Current Psychiatry Reports (2020) 22: 11
https://doi.org/10.1007/s11920-020-1134-9

MOOD DISORDERS (E BACA-GARCIA, SECTION EDITOR)

Apps for Depression: Are They Ready to Work?

Alejandro Porras-Segovia[1,2] · Isaac Díaz-Oliván[1,2,3] · Luis Gutiérrez-Rojas[4,5] · Henry Dunne[6] · Manon Moreno[1,2] · Enrique Baca-García[1,2,3,7,8,9,10,11]

Published online: 5 February 2020

Abstract

Purpose of Review To summarize the latest evidence about mobile phone applications for the management of depression.

Recent Findings Depression apps are very heterogeneous, given the absence of standards for their development, description, and evaluation. Randomized clinical trials show the effectiveness of some of these applications in reducing depressive symptoms. Attrition is an important issue whose evaluation is limited by the frequent use of incentives in the studies.

Summary The number of mobile applications for depression far exceeds the number of studies evaluating their efficacy and feasibility. Despite the limitations of the digital market, there are a small number of apps that have demonstrated sufficient effectiveness and tolerability to think of short-term clinical use. However, there are still barriers at different levels that may delay the implementation of these interventions in daily clinical practice.

Keywords Depression · m-health · e-health

Introduction

Depression is one of the main contributors to global burden of disease and has been a major public health concern for decades [1]. People with depression have a reduced expectancy of life, frequent physical comorbidities, and increased risk for suicide [2, 3]. Depression is still largely undertreated. To the high rates of non-response to conventional treatments, we have to add the shortcoming of new advances in the treatments of depression and the lack of access to existing ones. The World Mental Health surveys from 23 countries show that only 16.5% of patients with depression receive a minimally adequate treatment [4].

Mobile health may provide an exit to this stalled situation. The application of mobile phone technology to healthcare settings—usually known as m-health—is increasing in popularity. Above three quarters of mental health patients own a smartphone, and around 90% declare they use mobile apps regularly [5]. When asked about their opinion on m-health, most patients show a positive response, with three quarters declaring their interest in using a mobile application for improving their mental health [5]. Thanks to the widespread ownership of smartphones and the endless diversity of applications they can host, m-health represents a promising new approach to the management of mental disorders [6–8].

This article is part of the Topical Collection on *Mood Disorders*

✉ Alejandro Porras-Segovia
alexposeg@gmail.com

[1] Department of Psychiatry, Instituto de Investigación Sanitaria Fundación Jiménez Díaz, Madrid, Spain

[2] Department of Psychiatry, Hospital Rey Juan Carlos, Móstoles, Spain

[3] Madrid Autonomous University, Madrid, Spain

[4] Department of Psychiatry, Universidad de Granada, Granada, Spain

[5] Unidad de Hospitalización del Hospital Campus de la Salud, Complejo Hospitalario de Granada, Granada, Spain

[6] Brighton & Sussex University Hospital, Brighton, UK

[7] CIBERSAM (Centro de Investigación en Salud Mental), Carlos III Institute of Health, Madrid, Spain

[8] Universidad Catolica del Maule, Talca, Chile

[9] Department of Psychiatry, Hospital Universitario Fundación Jiménez Díaz, Madrid, Spain

[10] Department of Psychiatry, General Hospital of Villalba, Madrid, Spain

[11] Department of Psychiatry, University Hospital Infanta Elena, Valdemoro, Spain

Although this technology does not intend to replace human interaction, it may have some advantages compared with traditional treatments [9•]. m-health eliminates physical barriers, provides 24/7 access, and is relatively inexpensive [5, 10]. Additionally, patients may feel more comfortable discussing their symptoms through interactive software than face-to-face [10].

However, there appears to be two different rhythms in the development and implementation of m-health. Most health apps are commercially based, and while the market is growing exponentially, research cannot keep up the pace: the number of studies evaluating these apps is much lower than the number of apps available [11]. Also, there are few standards regarding the label, approval in clinical use, and methods of reporting and scoring these apps [12].

Choosing one application among such immense variety poses a challenge to mental health patients [13••]. Without guidance, apps for depression are at risk of devaluing their purpose and even becoming iatrogenic instead of therapeutic. For instance, if inadequately informed, patients may be led to believe a certain mobile intervention is sufficient and not seek the professional help they need.

In this review, we summarize the latest evidence about mobile applications for the management of depressive disorders. We sought to determine whether current m-health technologies for depression are ready for implementation in the clinical practice, and to identify the next steps to advance in the field.

Landscape of the Market

The lack of proper standards and reporting guidelines gets in the way when trying to define and characterize an app for depression. There are many apps in the market that claim to provide a treatment for depression, but not all of them deliver evidence-based interventions. This lack of regulation also makes it difficult to establish the exact number of apps for depression. While the total number of mental health applications is estimated to be over a thousand [13••], systematic searches of online marketplaces focusing on depression and applying selection criteria reveal around 278–310 depression apps [14–16].

Most apps for depression are commercially driven, while only a few are created by research teams and healthcare facilities. In a 2015 study exploring the market of apps for depression, only 5.3% of developers came from medical, academic, or research settings, while most of them were commercially oriented companies (29.5%), or did not reveal their affiliation (65.3%) [14]. Other aspects of the description, such as the type of treatment, or the evidence on which the app is based on, are often obscure or even misleading [14]. Similarly, Kumar et al. [16] found that only 9% of interactive apps for depression defined their scope. Moreover, some of the descriptions found in these apps could be misleading, as many make claims that users might be led to believe are medical and evidence-based, when in fact none of them has been approved by the FDA [17].

Contrary to what one might believe, being developed by a health or research institution does not guarantee adherence to evidence-based principles. Conversely, using evidence-based principles does not guarantee user satisfaction, or the popularity of downloads [15].

Regarding the availability of applications, the most common marketplaces to find apps for depression are Google Play Store and iPhone Apps store, which contain the highest number of apps for depression [14]. An important factor to take into account is that mobile apps developed by institutions are often not open for downloading on an e-market, but rather are provided for testing only for participants in the study.

Types of Apps and Characteristics

Applications for the treatment of depression are a heterogeneous group. Applications can be categorized by the features they offer, target population, technological aspects, developer, and theoretical framework.

Features

Regarding their features, text, audio, and video files are the most common means to deliver mobile-based interventions, mainly as a form of psychoeducation. Another frequent feature is logs that allow the user to register and monitor their progress in certain areas. Apps aiming for more complex forms of interaction incorporate live chats with different kinds of professionals, or even volunteers, in a similar approach to suicide hotlines. Some apps also offer in-built games to increase engagement, a concept known as gamification.

Types of Intervention

Therapeutic interventions for depression are numerous and varied. Apps that claim to provide a treatment for depression do so by interventions as varied as hypnosis, brainwave entrainment, music therapy, spiritual/faith-based, positive affirmation, breathing techniques, and yoga. However, the most common type of intervention is psychotherapy in its varied forms, and among these, cognitive behavioral therapy (CBT) is the most frequent.

CBT is an evidence-based psychotherapy that has proven effective in the treatment of depression. Although it is typically delivered face-to-face, there have also been successful attempts to administer it by e-health [18, 19], including Web-based interventions, and more recently mobile apps. There are

two basic features that act as criteria for CBT-based apps: a monitoring function—some kind of log, so that patients can register their daily status, including mood, thoughts, and/or physical sensations, and keep track of their progress; and a psychoeducational module through either text, video, or audio files destined to increase self-awareness and knowledge about one's own condition. CBT-based mobile applications offer behavioral and cognitive techniques, and usually include a function to monitor users' status (including their cognitions, emotions, behaviors, and/or physical sensations), along with a psychoeducational component.

Shen et al. described 10 apps available in the market that delivered evidence-based CBT for depression, while Hughet identified 12 apps consistent with a CBT framework [14, 15]. Among the CBT-based apps with the highest number of downloads are Depression CBT Self-Help Guide, and The Mood Tools–Depression Aid, both of which have a user rating above 4 out of 5 (average ratings were 4.2 and 4.3 out of 5, respectively) [15]. The highest rating was for The Depression Cure, available for iOS, which received an average rating of 4.5 out of 5 [15].

As for the CBT-based apps that have been empirically tested, we have the MoodHacker, which showed a significant reduction in depressive symptoms in a 2016 randomized clinical trial (RCT) that tested the application in a sample of 300 adults with clinically diagnosed depression [20].

In contrast, most CBT-based apps lack empirically tested studies. In fact, of the 12 apps identified by Huguet et al. available in the market, none of them had been tested for effectiveness [15].

There are also apps that are not specifically designed for the treatment of depression, but that can significantly help in the treatment by tackling some of the core symptoms of depression. This is the case with apps for the treatment of insomnia or the prevention of suicidal behavior.

Insomnia and other sleep disorders are a frequent feature of depression and have been associated with higher recurrence and resistance to antidepressant treatment [21]. Among the many tools for the management of sleep disturbances, we have the Sleepcare app, which tackles insomnia through CBT techniques and which has shown promising results after it was tested in community-dwelling adults [22].

Another of the potential uses of m-health technologies is suicide risk assessment and prevention. Mobile applications have been used in clinical settings to reduce the risk of reattempt. Berrouiguet et al. [23] followed up suicide attempters using a short messaging service (SMS), while Nuji et al. [24] designed a smartphone-based platform called the CASPAR (Continuous Assessment for Suicide Prevention And Research) that allowed patients to monitor their progress.

A transversal intervention can also be provided by medication and appointment reminders [25]. Improving treatment adherence and healthcare attendance is crucial, since lack of compliance is one of the most studied factors increasing treatment resistance [26].

One way to optimize the effect of m-health is to design applications for special populations, thus increasing the personalization of treatments. Some developers have focused on the particularities of certain groups, such as pregnant women [27•], the LGBT community [28], or children and adolescents [29]. The latter could benefit greatly from m-health interventions, since they are more proficient in the use of technology, and also present frequent problems of seeking professional health [30].

Effectiveness

Although studies evaluating the effectiveness of apps for depression are still far fewer than the applications in the e-market, an increasing number of RCTs are becoming available.

In 2017, Firth et al. performed the first meta-analysis of RCTs evaluating apps for depression. They found 18 studies testing 22 different m-health interventions, performed in either clinical or non-clinical populations. Pooled results from a total of 3414 participants showed that mobile applications reduced depressive symptoms to a significant greater extent than control interventions ($p < 0.001$). However, this clinical response was only observed in people with up to moderate depressive symptoms, but not in patients clinically diagnosed with mood disorders or anxiety. Authors also explored what features were associated with greater effectiveness, and they found that apps containing in-person interventions or cognitive training modules were significantly less effective [13••].

Since this meta-analysis, other clinical trials evaluating the effectiveness of mobile applications for depression have been conducted. Hur et al. evaluated the mobile application Todac-Todac in 34 participants with depression. The Todac-Todac is a CBT-based app designed to reduce negative beliefs in depressed people. The app was evaluated against a daily mood monitor that served as a control. After 3 weeks, both symptoms of depression and dysfunctional beliefs were reduced significantly more in the intervention group than in the control group [31•].

Pratap et al. evaluated the effectiveness of three apps for depression: *Project EVO*, which delivered a CBT intervention; *iPST*, which delivered a different psychotherapeutic intervention; and *Health tips*, which worked as a treatment monitor. These apps were effective for people with moderate symptoms of depression, and cognitive training was the most effective intervention [32•].

Table 1 summarizes the main findings regarding effectiveness.

Table 1 Main findings on effectiveness

Study	App name	Design	Sample	Effectiveness
Arean et al. [33]	iPST Project EVO Health Tips	RCT 12 weeks follow-up	626 adults with depression	77.0% improvement on mood (IMPACT—measured mood) ($p = 0.04$)
Baumel et al. [34]	7 Cups of Tea	Case-control 2 months follow-up	19 outpatients and community-dwelling adults	Decrease in EPDS scores ($p < 0.001$)
Birney et al. [20]	SuperBetter	RCT 10 weeks follow-up	300 adults with depression	Decrease in PHQ-9—measured depressive symptoms (partial eta = 0.021)
Corden et al. [35]	MedLink	Case-control 8 weeks follow-up	41 adults with depression	Decrease in PHQ-9 and QUIDS-C—measured depressive symptoms ($p < 0.001$)
Fogarty et al. [36]	Man Central	Quasi-experimental 5 weeks follow-up	144 men with depression	Improvements in depressive symptoms (PHQ-9), risk for depression (DRS), externalizing symptoms (CDR), and work and social functioning (SAS) ($p < 0.001$)
Furukawa et al. [37]	Kokoro-app	RCT 9 week	164 patients with major depression	Non-significant results
Goldin et al. [38]	Ascend	Longitudinal observational study 4 weeks follow-up	117 adults with depressive symptoms	Decrease in PHQ-9—measured depressive symptoms ($p < 0.001$)
Hur et al. [31]	Todac Todac	RCT 3-weeks follow-up	34 adults with depression	Decrease in BDI-II ($Z = -3.386$, $p = 0.001$) and situation-dependent STAI-X2 ($Z = -2.913$, $p = 0.004$) scores
Mantani et al. [39]	Kokoro-app	RCT 17 weeks follow-up	164 adults with major depression	Decrease in PHQ-9—measured depressive symptoms ($p < 0.001$)
Mo et al. [27]	Antenatal care apps	Cross-sectional	1304 community-dwelling pregnant women	Protective effect on antenatal depression (EPSD—measured, OR = 0.33, 95% CI 0.12–0.89)
Mohr et al. [40]	MedLink	Case-control 4 months follow-up	23 patients taking medication (12 with major depression)	Decrease in PHQ-8—measured depressive symptoms ($p = 0.008$)
Mohr et al. [41]	IntelliCare	RCT 4–8 weeks follow-up	105 adults with depression/anxiety	Decrease in PHQ-9 and GAD-7 scores ($p < .001$)
O'Toole et al. [42]	LifeApp'tite	RCT 4 months follow-up	139 patients with depression	Decrease on SSF II-R–measured suicide risk ($p = 0.008$, $d = 0.46$)
Pratap et al. [32]	iPST Project EVO Health Tips	RCT 3 months follow-up	1026 adults with depressive symptoms	Decrease in PHQ-9—measured depressive symptoms (beta = 2.66; $p = 0.006$)
Proudfoot et al. [9]	myCompass	RCT 3 months follow-up	720 adults with depressive symptoms	Decrease in PHQ-9—measured depressive symptoms $d = 0.22$ to $d = 0.55$)
Schlosser et al. [43]	PRIME-D	Case-control 8 weeks follow-up	36 adults with depression	50% reduction in PHQ-9—measured depressive symptoms
Silva-Almodovar et al. [44]	Sinasprite	Retrospective observational 6 weeks follow-up	450 app users	Decrease in PHQ-8 ($p < 0.001$), GAD-7 ($p = 0.002$), and CSE ($p < 0.001$) scores
Whitton et al. [45]	myCompass	RCT 8 weeks follow-up	231 adults with depression/anxiety	Improvement in DASS-21—measured depressive symptoms ($d = 0.22$ to $d = 0.55$)

BDI-II, Beck Depression Inventory-II; *CDR*, the Connor-Davidson Resilience Scale; *CSRI*, adapted Client Service Receipt Inventory; *DASS*, = Depression Anxiety and Stress Scales; *DRS*, Depression Risk Scale; *EPDS*, Edinburgh Postnatal Depression Scale; *GAD-7*, = Generalized Anxiety Disorder-7; *IMPACT*, Improving Mood-Promoting Access to Collaborative Treatment; *OR*, odds ratio; *PHQ-4*, Patients Health Questionnaire-4; *PHQ-8*, = Patients Health Questionnaire-8; *PHQ-9*, Patients Health Questionnaire-9; *QUIDS-C*, Quick Inventory of Depressive Symptomatology; *SAS*, = Social Adjustment Scale; *SSF*, = Suicide Status Form II-R; *STAI-X2*, = State-Trait Anxiety Inventory

Feasibility

There appears to be an inverse correlation between length of use and effectiveness [13••]. Consequently, if we want to achieve long-term clinical responses, attrition is a crucial battlefront. Attrition has two components: dropout and non-usage [46]. Even if participants complete the study follow-up, using the app tends to decrease over time. For instance, in the RCT performed by Pratap et al., participation halved after a month of follow-up. By that time, passively collected data were twice as much as actively collected information [32•].

Evaluation of feasibility is sometimes clouded by the use of incentives, which is controversial. In order to increase engagement and decrease dropouts, some studies reward the participants who complete the study. These incentives are usually in the form of shopping vouchers. This is the case of the study performed by Pratap et al. which rewarded those users that completed the 12-week assessment with Amazon gift vouchers worth 75$ [32•]. Bluewatch users were also rewarded with a shopping voucher, this time worth $20 [47]. Studies that use incentives are not assessing feasibility in real-world conditions, which limits the validity of their assumptions.

Regarding user satisfaction, those who have used the apps are generally happy with them, demonstrated by the fact that the average rating for depression apps in 2015 was 3.5 out of 5 stars [14]. A survey performed on US veterans attending a mental health center revealed that the features that patients found more attractive were increasing physical exercise, improvement of sleep, cognitive restructuring, and behavioral activation [48]. In contrast, the main reasons reported for not using a mental health app were lack of evidence of their effectiveness, privacy issues, and inability to find the right app [48].

Table 2 summarizes the main findings regarding feasibility.

Barriers to the Adoption of m-health

Results from qualitative studies and surveys done to both patients and healthcare professionals can give us an idea of the issues yet to be overcome for the adoption of m-health. Although patients are open to using mobile health applications, interest differs from actual use. A 2019 survey performed on veterans with either depression or anxiety disorders revealed that while 73.1% of them were interested in mental health applications, only 10.7% actually used one of them [48]. Similarly, a study exploring the use of m-health technologies in patients with post-traumatic stress disorder (PTSD) showed that only 10% of them used a health app, even if over half of them had manifested their interest in this kind of interventions [51].

Difficulty in finding the right app is another major problem. The market of m-health grows at a much faster pace than the research destined to validate these interventions. Moreover, m-health—or e-health for that matter—is not integrated in public health systems, which can raise suspicion among users and deprive them of the possibility of asking their healthcare provider what app should they use, if any. Without counsel, users interested in e-health are left with the apps description available on the online store. Shen et al. [14] found that most of these descriptions were insufficient and many of them did not provide information of the developer's affiliation, or the theoretical framework on which the intervention was based.

The non-integration of m-health into public health systems also implies that many may ignore the existence of mental health care apps, or distrust them as they are not covered by their health insurance [51]. In this regard, the UK's National Health System (NHS) has made an effort in starting to consider e-health as a therapeutic tool integrated in healthcare coverage [52].

Suspicion about privacy violation is another reason for patients' reluctance [50, 53]. Concerns about privacy are reported as a barrier to the use of apps by several studies [50]. Lack of privacy policies is a frequent issue in apps. Users care about privacy and one of the features that they value is that sensitive information, such as logs, is password protected [15].

Barriers related to the mental disorder itself also come into play. A study showed that veterans without PTSD were more interested in engaging in mental healthcare applications than their peers with PTSD, even though the latter group demanded more mental health services [54].

Healthcare professionals can also slow down the adoption of m-health in the clinical practice. There are several concerns among the medical community regarding the reliability of m-health interventions. The number of studies evaluating these apps is markedly lower than the number of apps itself [14], and most mental healthcare applications have not been explored in terms of tolerability and effectiveness. Training doctors, nurses, and other healthcare professionals in the use of mobile health technology is a crucial step to take for the implementation of this technology in the clinical practice [55].

Conclusions

Are depression apps ready to work? This is the question that arises after reviewing the (limited) evidence available on the matter. We have a number of apps that have proven effective in the treatment of depression relatively free of bias. Albeit small, this number would be sufficient to start implementing this advancement in the clinical practice. After all, only one antidepressive agent is necessary to start treating depressive patients with antidepressants. m-health presents the further advantage of the lack of physical side effects—although they can present other risks, such as psychological dependency. Why then is this technology not being used in clinical practice? There are several factors that can get in the way of using a treatment that are independent of the treatment itself. Apps for depression may be ready, but we are not.

Table 2 Main findings on feasibility

Study	App name	Engagement	Dropout
Arean et al. [33]	Project EVO, iPST, and Health Tips	Not evaluated	57.9% did not download the app*
Baumel et al. [34]	7 Cups of Tea	Average frequency of use: 175 min Average length of use: 12 times Most commonly used feature: the mobile program 94%	Not evaluated*
BinDhim et al. [49]	Depression Monitor	Average median of launches: 3.2 Average frequency of use: a range between 1 and 141 times (average excluding one-time users was 5.9 times)	Not evaluated
Birney et al. [20]	SuperBetter	Average frequency of use: 6 min/session Average length of use: 1 time per week, 5.7 trackable activities per week	Not evaluated
Corden et al. [35]	MedLink	Average median of launches: 23.8 times per user over 8 weeks	Not evaluated
Fogarty et al. [36]	Man Central	Not evaluated	Study attrition: 64.6% did not complete follow-up measures*
Goldin et al. [38]	Ascend	Not evaluated	Dropout rates of 27% and 15%
Mantani et al. [39]	Kokoro-app	Not evaluated	99% completed 50% 88% completed 6/8 sessions
Mo et al. [27]	Antenatal care apps (acAPPs)	Average use: 71.31%	Not evaluated
Mohr et al. [40]	MedLink	Average median of launches: 17.4 times over 4 weeks	96.6% assessments were completed
Mohr et al. [41]	IntelliCare	Average frequency of use: 195.4 times over 8 weeks. Average length of use: 1.1 min/day	90.1% completed 8 weeks*
Pratap et al. [32]	iPST Project Evolution Health Tips	Not evaluated	86% dropout rate after weeks*
Proudfoot et al. [9]	myCompass	Most used features: short motivational messages 68.4% and symptom tracking 61.5%	Retention rates 72.1% (post-intervention) and 48.6% (follow-up)
Schlosser et al. [43]	PRIME-D	Average length of use: 4.5 days/week	Not evaluated*
Silva-Almodovar et al. [44]	Sinasprite	Average frequency of use: 6 min/session Average length of use: 1 time per week	Not evaluated
Stiles-Shields et al. [50]	Thought Challenger	Average of completion times: 5 min or less	Not evaluated*

*Participants received some kind of incentive

The adoption of m-health interventions in the clinical practice depends on many factors. We can establish different levels of action, from regulatory bodies to the app users themselves, as well as developers and researchers—who are sometimes the same—and healthcare professionals. Tackling the barriers observed at certain levels cannot be done if some issues have not been solved previously in the levels above. For example, we have seen that users are often overwhelmed by the number of options available in the digital health market, and that they have difficulties in choosing the application that best suits their needs [14]. To solve this problem, the role of healthcare providers is essential: if they have sufficient understanding of digital mental health, they will be in a position to guide their patients to the best intervention. However, it is difficult for health professionals to do this if they have not received the necessary training, which in turn requires sufficient funding to organize refresher courses and workshops [56].

Similarly, developers need to improve apps' graphics and interface in order to make the software more attractive to patients [57, 58]. Quality of mobile software is increasing rapidly, but its uses are mainly commercially oriented. Without proper investment, there is a risk that the most useful application of this technology—that of serving public health—will be left using outdated software compared with its commercially oriented counterparts.

Figure 1 illustrates the different actions that can be taken at each level to overcome the barriers to the adoption of m-health in the clinical practice. This flow of influence goes in the opposite direction too: if authorities are not pressured from below, actions are unlikely to be taken. Users can also influence the actions and attitudes of healthcare professionals. In this regard, the interest and positive reception of psychiatric patients toward m-health should be a wake-up call [48].

The negative attitude of some professionals towards this technology is not unfounded but can close doors to further

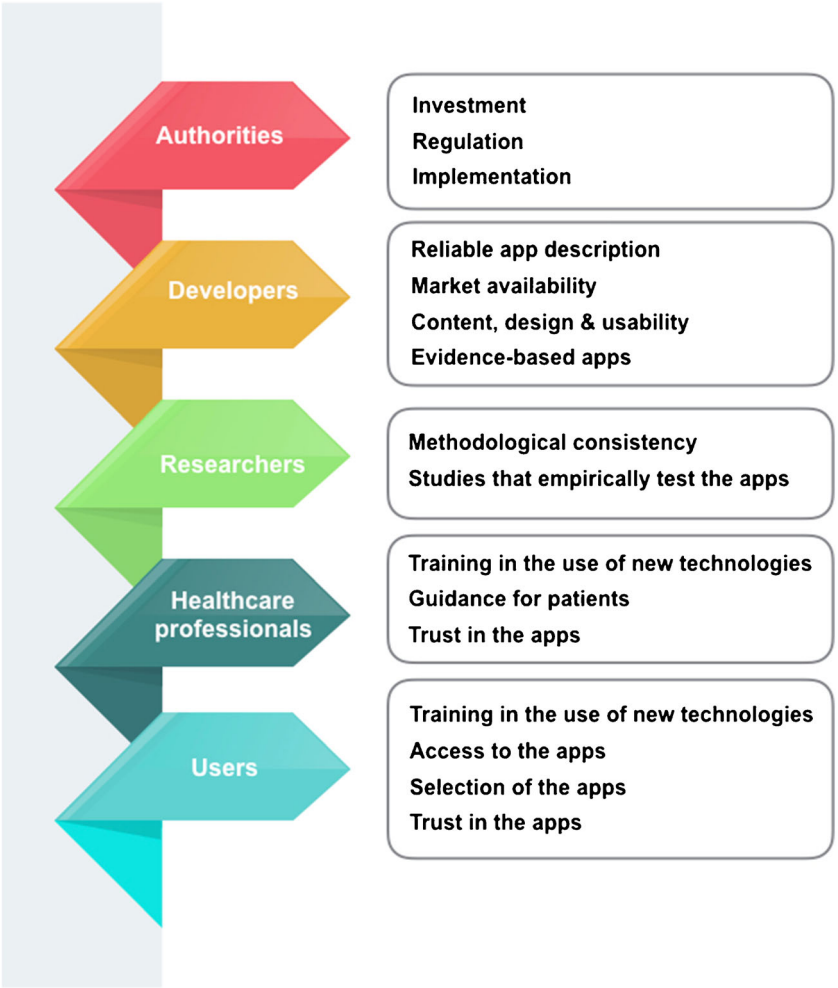

Fig. 1 Levels of action for reducing barriers to the adoption of m-health

advancement in the right direction. Developers also need to integrate the information coming from users and professionals in order to improve application designs and interfaces, and optimize them for use in clinical practice.

Another point of interest is the development of unified standards about the definition and reporting of mobile apps. The lack of standards in creating, evaluating, and reporting health apps is one of the main obstacles to the implementation of these interventions in clinical practice. In this regard, regulatory bodies have created a model for the assessment of health apps called the Digital Health Precertification Program (Pre-Cert Program), which is a crucial step toward the regularization of these interventions, and of e-health in general. This model aims to be based on real-world data, that is, performance in real conditions, the actual settings at which the apps will be used [59]. Other efforts toward the standardization of m-health include the system proposed by Chan et al. [60] to evaluate mobile apps based on three areas: usefulness, usability, and infrastructure.

Acknowledgments The editors would like to thank Dr. Pilar A. Sáiz for taking the time to review this manuscript.

Compliance with Ethical Standards

Conflict of Interest Alejandro Porras-Segovia, Isaac Díaz-Oliván, Luis Gutiérrez-Rojas, Henry Dunne, Manon Moreno, and Enrique Baca-García each declare no potential conflicts of interest.

Human and Animal Rights and Informed Consent This article does not contain any studies with human or animal subjects performed by any of the authors.

References

Papers of particular interest, published recently, have been highlighted as:
- • Of importance
- •• Of major importance

1. Murray C, Lopez A. Measuring the global burden of disease. N Engl J Med. 2013;369(5):448–57. https://doi.org/10.1056/nejmra1201534.
2. Lawrence D, Hancock K, Kisely S. The gap in life expectancy from preventable physical illness in psychiatric patients in Western Australia: retrospective analysis of population-based registers.

BMJ. 2013;346(may21 1):f2539. https://doi.org/10.1136/bmj.f2539.

3. Rivera M, Porras-Segovia A, Rovira P, Molina E, Gutiérrez B, Cervilla J. Associations of major depressive disorder with chronic physical conditions, obesity and medication use: results from the PISMA-ep study.
4. Thornicroft G, Chatterji S, Evans-Lacko S, Gruber M, Sampson N, Aguilar-Gaxiola S, et al. Undertreatment of people with major depressive disorder in 21 countries. Br J Psychiatry. 2017;210(02):119–24. https://doi.org/10.1192/bjp.bp.116.188078.
5. Peng W, Kanthawala S, Yuan S, Hussain SA. A qualitative study of user perceptions of mobile health apps. BMC Public Health. 2016;16(1):1158.
6. O'Dea B, Calear A, Perry Y. Is e-health the answer to gaps in adolescent mental health service provision? Curr Opin Psychiatry. 2015;28(4):336–42. https://doi.org/10.1097/yco.0000000000000170.
7. Poushter J. Smartphone ownership and internet usage continues to climb in emerging economies. Pew Res Cent. 2016;22.
8. Berrouiguet S, Perez-Rodriguez M, Larsen M, Baca-García E, Courtet P, Oquendo M. From eHealth to iHealth: transition to participatory and personalized medicine in mental health. J Med Internet Res. 2018;20(1):e2. https://doi.org/10.2196/jmir.7412.
9.• Proudfoot J, Clarke J, Birch M, et al. Impact of a mobile phone and web program on symptom and functional outcomes for people with mild-to-moderate depression, anxiety and stress: a randomised controlled trial. BMC Psychiatry. 2013;13(1). https://doi.org/10.1186/1471-244x-13-312. **An RCT evaluating the app myCompass. There was a significant decrease in depressive symptoms. Most used features were short motivational messages and symptom tracking.**
10. Torous J, Chan SR, Yee-Marie TS, Behrens J, Mathew I, Conrad EJ, et al. Patient smartphone ownership and interest in mobile apps to monitor symptoms of mental health conditions: a survey in four geographically distinct psychiatric clinics. JMIR Ment Health. 2014;1(1):e5. https://doi.org/10.2196/mental.4004.
11. Martínez-Pérez B, de la Torre-Díez I, López-Coronado M. Mobile health applications for the most prevalent conditions by the World Health Organization: review and analysis. J Med Internet Res. 2013;15(6):e120.
12. Tal A, Torous J. The digital mental health revolution: opportunities and risks. Psychiatr Rehab J. 2017;40(3):263–5. https://doi.org/10.1037/prj0000285.
13.•• Firth J, Torous J, Nicholas J, et al. The efficacy of smartphone-based mental health interventions for depressive symptoms: a meta-analysis of randomized controlled trials. World Psychiatry. 2017;16(3):287–98. https://doi.org/10.1002/wps.20472. **The first meta-analysis of RCTs evaluating apps for depression. Pooled results from 3414 participants showed a significant decrease in depressive symptoms.**
14. Shen N, Levitan M-J, Johnson A, et al. Finding a depression app: a review and content analysis of the depression app marketplace. JMIR MHealth UHealth. 2015;3:e16.
15. Huguet A, Rao S, McGrath P, Wozney L, Wheaton M, Conrod J, et al. A systematic review of cognitive behavioral therapy and behavioral activation apps for depression. PLoS One. 2016;11(5):e0154248. https://doi.org/10.1371/journal.pone.0154248.
16. Kumar S, Nilsen W, Abernethy A, Atienza A, Patrick K, Pavel M. Mobile health technology evaluation. Am J Prev Med. 2013;45(2):228–36. https://doi.org/10.1016/j.amepre.2013.03.017.
17. Wisniewski H, Liu G, Henson P, Vaidyam A, Hajratalli NK, Onnela JP, et al. Understanding the quality, effectiveness and attributes of top-rated smartphone health apps. Evid Based Ment Health. 2019;22(1):4–9. https://doi.org/10.1136/ebmental-2018-300069.
18. Mathiasen K, Andersen TE, Riper H, Kleiboer AA, Roessler KK. Blended CBT versus face-to-face CBT: a randomised non-inferiority trial. BMC Psychiatry. 2016;16(1):432.
19. Rathbone AL, Clarry L, Prescott J. Assessing the efficacy of mobile health apps using the basic principles of cognitive behavioral therapy: systematic review. J Med Internet Res. 2017;19(11):e399. https://doi.org/10.2196/jmir.8598 Review.
20. Birney A, Gunn R, Russell J, Ary D. MoodHacker Mobile Web app with email for adults to self-manage mild-to-moderate depression: randomized controlled trial. JMIR Mhealth Uhealth. 2016;4(1):e8. https://doi.org/10.2196/mhealth.4231.
21. Emslie G, Kennard B, Mayes T, Nakonezny PA, Zhu L, Tao R, et al. Insomnia moderates outcome of serotonin-selective reuptake inhibitor treatment in depressed youth. J Child Adolesc Psychopharmacol. 2012;22(1):21–8. https://doi.org/10.1089/cap.2011.0096.
22. Horsch CH, Lancee J, Griffioen-Both F, Spruit S, Fitrianie S, Neerincx MA, et al. Mobile phone-delivered cognitive behavioral therapy for insomnia: a randomized waitlist controlled trial. J Med Internet Res. 2017;19(4):e70. https://doi.org/10.2196/jmir.6524.
23. Berrouiguet S, Baca-García E, Brandt S, Walter M, Courtet P. Fundamentals for future mobile-health (mHealth): a systematic review of mobile phone and Web-based text messaging in mental health. J Med Internet Res. 2016;18(6):e135. https://doi.org/10.2196/jmir.5066.
24. Nuij C, van Ballegooijen W, Ruwaard J, de Beurs D, Mokkenstorm J, van Duijn E, et al. Smartphone-based safety planning and self-monitoring for suicidal patients: rationale and study protocol of the CASPAR (Continuous Assessment for Suicide Prevention And Research) study. Internet Interv. 2018;13:16–23. https://doi.org/10.1016/j.invent.2018.04.005 eCollection 2018 Sep.
25. Santo K, Richtering SS, Chalmers J, Thiagalingam A, Chow CK, Redfern J. Mobile phone apps to improve medication adherence: a systematic stepwise process to identify high-quality apps. JMIR Mhealth Uhealth. 2016;4(4):e132.
26. Bennabi D, Aouizerate B, El-Hage W, Doumy O, Moliere F, Courtet P, et al. Risk factors for treatment resistance in unipolar depression: a systematic review. J Affect Disord. 2015;171:137–41. https://doi.org/10.1016/j.jad.2014.09.020.
27.• Mo Y, Gong W, Wang J, Sheng X, Xu D. The association between the use of antenatal care smartphone apps in pregnant women and antenatal depression: cross-sectional study. JMIR Mhealth Uhealth. 2018;6(11):e11508. https://doi.org/10.2196/11508. **A cross-sectional study performed in 1304 pregnant women. The explored antenatal care apps had a significant protective effect on antenatal depression.**
28. Fleming J, Hill Y, Burns M. Usability of a culturally informed mHealth intervention for symptoms of anxiety and depression: feedback from young sexual minority men. JMIR Hum Factors. 2017;4(3):e22. https://doi.org/10.2196/humanfactors.7392.
29. Hetrick SE, Robinson J, Burge E, Blandon R, Mobilio B, Rice SM, et al. Youth codesign of a mobile phone app to facilitate self-monitoring and management of mood symptoms in young people with major depression, suicidal ideation, and self-harm. JMIR Ment Health. 2018;5(1):e9. https://doi.org/10.2196/mental.9041.
30. Grist R, Porter J, Stallard P. Mental health mobile apps for preadolescents and adolescents: a systematic review. J Med Internet Res. 2017;19(5):e176. https://doi.org/10.2196/jmir.7332.
31.• Hur J, Kim B, Park D, Choi S. A scenario-based cognitive behavioral therapy mobile app to reduce dysfunctional beliefs in individuals with depression: a randomized controlled trial. Telemed e-Health. 2018;24(9):710–6. https://doi.org/10.1089/tmj.2017.0214. **One of the most recent RCT on apps for depression; it evaluated the app Todac-Todac, showing a significant decrease in depressive symptoms and negative beliefs.**

32.• Pratap A, Renn B, Volponi J, et al. Using mobile apps to assess and treat depression in Hispanic and Latino populations: fully remote randomized clinical trial. J Med Internet Res. 2018;20(8):e10130. https://doi.org/10.2196/10130.
An RCT that tested the mobile applications iPST, Project EVO, and Health Tips. There was a significant decrease in depressive symptoms.

33. Arean P, Hallgren K, Jordan J, Gazzaley A, Atkins DC, Heagerty PJ, et al. The use and effectiveness of mobile apps for depression: results from a fully remote clinical trial. J Med Internet Res. 2016;18(12):e330. https://doi.org/10.2196/jmir.6482.
34. Baumel A, Tinkelman A, Mathur N, Kane J. Digital peer-support platform (7Cups) as an adjunct treatment for women with postpartum depression: feasibility, acceptability, and preliminary efficacy study. JMIR Mhealth Uhealth. 2018;6(2):e38. https://doi.org/10.2196/mhealth.9482.
35. Corden M, Koucky E, Brenner C, et al. MedLink: a mobile intervention to improve medication adherence and processes of care for treatment of depression in general medicine. Digit Health. 2016;2:205520761666306. https://doi.org/10.1177/2055207616663069.
36. Fogarty AS, Proudfoot J, Whittle EL, Clarke J, Player MJ, Christensen H, et al. Preliminary evaluation of a brief Web and mobile phone intervention for men with depression: men's positive coping strategies and associated depression, resilience, and work and social functioning. JMIR Ment Health. 2017;4(3):e33. https://doi.org/10.2196/mental.7769.
37. Furukawa T, Horikoshi M, Fujita H, Tsujino N, Jinnin R, Kako Y, et al. Cognitive and behavioral skills exercises completed by patients with major depression during smartphone cognitive behavioral therapy: secondary analysis of a randomized controlled trial. JMIR Ment Health. 2018;5(1):e4. https://doi.org/10.2196/mental.9092.
38. Goldin P, Lindholm R, Ranta K, Hilgert O, Helteenvuori T, Raevuori A. Feasibility of a therapist-supported, mobile phone–delivered online intervention for depression: longitudinal observational study. JMIR Form Res. 2019;3(1):e11509. https://doi.org/10.2196/11509.
39. Mantani A, Kato T, Furukawa T, Horikoshi M, Imai H, Hiroe T, et al. Smartphone cognitive behavioral therapy as an adjunct to pharmacotherapy for refractory depression: randomized controlled trial. J Med Internet Res. 2017;19(11):e373. https://doi.org/10.2196/jmir.8602.
40. Mohr D, Montague E, Stiles-Shields C, et al. MedLink: a mobile intervention to address failure points in the treatment of depression in general medicine, Proceedings of the 9th International Conference on Pervasive Computing Technologies for Healthcare. 2015. https://doi.org/10.4108/icst.pervasivehealth.2015.259042.
41. Mohr D, Tomasino K, Lattie E, 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;19(1):e10. https://doi.org/10.2196/jmir.6645.
42. O'Toole M, Arendt M, Pedersen C. Testing an app-assisted treatment for suicide prevention in a randomized controlled trial: effects on suicide risk and depression. Behav Ther. 2019;50(2):421–9. https://doi.org/10.1016/j.beth.2018.07.007.
43. Schlosser D, Campellone T, Truong B, et al. Efficacy of PRIME, a mobile app intervention designed to improve motivation in young people with schizophrenia. Schizophr Bull. 2018;44(5):1010–20. https://doi.org/10.1093/schbul/sby078.
44. Silva-Almodovar A, Surve S, Axon D, Cooper D, Nahata M. 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;6(3):e64. https://doi.org/10.2196/mhealth.9612.
45. Whitton A, Proudfoot J, Clarke J, Birch MR, Parker G, Manicavasagar V, et al. Breaking open the black box: isolating the most potent features of a Web and mobile phone-based intervention for depression, anxiety, and stress. JMIR Ment Health. 2015;2(1):e3. https://doi.org/10.2196/mental.3573.
46. Eysenbach G. The law of attrition. J Med Internet Res. 2005;7(1):e11. https://doi.org/10.2196/jmir.7.1.e11.
47. Fuller-Tyszkiewicz M, Richardson B, Klein B, Skouteris H, Christensen H, Austin D, et al. A mobile app–based intervention for depression: end-user and expert usability testing study. JMIR Ment Health. 2018;5(3):e54. https://doi.org/10.2196/mental.9445.
48. Lipschitz J, Miller CJ, Hogan TP, Burdick KE, Lippin-Foster R, Simon SR, et al. Adoption of mobile apps for depression and anxiety: cross-sectional survey study on patient interest and barriers to engagement. JMIR Ment Health. 2019;6(1):e11334. https://doi.org/10.2196/11334.
49. BinDhim N, Shaman A, Trevena L, Basyouni M, Pont L, Alhawassi T. Depression screening via a smartphone app: cross-country user characteristics and feasibility. J Am Med Inform Assoc. 2014. https://doi.org/10.1136/amiajnl-2014-002840.
50. Stiles-Shields C, Montague E, Lattie E, Kwasny M, Mohr D. What might get in the way: barriers to the use of apps for depression. Digit Health. 2017;3:205520761771382. https://doi.org/10.1177/2055207617713827.
51. Erbes CR, Stinson R, Kuhn E, Polusny M, Urban J, Hoffman J, et al. Access, utilization, and interest in mHealth applications among veterans receiving outpatient care for PTSD. Mil Med. 2014;179(11):1218–22. https://doi.org/10.7205/MILMED-D-14-00014.
52. Bower DJ, Barry N, Reid M, Norrie J. Designing and implementing e-health applications in the UK's National Health Service. J Health Commun. 2005;10(8):733–50.
53. Schueller SM, Neary M, O'Loughlin K, Adkins EC. Discovery of and interest in health apps among those with mental health needs: survey and focus group study. J Med Internet Res. 2018;20(6):e10141. https://doi.org/10.2196/10141.
54. Miller CJ, McInnes DK, Stolzmann K, Bauer MS. Interest in use of technology for healthcare among veterans receiving treatment for mental health. Telemed J E Health. 2016;22(10):847–54.
55. Kaipainen K, Välkkynen P, Kilkku N. Applicability of acceptance and commitment therapy-based mobile app in depression nursing. Transl Behav Med. 2017;7(2):242–53. https://doi.org/10.1007/s13142-016-0451-3.
56. Griebel L, Enwald H, Gilstad H, Pohl AL, Moreland J, Sedlmayr M. eHealth literacy research-quo vadis? Inform Health Soc Care. 2018;43(4):427–42. https://doi.org/10.1080/17538157.2017.1364247.
57. Anderson K, Burford O, Emmerton L. Mobile health apps to facilitate self-care: a qualitative study of user experiences. PLoS One. 2016;11(5):e0156164. https://doi.org/10.1371/journal.pone.0156164 eCollection 2016.
58. Yasini M, Beranger J, Desmarais P, Perez L, Marchand G. mHealth quality: a process to seal the qualified mobile health apps. Stud Health Technol Inform. 2016;228:205–9.
59. Lee TT, Kesselheim AS. U.S. Food and Drug Administration precertification pilot program for digital health software: weighing the benefits and risks. Ann Intern Med. 2018;168(10):730–2. https://doi.org/10.7326/M17-2715.
60. Chan S, Torous J, Hinton L, Yellowlees P. Towards a framework for evaluating mobile mental health apps. Telemed J E Health. 2015;21(12):1038–41. https://doi.org/10.1089/tmj.2015.0002.