying for transportation and childcare have also been noted.[3] Qualitative feedback indicated that participants generally interpreted ‘cost’ as meaning the cost of service for face-to-face therapy. In apps, cost of apps (i.e. cost of service) has previously been suggested as an inhibiting factor in adaptation of mobile technologies in community health settings and across general health app consumers.[30,31] Cost of apps

Table 2. Face-to-face delivery barriers.

Group	Variance	Consistency
1	Cost	Cost
2	Lack of insurance coverage	Lack of insurance coverage
	Stigma	Stigma
	Lack of motivation	Lack of motivation
	Concerns about effectiveness	Concerns about effectiveness
	Time for session travel	Time for session travel
	Time for session attendance	Time for session attendance
	Talking about private topics with someone not known	Talking about private topics with someone not known
	Being seen while emotional	Being seen while emotional
3	Discomfort talking about personal issues	Transportation
	Concerns about what friends, family will think	Childcare Misfit of therapy to needs
	Availability of care	
	Not wanting insurance documentation (i.e. somehow having a 'paper trail' indicating one participated in therapy)	
4	Distance	Distance
	Want to solve problems on own	Want to solve problems on own
	Time for between session activities	Time for between session activities
	Privacy	Privacy
	Fatigue	Fatigue
	Transportation Misfit of therapy to needs	Discomfort talking about personal issues
		Availability of care
		Not wanting insurance documentation

Note. Wording in table is identical to the wording the participants viewed on the cards. Groups are listed in order of greatest (1) to smallest (4) barriers. Variance represents clusters formed using mean ranks only (to indicate overall importance); Consistency represents clusters formed using mean ranks and standard deviations (to indicate consistency of importance).

has also been cited as a top user criticism in app user reviews.[32] However, participants identified the cost of data package (i.e. ancillary costs) as a primary barrier. This suggests that ancillary costs, which are possibly hidden or unclear to a user, are of greater concern than the cost of service. This shift in concern over cost is a difference between face-to-face and app delivery of interventions for depression. As apps are being designed and disseminated with an aim to overcome barriers to traditional intervention delivery mechanisms, overlaps in barriers with face-to-face interventions are particularly problematic. Cost appears to be a consistent concern across delivery mechanisms, however the focus appears to shift towards ancillary costs as opposed to service costs.

After cost, barriers to apps are related to user uncertainties around use of them as a delivery mechanism, such as data access and privacy, app functioning,

Table 3. App delivery barriers.

Group	Variance	Consistency
1	Concerns about effectiveness	Concerns about effectiveness
	Unsure who has access to data	Unsure who has access to data
	Cost of data package	Cost of data package
	Bugs in the system	Bugs in the system
	Wifi access	Wifi access
	Misfit of features to needs	Misfit of features to needs
2	Not enough feedback	Battery life
	Concerns over lack of guidance	Concerns over understanding content
		Time for interaction
		Notification burden No one caring about how I am doing
3	Lack of human interaction	Lack of human interaction
	Privacy	Privacy
	Lack of motivation	Lack of motivation
	Forgetting to use	Forgetting to use
	No scheduled time for use	No scheduled time for use
	Concerns over understanding content	Concerns over lack of guidance
	No one caring about how I am doing	Not enough feedback
4	Want to solve problems on own	Want to solve problems on own
	Stigma	Stigma
	Battery life	
	Time for interaction	
	Notification burden	

Note. Wording in table is identical to the wording the participants viewed on the cards. Groups are listed in order of greatest (1) to smallest (4) barriers. Variance represents clusters formed using mean ranks only (to indicate overall importance); Consistency represents clusters formed using mean ranks and standard deviations (to indicate consistency of importance).

guidance and efficacy. These findings are not surprising, given previous reports indicating that information about app privacy and theoretical efficacy are frequently not communicated to users. Indeed, the majority of privacy policies for currently available apps are missing, not focused on the app itself, or require college-level literacy for comprehension.[33] Additionally, a majority of health apps have been found to pose a threat to the security and privacy of user data.[34,35] While current users of health apps generally report trust in their accuracy,[31] efficacy related to cultural and symptom-specific factors have also been cited as potential barriers or concerns about smartphone intervention uptake.[36–38] Further, app functionality issues, such as errors and app crashes, have previously been identified as primary criticisms from general app users.[32,39] The barriers identified through card sorting are consistent with previously raised issues and concerns from app users.

Among other barriers identified for apps, concerns emerged regarding a potential lack of guidance and feedback. This issue may overlap with a less primary barrier identified via the card sorting task: lack of human interaction. Integration of human support in health interventions delivered via technology has been recommended, and included in apps and other technologies, for the purposes of improving adherence, communication with care teams, and improving quality of tool use.[40–42] However, the majority of currently available apps for depression do not include connection to human support, nor provide personalized guidance or feedback.[43] These findings highlight implications for design changes and improvements that better align with the needs and concerns of users.

Implications for design

The barriers identified in the present study relate to typical depression intervention (e.g. concerns about stigma), technology-mediated delivery of care (e.g. data privacy), and app-specific (e.g. data plan) issues. Despite the breadth of issues identified, the implications of these findings may be targeted specifically to the use of mobile apps as a delivery mechanism. Table 4 details implications for design based upon identified barriers to use and uptake of apps for depression. Implications and their rationale are detailed below.

Cost: With cost identified as a primary barrier in both face-to-face and app delivery, the design and marketing of apps for depression would likely benefit from transparency of possible costs, and an emphasis on avoiding hidden costs. While there is sometimes a cost associated with purchase of an app, participants indicated through qualitative feedback that their concern over cost is specific to the cost accrued through an

Table 4. Implications for the design of future apps for depression based on user perceived barriers.

Barrier	Cards	Design recommendation
Cost	Cost of data package	1. Provide choice of using cellular data package *versus* Wifi to utilize app features that require an internet connection
		2. Explicitly note amount and frequency of data requirements
Privacy and security	Unsure who has access to data, Privacy	1. Launch clear and concise privacy statement
		2. Initiate pop-up request for access to any possible features or data collected from the phone
Efficacy and functionality	Concerns about effectiveness, Misfit of features to needs, Bugs in the system, Wifi access	1. Provide video testimonials featuring demographically-representative people
		2. Conduct usability testing and quality assurance evaluations prior to deployment
		3. Require easily located help button (FAQ and live support connection)
Feedback, guidance, human support	Not enough feedback, Concerns over lack of guidance, Lack of human interaction	1. Provide coach support via phone, text, or messaging
		2. Use of algorithms based on context sensing or user behaviors on app

Note. FAQ = Frequently Asked Questions.

app's use of their data packages. This concern leads to two recommendations. First, users should be provided a choice of whether an app will utilize wireless data, or only use data when connected to a Wifi source. Second, users should be provided clear information at download on whether an app requires an internet or data connection, and how much and frequency. The majority of apps designed for the most prevalent health conditions do not require an internet or data connection for use following download;[44] users may therefore be making assumptions about the cost of apps due to data usage beliefs that are incorrect. Further research is needed to expand cost-effective means for use of apps to deliver depression interventions and how to transparently detail all costs and data requirements of these apps to users.

Privacy and security: Strategies and recommendations have previously been proposed to combat the critical issues of privacy and data safety in app design, including: data encryption, user access controls, privacy notices and creating privacy profiles.[34,45–48] However, to address user concerns in design through impacting user knowledge and awareness of data security and privacy, a clear and concise privacy statement at launch is recommended. Further, it is recommended that if the app accesses data from features on the phone or other apps, that this be stated explicitly. Users are more likely to view an app's access of private information as appropriate and acceptable if it fits their expectations of the app's function (i.e. a mapping app accessing current location via the GPS feature on the phone).[49] Therefore, at initial launch, apps delivering depression interventions should initiate a pop-up request for access to any possible features or data collected from the phone. Links to additional information should be provided to clearly and concisely detail: 1) why this access is needed, 2) if and how the app functionality will be impacted if this access is not allowed, and 3) the storage and confidentiality of retrieved data from these features. These permissions should also be editable over time, in case selected access permissions are inconsistent with later user interactions and needs of the app. Future research is required to understand the impact of these design recommendations on improving user comprehension and sense of control over app privacy and security.

Efficacy and functionality: Users expressed concern over an app's abilities to meet the treatment needs of depression, and to function with limited error (i.e. crashing, bugs in the system). To meet the concern over efficacy for a user's symptoms, video testimonials, featuring demographically representative people, are recommended for apps delivering interventions for depression. Information delivered via internet browsers has been found to be believed as specifically targeting a user and to be rated more favorably with the inclusion of video testimonials. This belief is strengthened, even when compared to similar testimonials presented via text or picture.[50] Further, video testimonials with demographically representative people have been noted as user requirements for other types of health apps.[51,52] User satisfaction with video testimonials may be evaluated before deployment via usability testing. Further, usability testing and quality assurance evaluations should be employed before releasing apps for depression, in an effort to identify and remove the likelihood of app crashes and bugs.[39,53] In addition, an easily located help option should be made available on apps delivering depression interventions, so users have the ability to troubleshoot, should app functioning become problematic. The help button should link with frequently asked questions (FAQs), as well as an option to connect with live support. Future evaluations of video testimonials and troubleshooting efforts are necessary to identify how concerns over efficacy and functionality are impacted by these changes.

Feedback, guidance, and human interaction: Given benefits identified in web-based delivery platforms, providing concurrent human support, such as coaching via phone, text, or messaging, has emerged as a possible solution to concerns over lack of feedback, guidance, and human interaction in apps delivering depression interventions.[7,42] Coaching has been identified as a means to enhance supportive accountability, a construct that is intended to increase adherence, which may impact outcomes in use.[54] Indeed, coached interventions have demonstrated significantly better adherence than non-coached interventions for depression.[55] Rather than provide therapeutic interventions, coaches are intended to increase engagement and motivation with a technology-delivered intervention by reinforcing successful use.[56,57] Aiding users in full and confident engagement with an app may address the issue of lack of guidance. A future design option may include algorithms that initiate feedback based on specific user behaviors or detected user contexts.[58,59] However, more research is needed to understand the best means to implement interventions related to passive behavior detection in those with depression. An increase in the use of human support via coaching will need to be evaluated for its impact on user perceptions of feedback, guidance and human interaction while using apps for the delivery of depression interventions.

Limitations

Limitations and caveats should be considered in the interpretation of these findings. First, while the sample size was sufficient for a card sorting task,[23] the sample was comprised of urban and primarily younger, non-Hispanic Caucasian users. This is despite efforts to recruit a diverse, urban sample. It is unclear how well these findings extend to users in differing geographical locations and demographic groups. Future research might consider implementing purposive sampling methods to insure more diverse samples and may consider exploring barriers based upon other demographic features, such as age (i.e. younger users might face different barriers than older users). However, the process of identifying barriers with participants in an in-person setting was established as feasible. Second, the sample was a mixed group of those with no depressive symptoms to those with severe depression, with the majority in the mild symptom range. It is unclear if similar groupings of barriers would be identified with a more severely depressed sample, or those with comorbid psychiatric or health conditions. Despite concerns of generalizability to more severe samples, this sample represents the diversity of symptoms experienced across the typically relapsing and remitting course of depression.[60–62] Third, it is possible that the participants inferred different meanings for the barriers listed on the cards. For example, the cards 'Unsure who has access to data' and 'Privacy' were typically ranked differently despite having similar meanings. While qualitative feedback was utilized to better understand rankings and groupings of the cards, future research utilizing card sorting to identify barriers would benefit from uniform definitions for each card. Additionally, as many barriers overlapped with typical concerns relating to technology broadly as a delivery mechanism, future research might explore barriers targeted specifically to apps. Indeed, the present study included barriers associated with depression treatment (e.g. stigma) and issues associated with broad use of technology as a delivery mechanism.[63]

Conclusion

To the best of our knowledge, this is the first identification of user-perceived barriers to apps via a card sorting task. Smartphones stand as a promising delivery mechanism for overcoming barriers to traditional delivery of depression interventions. However, while there is some promising initial evidence for the efficacy of apps as a behavioral intervention delivery mechanism,[10–14] a larger evidence base is required. In terms of barriers to uptake and use, cost remains a consistent barrier across face-to-face and app delivery of interventions. Other barriers to the use of apps for the delivery of depression interventions relate to uncertainties around apps as a technology mediated delivery mechanism. Implications for design to address these barriers include: limiting wireless data usage; clearly stating possible costs and privacy/access options at download, including demographically-representative video testimonials; conducting usability testing and quality assurance evaluations; and including human support. Future research should evaluate the impact of changes in design and marketing of mental health apps on perceptions of barriers for users with depression.

Contributorship: CSS researched the literature and conceived the study. CSS and EGL executed the research sessions. CSS wrote the first draft of the manuscript and EM, EGL, MJK, and DCM contributed to later drafts. All authors reviewed and edited the manuscript and approved the final version of the manuscript.

Declaration of Conflicting Interests: The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Ethical approval: This research was approved by Northwestern University's Institutional Review Board (IRB STU00099556).

Funding: The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This work was supported by the National Institute of Mental Health (F31 MH106321). This project was also supported by NIH/NCRR Colorado CTSI Grant Number UL1 RR025780. Its contents are the authors sole responsibility and do not necessarily represent official NIH views.

Peer review: This manuscript was reviewed by Anne Moen, University of Oslo and Vivek Furtado, University of Warwick.

Guarantor: CSS

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