

1 Reviewing and evaluating the functionality of top-rated mobile 2 apps for depression

3 Abstract

4 **Background:** In the last decade, there has been a proliferation of mobile apps
5 claiming to support the needs of people living with depression. However, it is
6 unclear what functionality apps for depression actually provide and for whom they
7 are intended.

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9 **Objective:** This paper aims to explore the key features of top-rated apps for
10 depression, including descriptive characteristics, functionality, and ethical concerns
11 in order to support better-informed design of apps for depression.

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13 **Methods:** We reviewed top-rated iOS and Android mobile apps for depression
14 retrieved from app marketplaces in spring 2019. We applied a systematic analysis
15 to review the selected apps, for which data was gathered from the two
16 marketplaces, and through direct use of the apps. We report an in-depth analysis of
17 app functionality, namely: *screening, tracking, and provision of interventions*. Of the
18 initially identified 482 apps, 29 apps met the criteria for inclusion in this review.
19 Apps were included if they remained accessible at the moment of evaluation, were
20 offered in mental health relevant categories, received a review score greater than
21 4.0 out of 5.0 contributed by more than 100 reviewers, and have depression as a
22 primary target.

23
24 **Results:** The analysis revealed that a majority of apps specify the evidence-base for
25 their intervention (62%, 18/29) while a smaller proportion describe receiving
26 clinical input into their design (41%, 12/29). All selected apps are rated as suitable
27 for children and adolescents on the marketplace, but 83% (24/29) do not provide a
28 privacy policy consistent with their rating. Findings also show that most apps
29 provide multiple functions. The most commonly implemented functions include
30 *provision of interventions* (83%, 24/29) either as digitalized therapeutic
31 intervention or as support for mood expression, *tracking* (66%, 19/29) of moods,
32 thoughts or behaviors for supporting the intervention, and *screening* (31%, 9/29) to
33 inform the decision to use the app and its intervention. Some apps include overtly
34 negative content.

35
36 **Conclusions:** Currently available top-ranked apps for depression on the major
37 marketplaces provide diverse functionality to benefit users across a range of age
38 groups, however guidelines and frameworks are still needed to ensure users'
39 privacy and safety while using them. Suggestions include clearly defining the age of
40 the target population and explicit disclosure of the sharing of users' sensitive data
41 with third parties. Additionally, we found an opportunity for apps to better leverage
42 digital affordances for mitigating harm, for personalizing interventions, and for

43 tracking multimodal content. The study further demonstrates the need to consider
44 potential risks while using depression apps, including the use of non-validated
45 screening tools, tracking negative moods or thinking patterns, and exposing users to
46 negative emotional expression content.

47

48 **Keywords:** depression apps, review, functionality, screening, tracking, intervention,
49 ethics

50 Introduction

51 Depression is a major affective disorder with significant socio-economic cost [32],
52 affecting over 300 million people worldwide [62] across the life span [9]. However,
53 access to treatment is problematic [37] given acknowledged barriers such as high
54 treatment cost, time constraints [37], geographical location [6], and stigma [6, 8, 37,
55 57]. With over 90% worldwide penetration [61], mobile phones have significant
56 potential to scale up the provision of interventions targeting depression [43]. They
57 are especially useful to reach users who do not normally seek professional support,
58 such as adolescents [24]. Prior work has already indicated a high user acceptance
59 and effectiveness of mobile delivered interventions for depression [20, 48]. The
60 number of mobile apps available on marketplaces offering treatment for depression
61 has also been growing rapidly [36, 43].

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63 The apps available on smartphone marketplaces provide access to a range of
64 interventions targeting depression [35, 52, 55], which people can select and
65 download to fit their needs [23]. Yet, users acting independently can only select
66 apps based on information that is available at the point of download, i.e., popularity,
67 user ratings, or app descriptions provided on the marketplaces. Evidence for
68 supporting assessment of the quality of an app, i.e., structured description of its
69 main features, evidence-based functionality, and potential risks are not reflected in
70 user ratings of apps [31, 54]. Neither do marketplaces require app developers to
71 provide such information [1, 14]. As a result, concerns have been raised regarding
72 the lack of an evidence-base for mental health apps [34, 52, 54] and poor regulation
73 of the major mobile marketplaces [28, 56, 64] hosting them. Prior work [58] has
74 also suggested the importance of having controlled clinical trials to determine the
75 efficacy of new therapeutic treatments. In this newly established field of mHealth
76 apps, most apps claim to be informed by evidence-based treatments, rather than
77 presenting rigorous evaluations of the app itself.

78

79 Besides efficacy, understanding patients (e.g., their characteristics, needs, and
80 behaviors) is also key for improving the uptake of apps [33, 58]. Most Human-
81 Computer Interaction (HCI) work on understanding [44, 45, 50] or supporting
82 depression has focused on designing and evaluating mobile technologies in research
83 contexts rather than marketplaces [5, 39, 60]. Scholarly work has also called for the
84 evaluation of commercial apps for depression to support the effective development
85 of the rapidly growing market of commercial apps [24, 36, 52]. However, such
86 evaluations tend to focus in isolation on specific aspects such as ethics [4], safety
87 [40], or on specific interventions such as Cognitive Behavior Therapy (CBT) or

88 Acceptance and Commitment Therapy (ACT) [24, 54]. Moreover, previous
89 evaluations tend to analyze app information from marketplaces without the actual
90 experience of using of the apps [52].

91

92 This paper addresses these limitations by focusing on a broader range of
93 interventions and functionality of the top-rated apps for depression. Thus, we
94 focused on the following research questions:

95 1) Which are the key functionalities of the top-rated apps for depression available
96 on iOS and Android marketplaces?

97 2) Is this functionality described and delivered in a way that supports user privacy
98 and safety?

99 **Methods**

100 This paper focuses on apps selected in spring 2019 from two major marketplaces:
101 iOS and Android whose analysis triangulates i) reviewing app ratings on
102 marketplaces to identify the top-rated apps for depression, ii) reviewing app
103 descriptions on marketplaces, and iii) experimental evaluation through author
104 interaction with the apps as expert HCI researchers [27, 29].

105 We now describe the selection process (Fig 1). The apps were initially identified
106 through two keywords: “depression” and “depressed” entered into App Crawler and
107 Google Play search engines. A script was used [21] to extract all apps shown in the
108 search results. The script automatically downloaded information for each app from
109 its marketplace, including name, category, marketplace description, price, review
110 score, and number of reviewers. This resulted in 482 apps, and after removing
111 duplicates, 444 apps were included in the later selection.

112 **App selection**

113 The strategy for app selection outlined in Figure 1 aimed to include top-rated
114 publicly available apps targeting primarily depression. From the initially identified
115 444 apps, we excluded those that: 1) have less than 100 reviews, 2) were
116 inaccessible at the time of selection, 3) belong to irrelevant marketplace categories
117 such as Social, Casual, Business, News, or Book, and 4) have average user review
118 scores lower than 4.0 (out of 5.0). The application of these criteria on the initial set
119 of 444 apps resulted in 94 apps for consideration.

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121 From these apps we further excluded those that do not focus primarily on
122 depression, by employing the following criteria: 1) the words “depression” or
123 “depressed” do not appear in the app’s title or marketplace description of the app,
124 2) the primary target is not depression (e.g., yoga tracker), and 3) their marketplace
125 description mentions that people with depression should not use the app. These
126 criteria led to 31 apps from which we further excluded two more apps as their
127 functionality was limited to the provision of therapy sessions to be purchased
128 online. The remaining 29 apps were analyzed in this review (see Multimedia
129 Appendix 1).

130 **Data extraction**

131 Descriptive characteristics of the apps were extracted from the information
 132 provided on the marketplace. These included *category, costs, target audience,*
 133 *whether they claimed to be evidence-based* (including explicit scientific
 134 *underpinning, and clinical input*), and data supporting analysis of ethical aspects
 135 such as the *privacy policy*.

136
 137 To extract data on app functionality, between June and Oct 2019, two rounds of
 138 experimental evaluation [27, 29] were used in which the authors as HCI experts
 139 interacted with the apps using both Android and iPhone mobile devices (i.e.,
 140 Samsung tablet and Xiaomi phone for Android apps, and iPhone for iOS apps). The
 141 entire set of apps was evaluated by two authors (CQ and CD), and six apps (20%)
 142 were evaluated by all authors. The coding scheme was iteratively revised until
 143 agreement among all coders was reached. The coding process was hybrid,
 144 integrating both deductive and inductive coding. Informed by prior work on the
 145 classification of mHealth apps [35], the deductive codes consisted of three main
 146 types of functionality of depression apps: screening, tracking, and provision of
 147 interventions (Table 1). The inductive coding [19] allowed the identification of
 148 specific sub-codes under each of the main functionality described above. For
 149 instance, screening function was broken down into sub-codes such as symptom
 150 monitoring, self-diagnosis, and basis for personalization.

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Functionality type	Functionality subtype	Definitions
Screening	Monitoring symptoms	The screening function is provided for monitoring depression symptoms during intervention
	Self-diagnosis	The screening function is provided for self-assessment of depression
	Basis for personalization	The screening function is provided as a basis for personalized intervention
Tracking	Tracking thought patterns	The tracking function supports the tracking of thought patterns
	Tracking mood patterns	The tracking function supports the tracking of users' mood patterns
	Tracking behavior as intervention progresses	The tracking function is provided for monitoring progress in following the intervention, including users' adherence to the intervention
	Tracking depression symptoms	The tracking function is provided for monitoring symptoms
Intervention	Thought diaries	The intervention is provided to help users identify and challenge their negative thinking patterns
	Psychoeducation	The intervention is provided as psychoeducational content

Mindfulness	The intervention is provided to help users improve mindfulness.
Behavioral techniques	The intervention is provided to motivate and guide users to perform positive behaviors
Mood expression	The intervention is provided for users to express their emotions
Other	The intervention is provided as emotional regulation strategies other than mindfulness.

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Table1. Main codes and sub-codes from functionality's evaluation

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Results

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The description of findings is organized in two parts. The first outlines a broader picture focusing on descriptive app characteristics, and their evidence base. The second part looks in more depth into specific functionality such as screening, tracking, and provision of interventions.

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Overview

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This section describes the main categories under which depression apps are classified on marketplaces, their target audience, and cost.

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Categorization. The 29 apps reviewed in this study belong to three categories used to describe apps on the marketplaces. The most popular category is Health & Fitness (62%, 18/29 apps), followed by Lifestyle (14%, 4/29 apps), and Medical (24%, 7/29 apps).

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Targeted audience (age group). An important finding is that app marketplaces rate all apps as suitable for non-adult users (Multimedia Appendix 2). Most of the selected apps were classified as being suitable for children from pre-school age: 79% (23/29) of apps were rated for ages 3+, 3% for ages 4+ (1/29), 3% for ages 12+ (1/29), 3% for ages 16+ (A7), and 10% with parental guidance (3/29).

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However, only 41% of the apps (12/29) provide a privacy policy intended to protect children's data. Half of these privacy policies (58%, 7/12) claim to restrict users to a specific age group, albeit this approach is inconsistent with the app's age rating on the marketplace. For instance, A8 states in its privacy policy that the app does not provide services to users who are younger than the age of 18; in contrast, it is rated on the marketplace as PEGI 3. This may be due to a mismatch between age rating definitions oriented around inclusion of material such as violent content, and healthcare apps which should have age restrictions due to the personal and sensitive nature of the content, and associated risk for harm.

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In addition, all of the apps apply the same design across all ages, and we did not find any customization for users who are children, such as involving in-app interactions to allow parents to collaborate or monitor their children while using the app [30].

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187 **Targeted audience (clinical nosology).** All included apps claim to target users
188 with depression. Most of the apps (69%, 20/29) represent “depression” as a lack of
189 wellbeing (e.g., feeling stressed or having low mood). Less than one-fifth of the apps
190 (17%, 5/29) actually represent depression as a mental disorder, while only one app
191 (A18) employs PHQ-9 [53] to assess the severity of symptoms. Another 14% of apps
192 (4/29) do not claim to target depression as a disorder, yet employ validated tools
193 for assessing users’ depressive symptoms. Furthermore, none of the apps claims to
194 target users with a specific level of severity (i.e. mild/moderate/severe depression).

195
196 **Costs.** An important finding is that although most of the apps (97%, 28/29) are free
197 to download, at least some of their costs are covered either directly or indirectly by
198 users (Multimedia Appendix 2). The direct costs consist of explicit charges for more
199 advanced features, while indirect costs relate to users’ forced consumption of in-app
200 advertisements. In-app purchase was offered by 66% of the apps (19/29 apps),
201 mostly as a subscription priced between \$3.99 to \$29.99 per month, or for accessing
202 online-therapy sessions (\$35/ hourly session over call, video or chat, A11).
203 Advertisements were provided by 34% (10/29) of apps, which raises privacy
204 concerns. Of the apps with advertisements, 80% (8/10) stated specifically in their
205 privacy policies that users’ information, captured for instance through cookies,
206 would be collected and shared with 3rd parties, including advertisers or analytics
207 providers. Only one app that offered advertisements claimed that users’ data would
208 not be collected or shared (A29), while the other app (A7) did not provide a privacy
209 policy in English. Only 17% (5/29) of apps that are free to download neither request
210 in-app purchase nor provide advertisement. Only one app requires purchase (for
211 \$4.99) prior to downloading.

212
213 **Evidence Base.** Developers of 62% of the apps (18/29) have specified a scientific
214 underpinning for their app design, while another 38% (11/29) do not make such a
215 claim (Multimedia Appendix 3). Almost half of the apps (48%, 14/29) claim to be
216 designed based on validated psychological treatments (e.g., CBT, ACT, DBT,
217 mindfulness). The remaining 14% (4/29) are designed based on theories pertaining
218 to gamification, hypnosis, and affirmations. However, only 7% of the apps (2/29)
219 provide direct evidence in the form of peer-reviewed scholarly work on the efficacy
220 of the app for reducing depression symptoms [25, 47], while another 34% of apps
221 (10/29) provide indirect evidence of efficacy of their underpinning theories without
222 referencing any academic work. For instance, eight apps (A3, A4, A5, A15, A16, A17,
223 A18, A28) are promoted as evidence-based therapeutic tools by claims that their
224 design is grounded on evidence-based treatments (i.e., Cognitive Behavior Therapy).
225 41% (12/29) are described as being designed with input from clinicians (e.g.,
226 psychologists, psychiatrists, therapists), while 59% (17/29) do not mention the
227 involvement of mental health professionals in their design.

228
229 **Medical disclaimer.** A medical disclaimer is presented in 66% (19/29) of the apps,
230 outlining that the app is not a replacement for clinical treatment (Multimedia
231 Appendix 3). However, 8 out of these 19 apps (58%, 11/19) only present this
232 disclaimer in their terms of use policy, which is hard to find and unlikely to be read

233 by users. Another 35% (10/29) of apps do not provide any disclaimer. No app
234 presented itself as an alternative to clinical treatments (i.e., drug treatment or face-
235 to-face psychotherapy).

236

237 **Clinical involvement.** All apps are designed to be used independently and do not
238 require professional guidance while using them (Multimedia Appendix 3). Five apps
239 (17%, 6/29) provide opportunities to involve health experts while using the app. Of
240 these, two apps support access to coaching and counseling sessions as an additional
241 intervention for a price ranging from \$29.99 per month (A27) to \$35 per hour
242 (A11). The other three apps allow users to share their in-app data (e.g., health
243 tracking report) with their health care providers.

244 **Ethical considerations**

245 **Negative content.** Aligned with the concerns raised by prior work that apps with
246 poor design present an increased risk of potential harm [42, 52], the results show
247 that, 2 out of 29 apps are categorized as so-called wallpaper apps. Such apps
248 support people “reflecting the true nature of the pain and loneliness in [your] heart
249 [...] give permission to feel the way you do” (A12). We found these two apps include
250 images or quotes capturing negative thinking (e.g., “Do you ever get in those moods
251 where you just don’t feel like existing”, A12). Surprisingly, these two apps with
252 potentially disturbing content are rated as PEGI 3 (A12) or PEGI 12 (A6) on the
253 marketplace, which indicates that the apps’ content merely includes bad language.
254 As prior studies [7, 10] have indicated, adolescents’ exposure to negative content
255 may trigger negative behavior such as self-harm. Therefore, there is a clear need to
256 explore safeguarding strategies for protecting vulnerable users such as those at risk
257 of self-harm or suicide, especially given that these two apps are highly-rated on the
258 marketplace, i.e., between 4.4 and 4.6 out of 5, and subsequently more likely to be
259 selected for use, adoption or appropriation [49].

260

261 **Safety.** Strikingly, despite the increased vulnerability of people living with
262 depression, 72% of apps (21/29) do not provide any information for handling or
263 preventing the risk of suicide (Multimedia Appendix 4). Only 28% of apps (8/29)
264 provide such information: in particular, most of these apps (63%, 5/8) provide
265 information on suicide prevention helplines or counseling websites, whereas 25%
266 (2/8) provide information advising users to contact local emergency services if in
267 critical risk of harm. One app (A18) assists users in creating a personalized safety
268 plan for handling crises.

269 **Functionality review**

270 We now discuss the functionality of reviewed apps such as screening, tracking, and
271 providing interventions.

272 **Screening**

273 Nine apps offer functionality to screen for depression; their features are
274 summarized in Multimedia Appendix 5. Almost half of the apps that provide
275 screening functionality (44%, 4/9) aim to assess changes in users’ depression

276 symptoms during engagement with the app-provided intervention. Interestingly,
277 despite the acknowledged benefit of personalization to support adherence[46],
278 most of these apps (75%, 3/4) provide predefined psychoeducation articles upon
279 informing users of their screening result, rather than app-based intervention to
280 address particular issues identified through screening. All four of these apps employ
281 the PHQ-9, a validated screening tool. An interesting outcome in this context relates
282 to the frequency of the screening. Two apps allowed periodic repeated measures of
283 users' depression (i.e., apps suggest or limit access to the screening tool only once in
284 a fortnight), while another two apps allow on-demand screening of users'
285 depression (i.e., users can access screening tools as frequently as they want with no
286 instructions regarding an appropriate frequency).

287
288 33% (3/9) of the apps provide standalone screening functionality for self-diagnosis
289 purposes. 2 out of 3 apps classified into this category provide only screening
290 functionality (A29, A24), while another app (A16) also provides mood regulation
291 strategies in addition to screening as its primary function. The first two apps (A29,
292 A24) do not use validated screening tools and do not provide direct in-app links to
293 professional help upon informing users of the severity of their screening results. We
294 found that the other app (A16) enables the potential benefits of screening whilst
295 avoiding harm; it provides support for psychoeducation or for discussing the
296 diagnosis and its implications with mHealth professionals [52, 54]. This app (A11)
297 provides screening as the main functionality through the use of ICD-10 [63], a
298 validated screening tool, and in-app links to professional support. A11 also allows
299 users to generate a report of the screening result to show to their own healthcare
300 professionals.

301
302 The other apps (2/9, 22%) provide a screening function later used to inform the
303 delivery of personalized app content. One app asks users to self-report their
304 disorder and symptoms (A19), while the other app uses a questionnaire as a
305 screening tool (A11), albeit providing neither the source of this questionnaire and
306 information on its validity nor evidence for the personalization of intervention. This
307 app offers in-app purchase of online therapy sessions, however, this is not
308 integrated with users' progress through the intervention or their screening results.

309 *Tracking*

310 Out of the 29 apps, 19 apps offer functionality for tracking at least one aspect such
311 as thoughts, moods, behaviors, or depression symptoms (Multimedia Appendix 6).
312 Apps that track multiple aspects serve different purposes: 90% of these apps
313 (17/19) support tracking to assist the provision of personalized intervention i.e.,
314 tracking thought changes for providing materials to apply within the intervention,
315 or tracking users' behavior for visualizing their progress and adherence to the
316 intervention. 37% (7/19) of the apps support mood tracking for revealing their
317 triggers and patterns. Another 26% (5/19) apps support tracking of symptoms of
318 depression through frequent use of screening tools, 1 of these 5 apps (A16) track
319 aspects such as thought changes, mood or physical condition (i.e., appetite, sleep)
320 over fortnightly periods to generate screening result.

321

322 Thought tracking is supported by 74% of the tracking apps (14/19), mostly
323 combined with mood tracking on the same data entry. Good practices for improving
324 usability have started to emerge, for instance in the form of templates for guiding
325 users through the tracking process (available in 79%, 11/14 apps). There is also an
326 opportunity to explore alternative modalities for mood tracking. From the selected
327 apps, we found that text is the most commonly employed modality for recording
328 thoughts (100%, 14/14 apps) and also moods (64%, 9/14 apps). Other modalities
329 such as emoticons are being used to record moods tagged with thoughts (44%, 4/9),
330 and scales for recording mood intensity (11%, 1/9). Opportunities also arise for
331 better representing the thought-logs, for instance introducing searching or filtering
332 functionality. Currently, all 14 apps present thought logs directly to users in
333 chronological order without the option of searching them.

334

335 Of the 42% apps (8/19) which track user behavior as progress through the
336 intervention, three apps automatically log users' adherence to the proposed usage
337 goals for app-delivered intervention (e.g., minutes spent on app-delivered
338 meditation), while five apps track user's achievement of positive behaviors
339 suggested by the app (e.g., socializing with friends, drinking water). Apps for the
340 latter purpose mostly require users to log their achieved activity themselves, while
341 one app allows automatic tracking (i.e., step-count, A13). In addition, only half of the
342 progress-tracking apps (63%, 5/8) provide a summary visualization of intervention
343 progress (two apps provide a graphical summary, e.g., A11 provides a calendar
344 view). Another three apps provide a textual summary, e.g., A17 displays the total
345 number of minutes of meditation, without providing a record of each specific
346 meditation). The other 38% of apps (3/8) provide direct access to textual logs with
347 no summary.

348

349 37% of the apps (7/19) support the understanding of mood patterns through
350 visualizations. Such apps often track moods alongside their triggering factors
351 (available in four apps), or physical conditions such as headache (available in four
352 apps): the aim of the former is to understand the reasons for changes in mood, while
353 the latter aims to reveal the impact of physical conditions on such changes. Despite
354 the clear purpose of supporting understanding articulated by developers, the
355 representation of logged data does not easily support the understanding of data
356 patterns. Even though a graphical view of mood changes over time is provided by all
357 seven apps, most of them (57%, 4/7) provide it separately from the graphical view
358 of other tracked factors (e.g., A14, A28, A11 provide a graphical view of mood
359 changes within a period of time, and a textual representation of mood triggering
360 factors). Another three apps (43%, 3/7) offer an integrated representation of
361 changes in physical condition with changes in mood, which may make it easier to
362 understand relationships between the two.

363

364 26% (5/19) of the apps automatically track screening results for symptom
365 monitoring. Most of these apps (4 out of 5) provide only a textual review of

366 screening results, in chronological order. Only one app (A28) also provides a
367 graphic visualization of changes in screening results.

368 *Interventions*

369 Five types of interventions were identified in the analysis (see Multimedia Appendix
370 7), reflecting a mixture of elements from psychological interventions, including
371 *thought diaries, psychoeducation, mindfulness, scheduling positive behaviors, and*
372 *others*. A distinct group of apps aims to support *emotional expression* rather than a
373 particular psychological intervention.

374
375 Thought diaries are a common intervention employed by one-third of
376 the apps (38%, 9/24). This intervention borrows from traditional CBT practice by
377 providing instructions for identifying negative thought patterns and for challenging
378 distorted thoughts. One approach to tailoring interventions is to employ guidance
379 for challenging real-time tracked thoughts or emotions. Most of these apps (78%,
380 7/9) provide thought diaries as tailored interventions consisting of guidance for
381 identifying and selecting personal challenging thought patterns to guide the writing
382 of reflective diaries. Another two apps provide a generic template to guide thought
383 diaries, rather than adaptive or personalized guidance.

384
385 Apart from thought dairies, another set of nine apps (38%, 9/24) provide specific
386 psychoeducation as intervention. Findings suggest that 44% (4/9) of such content is
387 provided to specifically fit users' depression assessment, while 56% (5/9) is non-
388 personalized, generic content.

389
390 Mindfulness [13] is another popular intervention (38%, 9/24) as most of the
391 selected apps include meditation (9 apps), grounding techniques (1 app, A26), or
392 breathing guides (1 app, A2). Four apps suggest a frequency of use for the
393 intervention, e.g., one meditation session per day (A1), whereas the others do not
394 specify a frequency of use. Two apps provide adaptive interventions (i.e., meditation
395 guidance) triggered by users' input (e.g., during users' conversation with AI-based
396 chatbot, A27, A28).

397
398 Another three apps provide other types of emotion regulation strategies, including
399 positive affirmations (1 app, A25), or hypnosis (2 apps, A10, A20). Customization of
400 intervention material is available in one app (A25), which allows users to create
401 positive affirmations and to audio record them.

402
403 17% (4/24) of the apps delivered interventions for scheduling positive behaviors
404 (or behavior activation). Aligned with prior work, personalization [45, 54] is a good
405 design principle for engaging users with app-delivered interventions. Three apps
406 offer tailored intervention materials by allowing users to enter positive behaviors
407 that they wish to schedule (e.g., A15, A18, A21), and another app (A11) provides a
408 personalized monthly plan based on the results of the users screening measures.

409 Other valuable design choices supporting engagement include offering peer-support
410 [54] during the intervention (1 app, A21), or using gamification for providing daily
411 intervention goals and rewards [22] for completed activities (2 apps, A11, A21).

412

413 A final category of apps is those helping users to express their emotions associated
414 with depression (21%, 5/24), either by sharing posts in online support groups or by
415 individually consuming art-based materials. Of the two apps providing peer-
416 supported mood expression, only one provides links to a 24/7 suicide helpline. Both
417 apps allow users to filter posts: one app (A23) allows users to set filter words (e.g.,
418 “suicide”) in order to hide posts including such words and safeguard themselves
419 from such content, while another app (A19) filters materials (i.e., posts in the
420 community) automatically, and only shows materials that relate to users’ self-
421 reported disorder and symptoms. Apps that fall in the latter category (60%, 3/5)
422 provide art-based content for expressing depressive moods. E.g., wallpaper pictures
423 with emotional quotes. An important concern, however, is that none of the
424 wallpaper apps provides any scientific background, or features to support access to
425 mental health services for users at risk of suicide or self-harm. Most of the content of
426 these three apps are negative, and only one of these apps also provides some
427 positive content, being also the only app that offers users the possibility of
428 personalizing the quotes.

429 Discussion

430 Principal findings

431 This paper indicates that the current top-ranked apps for depression provide
432 various features to benefit users across different age groups. The potential of this
433 newly established marketplace is promising, especially for reaching subgroups of
434 users such as adolescents, who are less likely to seek professional support offline
435 and thus could benefit from appropriately designed mHealth apps. For this purpose,
436 we discuss the need and opportunity for regulating the marketplace to safeguard
437 users and to ensure a positive impact from the use of apps.

438

439 We begin by considering the ethical principle of non-maleficence [3] within the top-
440 rated apps for depression. Firstly, a clearer definition of age restrictions on the
441 marketplace could better support users in general and younger users in particular
442 to select age-appropriate apps. We found age to be handled insufficiently and
443 inconsistently in current commercial apps, given that the age ratings on the
444 marketplace generally indicate the maturity of app content rather than the targeted
445 users for the app, and furthermore that these ratings were generally inconsistent
446 with information regarding the targeted age group. This risk is further heightened
447 by the conditions within the reviewed apps’ privacy policies including the sharing of
448 users’ data with third parties for commercial purposes.

449

450 A recent systematic review of HCI work on affective health technologies also
451 identified potentially harmful aspects of tracking applications such as the provision
452 of negative mood or thinking patterns with insufficient professional support,

453 inadequate screening, and insufficiently founded diagnosis claims based on tracked
454 data [50]. With respect to communicating negative content, we see apps supporting
455 the consumption of publicly shared emotional expressions of depression generated
456 by others (A6, A12). We further advocate that developers should consider the
457 presence of negative content when selecting an age rating on the marketplace, as
458 consumption of such content may lead to harmful behavior among adolescent users.
459

460 In addition, this paper systematically reviewed and analyzed the apps' functionality.
461 The result inspires recommendations to guide developers to further leverage digital
462 affordances to mitigate harm, to deliver personalized depression treatments, as well
463 as to track multimodal content. For instance, for apps that provide screening
464 functionality, there may be a tendency to overclaim symptom screening informed by
465 non-validated screening tools rather than using validated ones, e.g., developers of
466 A24 and A29 prominently state their apps' effectiveness in clinical practice on the
467 marketplace, but do not provide scientific validation for the screening tools
468 employed. In addition, with regard to the increased vulnerability of depressed
469 individuals, we find limited direct access to professional help when screening
470 results are communicated to users. For instance, in general, 76% (22/29) do not
471 provide immediate access to suicide prevention or online counseling helplines
472 (Multimedia Appendix 3).

473 **Safeguarding users while accessing and consuming negative content**

474 Risk of harm can be identified with respect to the viewing of strongly negative
475 content from others within emotional expression apps for depression. Our findings
476 highlight strong ethical concerns around these apps. While arguably beneficial for
477 people creating it [41], such content might have a negative effect on those viewing it,
478 especially given that depressed individuals have a tendency towards rumination
479 [11]. We suggest that such apps should include safeguards for users viewing highly
480 negative content. Moreover, developers of such apps could limit views of negative
481 content, especially given that these two apps are also accessible to adolescent users,
482 who are susceptible to engage in "problem" or "at-risk" behaviors [30]. One
483 deployed strategy was to automatically cover negative keywords within app-
484 provided content and to offer a pop-up window with free psychological counseling
485 helpline every 3 times when users choose to reveal hidden negative words (A23).
486

487 Additionally, apps not specifically designed for children and adolescents, but with a
488 child-friendly age rating on the marketplace should consider introducing
489 customizable designs for non-adult users. It has previously been suggested that
490 providing support and treatment sessions with parents, teachers, and siblings
491 should be seriously considered when administering treatment to children with
492 depression [30]. Therefore, we suggest that designers of such apps should consider
493 mechanisms to engage parental support or supervision while children or
494 adolescents are using these apps.

495
496 An interesting issue with respect to apps supporting the tracking of mood and
497 thought patterns is the unfiltered presentation of these data when predominantly

498 negative content is being tracked. Apps tracking thoughts only provide access to
499 tracking-logs in chronological order, and this presents a two-fold limitation. Firstly,
500 such visualizations can be browsed but not queried in order to retrieve a specific
501 entry. Secondly, browsing such logs may trigger vivid recall when they capture
502 negative content and may increase the risk of rumination [45].

503 **Safeguarding users while selecting age-appropriate apps and sharing private data**

504 The suggestions discussed in this section target particularly the developers of
505 marketplaces hosting apps for depression. Previous findings suggested that the
506 regulation of such apps regarding data privacy remains inadequate [39, 40, 64], and
507 reported the prevalence of health-related apps selling users' data to third parties.
508 Survey studies have also indicated that the general public is less inclined to share
509 their healthcare data with technology companies [39]. The identified limitations of
510 the privacy policies for the reviewed apps illustrate that these concerns can be
511 better addressed. 24% of the apps (7/29) failed to provide any privacy policy in
512 English or in a reliable source (Multimedia Appendix 2). Additionally, aligned with
513 prior studies [12, 58], the current privacy policies may be difficult to comprehend
514 by typical users. We thus call for developers to improve the readability of privacy
515 policies and support the suggestion of making them easy to read at a 6th Grade
516 reading level [58].

517
518 Another concern is protecting the privacy of users' health data, and in particular the
519 data of young people while using depression apps. More than half of these apps
520 (83%, 24/29) fail to provide privacy policies that specify strategies to protect
521 children's data (55%, 16/29). Secondly, our findings also show that although most
522 of the apps are free to download, they normally come with in-app purchases for
523 additional features or advertisements. Regarding advertisement, we found 80%
524 (8/10) of apps that use advertisements declare that they share users' data for
525 commercial purposes.

526
527 All of the reviewed apps are rated as suitable for children and adolescents on the
528 marketplace, while one fifth (24%, 7/29) specifically claim to restrict access from
529 young users. This finding demonstrates the need for developers of marketplaces
530 that host depression apps to increase the transparency of their standards. For
531 instance, Google specifies that [2] their age rating is not for describing the apps'
532 target user group, but rather for describing the minimum maturity level of content
533 in apps such as violence, drugs, and profane language.

534
535 Surprisingly, however, no statement regarding data sharing or targeted users' age
536 range could be found on the app descriptions in the marketplace to support users
537 making an informed decision at the point of downloading the app. The age rating
538 may be specifically misleading to parents when they are selecting age-appropriate
539 apps for their children, as developers only claim age restrictions in the privacy
540 policy, We advocate a clearer definition and regulations for age rating of depression
541 apps on marketplaces.

542

543 Additionally, we argue that users should be informed upfront of the risk of having
544 their sensitive data shared with third parties for commercial purposes. The
545 prevalence of health-related apps selling users' data to third parties has been
546 previously reported [40, 59, 64]. Thus, we argue for the responsibility on the
547 marketplaces' developers to ensure consistency of privacy-related information in
548 the app description on the marketplaces when compared to its privacy policy, or to
549 ensure that the privacy policy is included directly within the app.

550 **Safeguarding users while screening depression**

551 Prior studies [59] have reported the tendency of commercial depression apps to
552 blur the line between depression as a lack of wellness or as a mental disorder, which
553 aligns with our findings. Additionally, none of the apps examined claim to target a
554 specific level of depression severity. While apps may potentially reach a wider range
555 of users by following such a strategy, it may be more difficult to formulate
556 appropriate safeguards for users whose depression leaves them with higher levels
557 of vulnerability [59]. Additionally, we found that most depression apps tend not to
558 undergo a rigorous evaluation of their intervention components, but instead rely on
559 designing the app based on evidence-based theory [58]. Apps with insufficient
560 evidence of efficacy present challenges as they may risk misinforming patients [59].
561 We advocate clear communication of the targeted user groups for mHealth apps,
562 and marketplace guidelines to match the required level of evidence for each app, as
563 well as the condition and risks of their specifically targeted user group.

564
565 App-based depression assessment is potentially valuable in supporting individuals
566 with depression concerns to seek help, and share their electronic health information
567 with health professionals [52, 58]. In addition, health data collected by users could
568 support professionals' understanding of users' symptoms, which could support
569 diagnosis and the delivery of clinical treatment. Despite these potential benefits, the
570 top-rated depression apps reviewed seldom support this usage. Only 1 of 8 apps
571 offered the option of generating reports of screening outcomes for sharing with
572 mental health professionals.

573
574 Although PHQ-9 is the most used tool for depression screening, 3 out of 8 apps use
575 non-validated screening tools, and information about screening tools and their
576 scientific underpinning is seldom provided within app descriptions. We recommend
577 that app developers use validated screening tools and provide basic information
578 about the tools and their validity.

579
580 Findings also indicate that tools intended for screening employ periodic repeated
581 measures such as PHQ-9 [53] also tend to be used within apps during daily tracking.
582 The latter, however, may be better suited to more lightweight ecological momentary
583 assessment measures [15] rather than depression diagnosis measures. We also
584 found a few emerging practices addressing this concern by suggesting an
585 appropriate frequency for screening, or even limiting the frequency of access to
586 screening tools (A16, A28). We thus suggest that app developers decouple the use of
587 periodically repeated measures such as PHQ-9 for the purpose of depression

588 screening, and the use of ecological momentary assessment for more frequent daily
589 tracking of mood, thoughts, behavior patterns, and symptoms of depression [17].

590 **Opportunity to improve apps for depression by leveraging digital affordances**

591 An important challenge of mobile apps for depression is attrition [18, 45]. Previous
592 work suggested the value of personalization for improving users' engagement with
593 apps [16, 45, 54], as well as the value of accessing social support [54] and involving
594 concepts from gamification [22]. In the future, this may involve the provision of real-
595 time adaptive personalization of intervention content to the tracked thoughts or
596 emotions [17]. However, despite the potential of mobile technology to deliver
597 personalization, apps supporting it are limited. Exceptions here include the use of AI
598 chatbot conversational agents (A27, A28) to respond in real-time to users' currently
599 recorded thoughts, instead of generic (not personalized) psychoeducational content.
600 Personalization can also be extended to the schedule of activities within an app-
601 delivered intervention. However, only one of the reviewed apps (A11) offered a
602 personalized intervention plan based on users' screening results. There is an
603 opportunity to better leverage digital affordances for personalization when
604 designing apps for depression.

605
606 Findings also indicate that tracking within depression apps is focused on capturing
607 users' mood patterns or thought patterns, as well as their engagement with app-
608 delivered interventions. However, these distinct types of tracked content are seldom
609 available together in one app. We argue for the value of simultaneously capturing
610 both thinking and emotional content as these can support better encoding at the
611 moment when an event occurs and better retrieval later on [26, 51]. We also suggest
612 that integrating such tracked content with a record of progress with, and completion
613 of intervention activities could better allow users to understand the value of the app
614 for their wellbeing. Such combined visualization could further support users'
615 engagement and motivation to continue to use the app-delivered intervention.

616 **Conclusions and Future work**

617 The rapid increase of mobile apps for reducing depression can benefit from a closer
618 look and evaluation of the functionality such apps actually deliver, and the potential
619 ethical issues that they raise. From a systematic analysis of 29 top-rated depression
620 apps on the major marketplaces, we suggest that developers of marketplaces should
621 regulate depression apps in order to mitigate ethical risks including missing,
622 inadequate, or inconsistent privacy policies, i.e., sharing data with third parties,
623 child data protection, and safeguarding of vulnerable user groups. In addition, the
624 analysis of app functionality provided new insights into opportunities for mitigating
625 harm regarding the consumption of the negative content, unrestricted access by
626 children, and related privacy concerns, and the provision of screening employing
627 tools with less scientific validation.

628
629

630

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