

Depression Management: A Descriptive Evaluation of Depression Apps in the Google Play Store

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Abstract – This research explores how mobile app features and functionality can influence its usage for depression management and overall mental health. It examines the functionalities and features of depression apps associated with the app download count. A search of “Depression” apps carried out in December 2017 using the Google Play Store retrieved 248 apps related to depression. Over 80% of the apps had mainly singular purposes of psychoeducation (36 %), therapeutic treatment (25.2%), medical assessment (18.3%), symptom management (13%), support resources (17%), non-medical functions (14.78%) while forty-six (20%) apps had multiple functions. An app’s number of installs was positively correlated with the rating, number of raters and user interface; but negatively correlated with cost and content rating. Symptom tracking apps were most installed, while medical assessment apps were found not to be the choice apps for Depression management.

Keywords – apps, depression, mental health, medical assessment.

1. Introduction

Depression leads to diminished quality of life and increased medical morbidity [1], and it is now the third leading contributor to global healthcare costs

DOI: 10.18421/TEM83-17

<https://dx.doi.org/10.18421/TEM83-17>


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Received: 04 June 2019.

Revised: 24 July 2019.

Accepted: 30 July 2019.

Published: 28 August 2019.

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[2]. While pharmacotherapy constitutes a part of the answer, two thirds of depressed primary care patients would prefer psychological treatments. Effective psychological treatments, however, are frequently not available [3]. Barriers to receiving such a care include transportation problems, time constraints, cost of treatment, lack of resources and emotional resistance (concern about what others might think, discomfort talking about problems with a therapist) [4]. Low socioeconomic status, low mental health literacy, as well as cultural beliefs and stigma are also associated to a reduced access to psychological treatments [1].

Information technologies have the potential to help in reducing these barriers in order to access the care. Remote care can be provided through technology, in areas with limited or no specialists [5]. Along with the generalization of smartphones, dedicated mobile applications started to address mental health or lifestyle and behavior modification, such as diet and weight loss [6]; physical activity; sedentary behavior [8]; pediatric weight loss, healthy eating and physical activity [9]; smoking cessation [10]; eye-care [11]; asthma management [12]; first aid [13] cannabis [14]. Considering the disruptive and deep penetration of mobile apps, it becomes imperative to explore and evaluate app quality, app features or characteristics that influence download, usage and ratings (sometimes referred to as popularity indicators), and provide optimum user satisfaction. Prior studies revealed cost as an important variable affecting user satisfaction. In [16], free diet apps received higher average ratings (higher satisfaction) as compared with the apps with in-app purchases, whereas in [17], expensive apps received higher average ratings.

Mental health apps can improve mental health literacy, minimize stigmatization and its effects, conduct community-based outreaches and engagement, self-management, and medication tracking to ensure authenticity [18]. These apps can act as stand-alone self-help programs or as co-treatment components in corporate wellness programs. Previous research suggests that mental

health interventions delivered through the mobile apps can be effective in treating a range of mental health disorders, such as depression, stress, anxiety [19]. Health apps can serve for prevention and treatment of mental health through self-assessment, symptom tracking and monitoring, education, therapy and training [1], [20], treatment [21]. In [20], a framework for evaluation mobile mental apps was proposed. The framework suggests 3 dimensions: *usefulness, usability and integration and infrastructure*; and a categorization based on health provider’s workflow. In another work, depression apps were categorized according to their purposes including *therapeutic treatment, psychoeducation, medical assessment, symptom management, supportive resources and multipurpose* [1]. Drawing on these categories, this research explores how functionality could affect the use of mobile apps for depression management and overall mental health. The aim is to examine the functionalities of depression mobile apps. In addition, this work also seeks to identify features of depression apps (app characteristics) which are associated with the app download count.

2. Methodology

We conducted a systematic review of the applications addressing depression available on the Google Play store. The search was carried out in December 2017. Apps that featured the term “depression” in its title or store description were retrieved. The search returned 248 apps related to depression. Eighteen apps namely non-English apps were excluded, leaving a final sample of 230 apps.

Data Extraction, Coding and Analysis

For each application, the following data was retrieved: *category, rating (average number of stars), number of raters, total installs, cost (free or paid), content ratings, user interface (static or dynamic) and app description*. The categorizations proposed by [1] formed the foundation for the functional taxonomy. Coding was performed by two researchers for all the apps with a Cohen’s Kappa (k) of 72%, (k = 0.70), indicating a substantial agreement between the two raters according to Landis’ guidelines in [22]. Both raters arrived at a consensus on the apps with disagreements. The final coding scheme for the content analysis is presented in Table 1. Statistical analysis was done using IBM SPSS Statistics version 25. Correlation analysis was carried out to identify linear relationship among the app variables.

Table 1. Content Analysis Final Code

Variable	Description
Application	
Name	Application Name
Category	App category in the Google Play store
Rating	Average user star rating
Number of Raters	Number of Raters
Total Installs	Frequency of Installs represented by the following:
Cost	Free: No cost attached for download. Paid: Cost implication for download or in-app purchases
User Interface	Information: Static User interface, allows little or no interaction with the user. Tool: Dynamic user interface; allows interaction, data input and output e.g games. Psychoeducation: Educational materials for educating, training or informing users including books, guides, news or journal articles, commentaries/opinions, tips, and lessons Medical Assessment (Diagnosis): Allows users to screen, diagnose, assess risk, assess self, determine treatment Symptom Management: Allows users track symptoms, gather history, include physical health data and provide useful, comprehensible output Supportive Resources: Provides referrals for help, connects users with support e.g. emotional and social support; treatment interventions for acute or chronic use: Emotional Support (ESR), Social Support (SSR), Treatment Support/Interventions (TSR) Therapeutic Treatment: Provides therapy and includes functions that support relaxation such as Hypnosis; mindfulness, meditation, spiritual/faith-based solutions; holistic therapy Non-Medical Functions: include motivational quotes, wall papers, screen savers and games
Functional Taxonomy	

The number of apps designed for the specific functions provides only a partial understanding of the public’s interests for this app. To get a better understanding of how desirable each category was, we computed how many times each feature was downloaded by using the mid-range value of “Total installs”. For instance, an app whose total installs was 100,000 to 500,000 was estimated to have been downloaded 300,000. This was then aggregated by category.

3. Results

50% of depression apps (n=115) belonged to the health and fitness category, closely followed by the medical (n=51, 22.2%) and lifestyle (n=20, 8.7%) categories. The number of installs was depicted in ranges: 93 apps (n=93, 40.4%) were installed less than 1000 times (the most frequent installation range), while 1 app, “*Nature Sounds Relax and Sleep*” (0.4%) was installed in the 5 million to 10 million range. The descriptive statistics of the apps are presented in Table 2.

Table 2. Overview of Mobile Depression Apps

All (N=230)	
Category	
Adventure	1
Books and References	12
Education	7
Entertainment	6
Health	2
Health and Fitness	115
Lifestyle	20
Medical	51
Music and Audio	1
News and Magazine	1
Parenting	1
Personalization	7
Simulation	1
Social	4
Trivia	1
Total	230
Installs	
1-1000	93
1,000 - 5,000	39
5,000 - 10,000	23
10,000 - 50,000	32
50,000 - 100,000	7
100,000 - 500,000	22
500,000 - 1,000,000	3
1,000,000 - 5,000,000	4
5,000,000 - 10,000,000	1
Total	224
Missing	6
Total	230
User Interface	
Static (Information)	123
Dynamic (Tool)	107
Total	230
Cost	
Free	207
Paid	23
Total	230

Content Rating

Everyone	195
Mature (17+)	2
Teen	10
Unrated	23
Total	230

• Depression App Functions

Psychoeducation apps were mostly e-books providing information on depression, and tips for depression management, self-help guides, reference manuals; others were learning modules in audio or video formats, designed to teach users. The authenticity of the information in these materials cannot be ascertained as majority was not designed with the involvement of certified psychologists or academics and did not follow clinical guidelines. There is a fear regarding the dissemination of biased, incomplete or insufficient information to unsuspecting users. The most frequency of installs was less than 1000, which is a pointer to precautionary measures taken by proposed users before installing these apps.

Therapeutic treatment apps offered Cognitive Behavioral Therapy (CBT), Acceptance Commitment Therapy (ACT), the Hospital and Anxiety Depression Scale (HADS), the Center for Epidemiological Studies Depression (CES-D) Scale, Hypnotherapy, coping skills, mindfulness, Sooma Depression Therapy (SDT) and a few spiritual/faith-based and color-based therapies; with most apps focusing on CBT. CBT is a leading behavioral treatment for mental health [14]. Web-based CBT has proven to be an effective treatment for depression [15] and it well suited for delivery through an app. App-based CBT will provide convenience of the symptom and mood tracking in real time (symptom management), suggesting the multi-functions of these apps.

The medical assessment category was made up of all apps acting as screening tools (self-help) that allowed users to self-diagnose for depression. The screening and medical assessment made use of validated scales such as the Depression, Anxiety and Stress Scale (DASS), Geriatric Depression Scale (GDS), Hamilton Rating Scale for Depression (HRSD), Burns anxiety and depression test, Zung Self-Rating Depression Scale, to assess the presence and severity of depression. Depression is the major health problem in primary care and detection remains a challenge. By assisting individuals in identifying the onset of mental health issues, these apps can help to address this challenge. Self-assessment will preempt users to communicate and visit health facilities and physicians. However, the efficacy of these scales for self-help has not been widely

reported in literature [15]. There is a need for empirical evaluation of these apps in order to validate their use for self-help and assessment. Developers in this category have disclaimers in place, and emphasize the fact that users should not replace the role of physician diagnoses with the app; hence, physician opinion should be sought.

According to symptom management, apps in this category allowed users to track their moods over time, as well as other risk factors, track lifestyle and behavior, and keep journal entries of their feelings. Apps providing supporting resources addressed emotional needs of users, provided communities and support groups in which users could discuss their experiences and feelings without condemnation or stigmatization, creating social networks. Some of the apps also connected users with professionals and helplines on-demand. A new function was identified which we classified as non-medical functions. Some of the apps utilized phone utilities to provide depression specific messages, tips and quotes such as wallpapers and screen savers; others were designed for gaming purposes while some made fun of depression. The aim of these category extends beyond medical functions such as depicting depression as horror and scary.

Over 80% of the apps had mainly singular purposes of psychoeducation (83, 36 %), therapeutic treatment (58, 25.2%), medical assessment (42, 18.3%), symptom management (30, 13%), support resources (39, 17%), non-medical functions (34, 14.78%). Forty-six (20%) apps had multiple functions. Among the apps providing supporting resources, 17 provided emotional support (7.4%), 13 provided social support (5.7%), 20 provided

treatment support (8.7%) while 3 apps provided multiple supports. Psychoeducation apps mostly had static user interface (n=82), not allowing any user input, hence no output. Depression apps were also designed to offer behavior interventions or therapy, with the therapeutic treatment category having the most apps after psychoeducation, (n= 58). Apps in a therapeutic treatment category also had the most frequency of downloads less than 1000, they were mostly free and designed for all audiences. The analysis of total installs (Table 3) revealed significant discrepancies between app count and app installs. For instance, while 36% of apps feature psychoeducational features, only these apps have the amount to 15% of installs. At the extreme, Medical assessment features are present in 22% of depression apps, but in only 5% of total installs. Conversely, Therapy features are only present in one of three apps (34%) but they are present in a whopping 72% of total installs, while non-medical features account for only 14% of apps but 31% of installs. In other terms, the average number of installs ranges from 28,186 for medical assessment apps to 280,000 for therapy and non-medical apps.

To tease out the independent effect of each feature, we further computed the average installs for apps that featured only a specific category, versus apps offering multiple features. On average, apps with a single feature were downloaded only 91,369 times as against a count of 244,451 for multiple features apps. Psychoeducation apps are downloaded only 2,857 times on average versus 160,056, when they are present in multi-features apps. At the other extreme, symptom tracking-only apps are downloaded 400,000 on average versus only 91,750 when they are a part of multi-feature apps.

Table 3: Count and Installs of Depression apps by Category

	Count	%	Total estimated installs	Installs as % of all depression installs	Average installs per app
Psychoeducation	83	36%	4,481,500	15%	53,994
Single feature	56		160,000		2,857
Multiple features	27		4,321,500		160,056
Symptom tracking	30	13%	5,829,000	19%	194,300
Single feature	10		3,994,000		399,400
Multiple features	20		1,835,000		91,750
Social Support Resources	27	12%	3,192,000	11%	118,222
Single feature	10		1,547,000		154,700
Multiple features	17		1,645,000		96,765
Medical Assessment	51	22%	1,437,500	5%	28,186
Single feature	37		720,500		19,473
Multiple features	14		717,000		51,214
Therapy	77	34%	21,593,000	72%	280,429
Single feature	33		7,161,500		217,015
Multiple features	44		14,431,500		327,989
Non-medical	34	14%	9,551,500	31%	280,348
Single feature	21		1,675,500		79,786
Multiple features	13		7,876,000		605,846
Total all apps	228	100%	30,170,000	100%	152,598
Single feature	167		15,258,500		91,369
Multiple features	61		14,911,500		244,451

4. Discussion

The analysis of installs suggests a discrepancy between what developers offer and what users want. While educational material is the most prevalent feature in depression apps, a very small count of installs of pure educational apps (2,857) suggests that there is little appetite in the public for that feature. This may account for the nature of the device, smartphones, which may not be perceived as the best media to educate oneself about complex problems, such as mental health issues. Conversely, Therapy-only apps are downloaded on average 217,015 times and therapy features in 72% of all installs, suggesting that for users, this is the key for using depression apps. Symptom tracking apps, which are installed 400,000 times on average as single feature app, are also very popular. This suggests that the personal nature of smartphones, and the fact that users almost always have these devices on them, make them perceived as a tool appropriate to track and change everyday behaviors. Finally, the very low install count of medical assessment apps, both single and multi-features apps, suggests that not only there is strong resistance from users to diagnose themselves using their smartphones, but that such features may even deter users from installing any apps that feature them. The lack of evidence regarding clinical validity of almost all these apps associated with the serious consequences of a depression diagnosis may explain the caution of users to come anywhere near such assessments. Developers should be extremely careful

and provide reassurances about their clinical validity before offering such features.

The results from the stepwise design of the functional taxonomy provided some insights into user's preferences and expectations of depression apps. Some apps targeted multiple conditions e.g. sleep, anxiety or other risk factors of depression. Depression apps reviewed in this study provided evidence which were consistent with functions identified by [1]. The correlation analysis results showed that apps with high average ratings, high number of raters and dynamic user interfaces were most downloaded and installed. Apps with subscription charges and restrictions on the content ratings recorded least downloads. This further suggests cost, average ratings and number of raters are predictors of app usage.

Quality remains an issue of growing concern for mobile apps [7]. This study provides predictors of usage and popularity of depression apps in the Google Play store while also identifying the functions. However, user's feedback in the form of reviews were not analyzed. User reviews are an integral component of apps and they predict app quality, along with user satisfaction. There is limited empirical evidence on the theoretical analysis of depression apps review. Theories tend to help in the design of transferable and measurable interventions; hence, a research is needed to explore the extent to which health behavior theories are incorporated into

these apps, and the acceptability and feasibility of using apps for depression management. This will provide evidence-base on the efficacy of mobile mental health apps. The issue of privacy and security also remains a concern, considering the sensitivity of mental health, and its attendant risks. Developers issue privacy policy, but the extent is not known, and there are no protocols that protect the privacy and security of personal health information shared in cyberspace and networks. Apps should be carefully screened on whether their use could compromise user's privacy. Smartphones and tablets are potential tracking tools, making use GPS features to collect precise, real time location data or using geo-targeting.

5. Conclusion

This study was solely based on the information available in the Google play store description e.g. category, user rating, content rating, in order to understand the characteristics and presentation of depression apps to prospective users. Information is a subject to the inclusion criteria that is put in place by the app store and the developers. The apps included in this study were not installed for further validation comprising the information provided in the description. As a continuation of this work, the text analytics performed on the reviews will be expanded to cover larger datasets and longer time periods in order to draw more generalized conclusions.

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