Is a Self-Monitoring App for Depression a Good Place for Additional Mental Health Information? Ecological Momentary Assessment of Mental Help Information Seeking among Smartphone Users

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ABSTRACT

Mobile devices and apps offer promising opportunities for both patients and healthcare professionals, for example, to monitor and assess health status, and also to provide relevant health information. However, health information seeking within a mood-tracking app has not yet been addressed by research. To bridge this gap, the depression-related health information seeking of 6,675 users of a mood-tracking smartphone app was unobtrusively monitored. The study shows that self-monitored depressive symptoms are associated with higher depression-related information seeking within the app. Health information seeking was low in general, with differences across 12 depression-related topics (e.g., depressive thoughts, a depression diagnosis, or depression facts), but the findings are also promising as the smartphone app was shown to be a place where users can inform themselves about health topics related to the main purpose of the app. Smartphone apps would therefore seem to be a vehicle through which to provide additional health information about, for example, comorbidities, or pre- or post-interventions, even going beyond the original purposes of such mobile health (mHealth) monitoring apps.

Depressive disorders are the most prevalent mental health condition in high- and middle-income countries (Kessler & Bromet, 2013) for which wide-ranging treatment options and mobile apps are available (Shen et al., 2015). However, three quarters of primary care patients with depression in urban areas identified at least one structural, psychological, cultural, or emotional barrier to accessing depression therapy or treatment (Mohr et al., 2010). The main determinant for seeking professional help for mental health problems is the severity of symptoms (Oliver, Pearson, Coe, & Gunnell, 2005), and oftentimes, non-professional help and lay support represent the first steps toward help-seeking. More recently, however, it has also been shown that mood self-monitoring predicted lower depression and anxiety levels (Bakker & Rickard, 2018), possibly through higher emotional self-awareness.

Mental health apps have the potential to effectively improve access to treatment through evidence-based self-monitoring and self-help, depending on the depressive symptomatology (Proudfoot et al., 2010). Even individuals with sub-threshold depression (Kroenke, 2017) can profit from smartphone self-monitoring, track their treatment progress, and reconnect with their environment (Ekers et al., 2014). Importantly, eHealth applications can help to overcome barriers set by traditional health systems through user-centered design, interactivity, social connectivity, and multimodality that integrates health assessment and health information into a single source (e.g., Kreps & Neuhauser, 2010). However, the link between self-monitoring and health information seeking within the same smartphone app has not yet been explored. Thus, it is still unclear if a self-monitoring app for depression would actually be a good place for the provision of additional health information linked to depression.

This paper therefore combines two aspects that are usually treated separately: On the one hand, do smartphones facilitate health information seeking (Myrick & Willoughby, 2017), and on the other hand, do smartphone apps facilitate self-monitoring, particularly if health concerns are more serious (Fox, 2013)? Evidence on user engagement with self-monitoring apps and their effects on health is still limited (Rubanovich, Mohr, & Schueller, 2017) and virtually absent in conjunction with health information seeking. However, Montagni, Cariou, Feuillet, Langlois, and Tzourio (2018) report that in a French sample, only a few individuals (72/498, ~14.5%) used at least one health-monitoring app to look up health information, while virtually everybody (450/476, ~94.5%) had searched online for health-related information in the previous year, including information about depression (243/476, ~51.1%). Yet, it remains unclear as to how many of these health-monitoring apps included information sections or were also used for this ancillary affordance. Relatedly, Rubanovich et al. (2017) explored the use of different kinds of health apps among people with depressive symptoms,

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including apps that explicitly had the purpose of containing helpful information. The study not only shows that users used 19.4% of the apps for more than one affordance, but that the developers intended 57.6% of the same apps to serve multiple purposes.

Information seeking is, in general, one of the strongest predictors of turning to the media relative to other media affordances, and this is largely independent of depressive symptoms (Scherr, 2016, 2018). More specifically, smartphone self-monitoring is arguably linked to other technical affordances that have beneficial health effects including the promotion of access to mental health services, and the reduction of stigma. For example, monitoring both the emotional ups *and* downs of depression can arguably help in challenging negatively-biased self-perceptions, reducing mental health stigma, and promoting professional help-seeking.

Patient empowerment for fighting depression

There are many barriers to help-seeking in the context of mental illness with stigma (including self-blame, shame, and help-seeking inhibition), with mental health knowledge being among the most relevant. Specifically, a knowledge–contact intervention presenting mental health facts effectively improved mental health literacy among adolescents, while a smartphone intervention including information materials on stigma, mental health, and help-seeking reduced self-stigma among adults (Milner et al., 2018). Thus, exposure to factual knowledge about mental health helps people to disclose their issues to others and, ultimately, to seek professional help (e.g., Pinto-Foltz, Logsdon, & Myers, 2011). Mental health knowledge includes knowledge and beliefs about risk factors, causes, types of self-help interventions, finding professional help, and sources of mental health information (Jorm, 2000). The societal stigma linked to depression often deters people from seeking professional help due to a dissonance between how they would like to see themselves and their beliefs about mental illnesses (Clement et al., 2014). However, help-seeking can be supported through self-assessment and self-awareness (Kauer et al., 2012), self-disclosure (Henderson, Robinson, Evans-Lacko, & Thornicroft, 2017), or through exposure to health information (Costin et al., 2009). Overall, research supports the notion that knowledge about depression (as part of mental health literacy) can ultimately increase help-seeking; among younger people, particularly if that information is presented in online apps or on websites (Burns & Rapee, 2006), ultimately reducing the odds of them developing moderate to severe depressive symptoms.

Smartphone apps, depression, and information seeking

Smartphone apps to self-monitor mental health indicators often serve multiple purposes including them being a resource for information about risk factors, causes, types of self-help, and where to find professional help (Rubanovich et al., 2017; Shen et al., 2015). Being multimodal and omnipresent in our everyday lives, smartphone apps are especially apt to provide such combinations of self-assessment and information that ultimately could increase mental health literacy if the apps contain decent information and are properly used. Moreover, assuming that there are online disinhibition effects (Suler, 2004), smartphone apps should represent only a small burden in this regard in terms of self-monitoring and self-disclosure. A few studies provide some initial evidence that smartphones could in fact be useful for depression screenings; however, this aspect still lacks any systematic scientific assessment (Van Ameringen, Turna, Khalesi, Pullia, & Patterson, 2017).

The first empirical evidence shows that cognitive training and psychotherapy apps can effectively reduce depressive symptoms through the provision of knowledge (e.g., Arean et al., 2016), with more clinical trials on the way (e.g., Giosan et al., 2017). Importantly, depression has also been associated with lowered physical activity levels (Camacho, Roberts, Lazarus, Kaplan, & Cohen, 1991), which has been linked to maintaining depression (Mammen & Faulkner, 2013). However, the use of self-monitoring apps seems to be unrelated to depression (Abu Rahal, Vadas, Manor, Bloch, & Avital, 2018), and even depressed individuals still use their apps as much as non-depressed individuals (BinDhim et al., 2015). Above and beyond the self-monitoring of mental health indicators with smartphone apps, other forms of journaling such as "keeping track in their heads," using a notebook/journal, or medical devices are common and particularly helpful for disease management and therapy adherence among patients with chronic conditions (Fox, 2013). In fact, individualized mobile phone services yielded better blood sugar levels among diabetes patients than self-monitored glucose levels or routine care did (Lim et al., 2011). Importantly, among older patients, smartphone ownership (in contrast to mobile phones) is comparably low and represents an important technological barrier to smartphone self-monitoring (Tanenbaum, Bhatt, Thomas, & Wing, 2017). However, smartphone apps offer the chance of providing users with health information in addition to self-monitoring – a combination of affordances that has not yet been explored in much depth.

Specific affective responses usually play a role in health information seeking (see Kahlor, 2010). For example, Myrick (2017) argues with the appraisal theory of emotions that emotions and information seeking could form a reciprocal relationship with emotions being able to influence information-seeking patterns, and with specific found information evoking certain emotions. An information–emotion correspondence is arguably more persuasive (Nabi, 2003) and self-reinforcing; it has therefore been employed in emotion-based message tailoring. Furthermore, building on social cognitive theory, Myrick (2017) argues that an affect links with outcome expectations and the perceived self-efficacy of successfully finding relevant health information, thereby influencing health information seeking. However, Myrick (2017) found a limited influence from emotions on health information seeking, and no influence from emotion-based message tailoring on attitudes toward a health information website, which was, moreover, largely independent of its perceived relevance. It thus remains open as to how a self-monitoring smartphone app for mood states could actually facilitate further information seeking about depression, given that the app represents an extreme form of information–emotion correspondence (i.e., self-monitored affect states *are* the main app content).

This is important to study further given that health information seeking can encourage healthy lifestyles, preventive behaviors, and help people to admit to treatment or therapy being required for both physical and mental illnesses. In recent years, health-related smartphone apps have also become increasingly relevant for therapy, health information, and health assessments. For instance, Shen et al. (2015) analyzed a sample of 243 smartphone apps that have been released on the app stores for major mobile phone platforms and that carry the word "depression" in either their title or description, are targeted at health consumers rather than at healthcare professionals, and are available in English (or with an English translation): 33.7% (82) of these apps had the main purpose of providing therapeutic treatment, 32.1% (78) offered psychoeducation, 16.9% (21) medical assessment, and 7.4% (18) had multiple purposes (e.g., news, exercises, diets), with only 3.7% (8) of the apps being characterized as mood trackers, 2.9% (7) as depression trackers, and with 2.9% (7) of them having elements of positive affirmation (Shen et al., 2015, p. 9).

The present study

The lack of empirical evidence about the use of smartphone apps for enhancing mental healthcare has recently been criticized (Van Ameringen et al., 2017). Smartphone apps have the potential to not only provide mental health literacy through mood tracking or the self-assessment of depressive symptoms, but they also offer the chance of providing knowledge about mental health. The present study investigates how self-monitored depressive symptoms link with depression-related information seeking within a mood-monitoring smartphone app. Therefore, app use was unobtrusively tracked and it included information about users' self-assessed depressive symptoms; information about the use of a depression knowledge section within the app was also monitored. User data were collected anonymously by the app developer in line with the terms of use. Hence, the data allowed us to explore the relationship between self-monitored depressive symptoms and health information seeking but without the possibility of distinguishing between user characteristics.

The article addresses the following research question:

RQ1: To what extent are self-monitored depressive symptoms associated with additional health information seeking about depression in a separate knowledge section within the same smartphone app?

Methods

About the dataset

The data used to answer the research question stem from a collaboration with the start-up company *Moodpath* (https://mymoodpath.com/en/) whose mood-tracking app is not only certified as a medical product, but also includes a knowledge section about depression. The app has been developed in line with cognitive behavioral therapy and in collaboration with therapists, psychologists, and psychotherapists, and the app has been continuously validated in clinical studies. Importantly, the app's terms of use explicitly allow for the analysis of log data for academic research, which is particularly relevant given the sensitivity of the data and the rising awareness of data protection issues.

The obtained data contained information about the app usage of 6,675 users of the mood-tracking app *Moodpath* that has been available for smartphones at no cost. In line with the terms of use, no further identifying or descriptive data about the users such as their age, sex, or education were collected. However, users who downloaded and installed the mobile app agreed that their use patterns would be monitored, and that the resulting data might be used for academic research.

As part of the main function of the app, users who agreed to the terms and conditions were asked on up to three occasions a day to indicate the momentary prevalence of their key or associated depressive symptoms, as well as differential diagnostic criteria oriented toward the ICD-10 criteria for depression. The questions were asked as sets of 3 out of 48 questions (for a screenshot, see the left panel of Figure 1).

The app algorithm ensures that the three assessments are equally distributed throughout the day. If users did not respond within an adequate time frame, the set of questions was skipped and replaced by another one at the next assessment point that day. An algorithm meant that all symptoms were asked about at least twice to each user within a timeframe of at least 14 days depending on how many questions were skipped. Some depressive symptoms were operationalized using two items, while others were captured using single items. In each assessment session, users answered three yes/no questions about the momentary prevalence of three key or associated depressive symptoms. In case a symptom was prevalent, users were asked to answer a follow-up question about the degree to which the symptom was weighing upon them on a 4-point scale ranging from 1 = *not at all* to 4 = *extremely*. Although not of interest for the present study, this question was visually depicted as weights of different sizes that users had to draw into a virtual backpack in order to answer the question.

Besides the depression self-monitoring function, the app also offers a knowledge section that covers 12 depression-related health information subsections (see right screenshot in Figure 1). Hence, the dataset contained information about the prevalence of depression symptoms and the number of information sections chosen by each user. Data about the users' depressive symptoms as well as their visits to the knowledge section were collected over the course of 14 weeks from September 2016 to January 2017. In line with the ICD-10 diagnostic criteria for depression, only users who monitored their depressive symptomatology for at least 2 weeks were included in the analyses.

Measures

Depressive symptoms according to the ICD-10 criteria

Within the app, the three ICD-10 key symptoms of depression were captured: 1) a depressed mood, 2) a loss of interest or pleasure, and 3) a decrease in energy or increased fatigue. Moreover, the seven associated depressive symptoms according

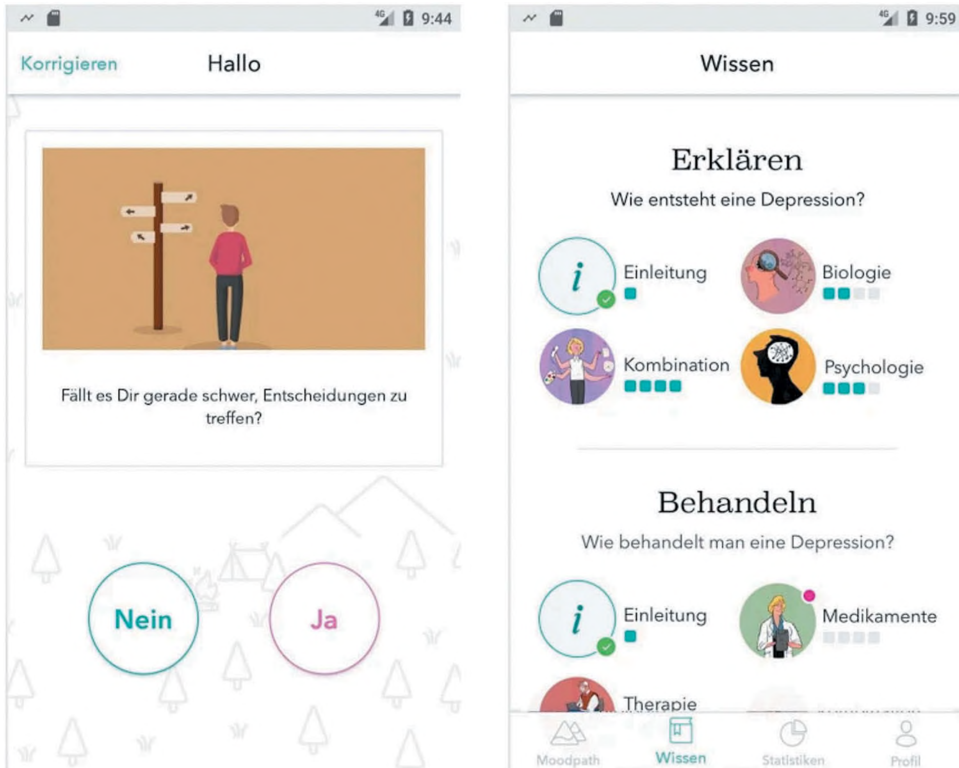

Figure 1. Screenshots of the mood-tracking smartphone app *Moodpath* with the main self-monitoring function (left panel; top-to-bottom translation: "Is it currently hard for you to make decisions?" | no–yes), and a knowledge section (right panel; top-to-bottom translation: Explanation: How does depression develop? | Introduction – biology – combination – psychology | Treatment: How is depression treated? | Introduction – medication – therapy).

to the ICD-10 were monitored including 1) sleep disturbance, 2) appetite disturbance, 3) recurrent thoughts of death, 4) inability to concentrate or indecisiveness, 5) psychomotor agitation or retardation, 6) reduced self-esteem or self-confidence, and 7) ideas of guilt and unworthiness (WHO, 2010). The sum of weekly key and associated symptoms showed good reliability (Key symptoms: Cronbach's $\alpha = .868$; associated symptoms: Cronbach's $\alpha = .921$) and was aggregated for each user (Key symptoms: $M = 5.64$, $SD = 2.60$; associated symptoms: $M = 11.45$, $SD = 5.39$). An overview of all measures (key vs. associated ICD-10 symptoms; operationalizations; question wordings) is presented in Table 1.

Health information seeking

Within the smartphone app is a knowledge section that users can voluntarily go to (i.e., users are at no point directed toward the knowledge section). Hence, health information seeking for different topics related to depression reflects self-motivated behavior. The knowledge section includes three superordinate sections that are subdivided into smaller subsections (*signs of depression*: facts, body, feelings, thoughts, behavior; *explaining depression*: psychology, biology, combinations of both psychology and biology; *treatment of depression*: psychotherapy, medication, self-help, diagnosis). Moreover, each of the three superordinate sections starts with an additional introductory section. The number of visits to each subsection was monitored by the app. Average numbers of visits for each knowledge subsection were calculated per user based on the sum of their weekly visits. The number of average weekly visits per user as well as the standard deviations are shown in Table 2.

The single most frequently visited knowledge section was about bodily signs of depression with $M = 1.1$ ($SD = 1.7$) average visits per week.

Results

The average (with standard deviations) weekly visits for the 12 different knowledge sections and the correlations among them are depicted in Table 2. To counteract type I error inflation in multiple comparisons, a Bonferroni correction was applied; the focus here will be on the strongest (i.e., $r > .70$) and weakest (i.e., $r < .30$) correlations.

Seeking information about the biological causes of depression were strongly correlated with its psychological causes ($r = .735$, $p < .001$) and with combinations of both psychological and biological causes ($r = .789$, $p < .001$). Furthermore, information seeking about how depression is diagnosed correlated strongly with its most usual forms of medication ($r = .782$, $p < .001$), psychotherapy ($r = .721$, $p < .001$), and possibilities for self-help ($r = .724$, $p < .001$). Users who sought information about depression-related thoughts also sought information about specific behaviors in the course of depression ($r = .722$, $p < .001$). Finally, information about psychotherapy and medication were also strongly correlated ($r = .770$, $p < .001$), as well as information about self-help and psychotherapy ($r = .705$, $p < .001$). In contrast, users who read about depression facts sought less information about a depression diagnosis ($r = .257$, $p < .001$), medication ($r = .264$, $p < .001$), or self-help ($r = .269$, $p < .001$).

Table 1. Overview of the measurement and operationalizations of depression within the self-monitoring app.

	Operationalization	(In-App) Question Wording
ICD-10 key symptoms of depression		
Depressed mood	Hopelessness	Are you feeling hopeless?
	Sadness	Are you feeling down and sad?
Loss of interest or pleasure	Loss of joy	Do you have less pleasure in doing things you usually enjoy?
	Loss of interest	Do you feel like you are not interested in anything right now?
Decrease in energy or increased fatigue	Energy	Do you currently have significantly less energy?
	Exhaustibility	Are you feeling up to your tasks?
ICD-10 associated symptoms of depression		
Sleep disturbance	Sleep disturbances	Did you sleep badly last night?
Appetite disturbance	Appetite loss	Do you have less or no appetite today?
Recurrent thoughts of death	Thoughts about death	Do you currently think about death or dying?
Inability to concentrate or indecisiveness	Inability to make decisions	Is it hard for you to make decisions currently?
	Inability to concentrate	Is it hard for you to concentrate currently?
Psychomotor agitation or retardation	Inhibition	Are you speaking or moving more slowly than usual?
	Restlessness	Do you feel unsettled or sense an inner unrest or agitation?
Reduced self-esteem or self-confidence	Self-confidence	Is your self-confidence clearly lower than usual?
	Self-esteem	Are you feeling up to your tasks?
Feelings of guilt and unworthiness	Feelings of worthlessness	Do you think you are worth less than others right now?
	Feelings of guilt	Have you been blaming yourself lately?

Answer format yes–no. If yes is chosen, the impairment is specified on a scale ranging from 1 = *not at all* to 4 = *extremely.*

In order to explore how information seeking about depression-related information operates as a function of depressive symptomatology, Pearson correlations with two-tailed significance tests were calculated using the ICD-10 key and associated symptoms separately. Only users for whom information about depressive symptoms was completely available for 2 weeks or more (i.e., the minimum timespan of a depressive episode) and who looked up information within the knowledge section at least once were included (n = 5,170): 95% confidence intervals were calculated for the correlation coefficients based on 1,000 bootstrap samples (bias corrected and accelerated).

As indicated in Figure 2, most Pearson correlation coefficients ranged between .05 and .10, indicating small but significant positive associations between depressive symptoms and health information seeking. The strongest correlations were found between all predictors and seeking information about a depression diagnosis (ICD-10 key symptoms: r = .092, p < .001; ICD-10 associated symptoms: r = .088, p < .001), the combined biological and psychological roots of depression (ICD-10 key symptoms: r = .092, p < .001; ICD-10 associated symptoms: r = .084, p < .001), and self-help (ICD-10 key symptoms: r = .086, p < .001; ICD-10 associated symptoms: r = .084, p < .001). However, depressive symptomatology was unrelated to seeking information about the body or facts about depression (i.e., the 95% confidence intervals of the correlation coefficients include the zero-effect line).

The associations between key depressive symptoms and information seeking also hold true in the multivariate regression model, as indicated in Table 3. The average number of weekly visits to the 12 knowledge sections per user was significantly higher for users with more key depressive symptoms for most knowledge sections.

However, seeking information about facts (B = .007, SE = .006, p = .254) and the body (B = .006, SE = .010, p = .524) were not associated with key symptoms of depression.

Post hoc analysis

However, as indicated in Table 2, users read on average only one information section per week, mostly because they simply did not choose to read anything within the information section at all. Therefore, given this outcome distribution, we calculated logistic regressions in order to determine odds

Table 2. Correlations between unobtrusively captured information seeking within 12 knowledge sections in a mobile phone app to monitor depressive symptoms based on aggregated user data from September 9th 2016 to January 5th 2017.

Variables	1	2	3	4	5	6	7	8	9	10	11	12
1. Biology	–											
2. Diagnosis	.613***	–										
3. Facts	.333***	.257***	–									
4. Thoughts	.566***	.453***	.530***	–								
5. Feelings	.407***	.317***	.665***	.694***	–							
6. Combination	.789***	.654***	.308***	.535***	.394***	–						
7. Body	.415***	.317***	.575***	.614***	.546***	.374***	–					
8. Medication	.632***	.782***	.264***	.471***	.339***	.671***	.326***	–				
9. Psychology	.735***	.539***	.344***	.521***	.394***	.683***	.406***	.528***	–			
10. Psychotherapy	.662***	.721***	.305***	.492***	.367***	.686***	.366***	.770***	.582***	–		
11. Self-help	.596***	.724***	.269***	.442***	.321***	.611***	.329***	.695***	.503***	.705***	–	
12. Behavior	.531***	.419***	.526***	.722***	.682***	.508***	.495***	.429***	.489***	.465***	.422***	–
M	0.2	0.2	0.7	0.7	0.5	0.1	1.1	0.2	0.4	0.2	0.2	0.4
SD	0.7	0.7	1.1	1.6	1.2	0.4	1.7	0.8	0.9	0.7	0.6	1.0

Intercorrelations are based on 5,170 weekly average selections of knowledge sections by 6,675 individual users who actively used the smartphone app *Moodpath* for at least 2 weeks over a 4-month observation period (September 2016–January 2017); the selection of knowledge sections was aggregated per day and per user. Pearson correlations between the selected knowledge sections with a two-tailed significance test with Bonferroni correction are presented below the diagonal. Means and standard deviations are presented in the horizontal rows at the bottom.
All measures are metric, since people could select knowledge sections as often as desired during the monitoring period. Higher scores are indicative of a selection of more knowledge sections within the app. "Combination" refers to combinations of both psychological and biological causes of depression.
*** p < .001

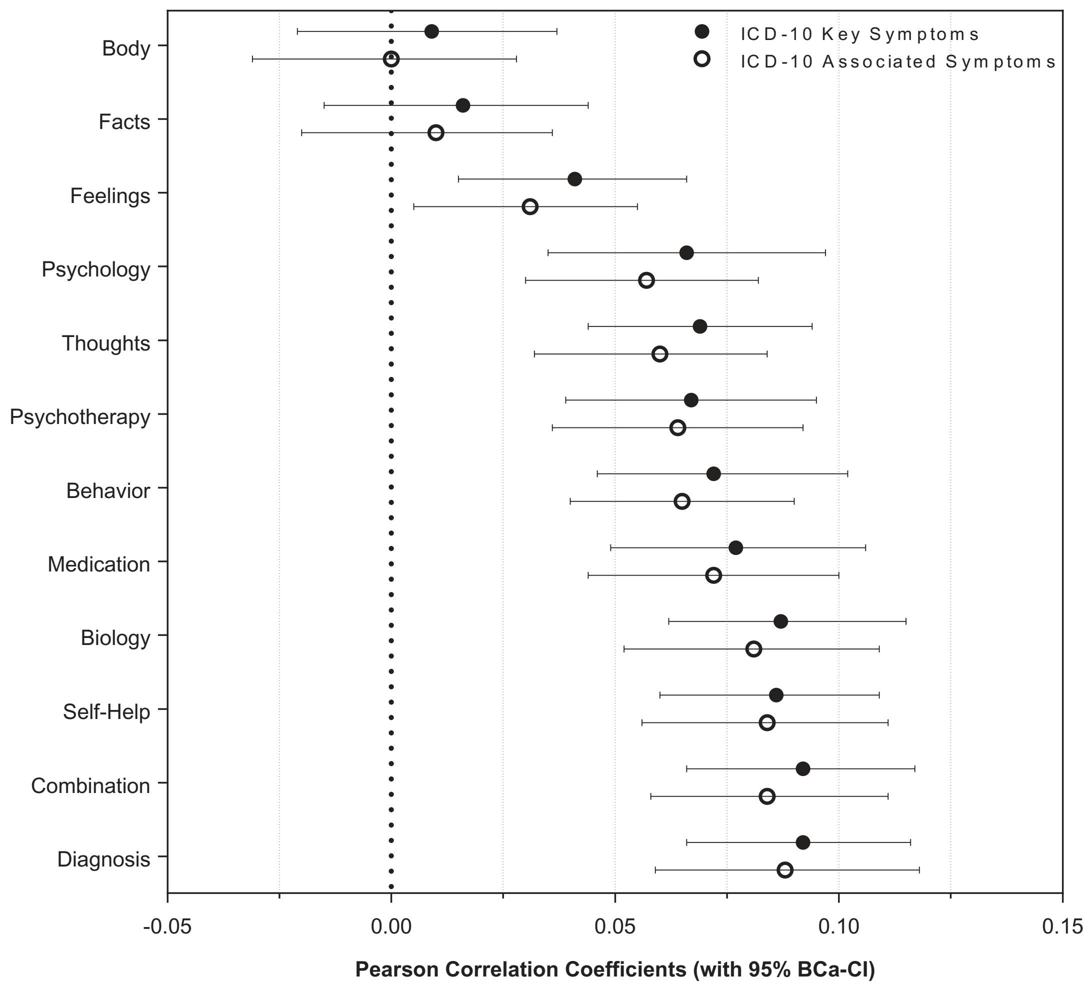

Figure 2. Correlations between mean depression scores and seeking information on 12 different depression-related topics within a depression-monitoring app (n = 5,170 individual users). "Combination" refers to combinations of both psychological and biological causes of depression.

Table 3. Regression of ICD-10 key symptoms of depression on health information seeking in different knowledge sections within a smartphone app to monitor depression.

	Multivariate Regression		
	B	*SE*	*p*
In-App Knowledge Section	$\Delta F(12, 4925) = 37.996$, $p < .001$		
Biology	.026	.004	< .001
Diagnosis	.026	.004	< .001
Facts	.007	.006	.254
Thoughts	.044	.009	< .001
Feelings	.019	.007	.003
Combination	.013	.002	< .001
Body	.006	.010	.524
Medication	.025	.004	< .001
Psychology	.024	.005	< .001
Psychotherapy	.018	.004	< .001
Self-help	.022	.004	< .001
Behavior	.028	.005	< .001

The multivariate regression is based on N = 5,170 users of a depression self-monitoring app who read in a knowledge section about depression as part of the smartphone app; significant results are in bold print. More details about the knowledge section are provided in Table 4.

ratios for reading a specific knowledge section depending on the amount of key or associated depressive symptoms.

Table 4 shows that especially the ICD-10 key symptoms of depression were associated with increased information seeking in most knowledge sections with the exception of information about the diagnosis, medication, psychotherapy, and self-help in depression. In contrast, ICD-10 associated symptoms of depression were only associated with significantly lower odds of reading about feelings associated with depression.

Discussion

Depressive disorders are among the most prevalent mental disorders in high- and middle-income countries (Kessler & Bromet, 2013) for which oftentimes at least one structural, psychological, cultural, or emotional barrier to accessing depression therapy or treatment can be identified (Mohr et al., 2010). Recent technological developments such as smartphone apps, however, can facilitate health information seeking (Myrick & Willoughby, 2017) and self-monitoring (Fox, 2013). Specifically, self-monitoring depressive symptoms increases self-awareness and can thereby lower depression and anxiety levels (Bakker & Rickard, 2018). It has been argued that smartphone apps could help to increase mental health knowledge (e.g., beliefs about risk factors, causes, types of self-help interventions; see Jorm, 2000), and thus empower people to disclose their issues to others, which may ultimately facilitate professional help-seeking (e.g., Pinto-Foltz et al., 2011). Although

Table 4. Odds ratios of reading in different knowledge sections within a smartphone app to self-monitor depressive symptoms depending on key and associated ICD-10 symptoms of depression.

		ICD-10 Key Symptoms			ICD-10 Associated Symptoms		
Sections	*Exemplary Content Elements*	*OR*	*SE*	*p*	*B*	*SE*	*p*
Biology	*Chemical messengers; heredity*	**1.22**	**.073**	**.001**	.988	.029	.668
Diagnosis	*"Mild" depressive episode; "moderate" or "severe" forms*	1.08	.071	.255	1.05	.034	.153
Facts	*Prevalence; progression*	**1.13**	**.049**	**.004**	.991	.021	.665
Thoughts	*Negative thoughts; rumination*	**1.17**	**.055**	**.001**	.982	.022	.424
Feelings	*Grief; emotions during depression*	**1.22**	**.056**	**< .001**	**.957**	**.021**	**.049**
Combination	*Vulnerability; stress*	**1.23**	**.081**	**.002**	.991	.032	.775
Body	*Appetite; sleep*	**1.13**	**.049**	**.005**	.986	.020	.499
Medication	*Neuroleptics; sedatives*	1.11	.070	.093	1.02	.032	.451
Psychology	*Negative schemata; learned helplessness*	**1.18**	**.061**	**.001**	.985	.024	.541
Psychotherapy	*Cognitive behavioral therapy; side effects of therapy*	1.09	.066	.157	1.03	.030	.380
Self-help	*Activities and exercise; friends and family*	1.06	.065	.322	1.04	.031	.138
Behavior	*Social withdrawal; substance use*	**1.18**	**.057**	**.001**	.098	.023	.418

The logistic regression is based on N = 5,170 users of a depression self-monitoring app who read in a knowledge section about depression as part of the smartphone app; *OR* are odds ratios; significant results are in bold print.

self-monitoring smartphone apps are popular (Huguet et al., 2016; Shen et al., 2015) and can help overcome traditional barriers to mental healthcare (e.g., Dogan, Sander, Wagner, Hegerl, & Kohls, 2017; Kreps & Neuhauser, 2010), one specific question, however, has remained largely unexplored to date; namely, whether a mood-tracking smartphone app can also convey health information about depression and is actually used for this additional affordance.

To pioneer addressing this question, the present study presents an analysis of the log data from a smartphone app to self-monitor depressive symptoms that was publicly available and free to download. The present study builds on the unobtrusively monitored data of 6,675 app users who used *Moodpath* from September 2016 to January 2017. In line with the terms of use, we only analyzed log data that offered insights into app use patterns but contained no descriptive information about the users. The log data contained two different kinds of information: three key and seven associated ICD-10 symptoms of depression and their severity, as well as the number of visits to a knowledge section that includes 12 different subsections related to depression. The log data analyses of users with sufficient information about their depressive symptoms and who visited the knowledge section (n = 5,170) showed specific information-seeking patterns. For example, people who wanted to know about the causes of depression sought information about biological, psychological, and combined causes of depression, and users who read about the diagnosis of depression also read about medication, psychotherapy, and self-help. The ICD-10 key symptoms of depression seemed to be especially strong predictors of depression-related information seeking except for information about the diagnosis, medication, psychotherapy, and self-help aspects.

Conceptually, the present study contributes to the body of literature on affective responses in health information seeking (see Kahlor, 2010; Yang, Aloe, & Feeley, 2014). The link that was found between a self-assessed depressed mood and mental health information seeking supports the general notion of a reciprocal correspondence between emotions and information seeking (Myrick, 2017; Nabi, 2003). More specifically, however, depressive symptoms that link with information seeking refine and extend conceptualizations of affective responses within risk information seeking (Kahlor, 2010). While the predominantly negative affective responses such as worry, anger, or fear seem to trigger perceived information insufficiency and only indirectly increase information seeking, there might be a more direct link between affect and information seeking in depression. Risk information-seeking models typically assess immediate affective responses to a hazard, but depressive symptoms could in fact be included in the model as an individual predisposition to (health) risk information seeking.

In the present context, self-monitoring depressive symptoms can be understood as a form of routine health risk information seeking. In this scenario, mood states may be more directly linked to actual information seeking. Interestingly, key depressive symptoms were especially linked to information seeking about aspects of depression that go beyond information that someone would normally obtain when in therapy (i.e., the biological background of depression, combined bio-psychological causes of depression, feelings that people with depression typically experience). Even though the terms of use on which these ecological momentary assessment data are based did not allow for a more in-depth analysis, we would encourage follow-up research. Particularly, key symptoms of depression appeared to be linked to information seeking, whereas the associated symptoms of depression were either unrelated to information seeking or were even related to information avoidance.

Importantly, however, in-app information seeking was low in general, similar to Montagni et al. (2018) study that also found that only a small number of individuals report health information seeking in smartphone apps, with diverse reasons for low engagement (Torous, Nicholas, Larsen, Firth, & Christensen, 2018). While information seeking is generally a strong predictor of media use in conjunction with depression (Scherr, 2016, 2018), it seems that self-monitoring apps for depression arguably represent other technical affordances relevant for mental healthcare. Interestingly, there is a mismatch between app developers' and users' perceptions of app affordances, with developers usually overestimating the number of affordances of their apps relative to users (Rubanovich et al., 2017). However, our study shows that a smartphone app can stimulate multiple, simultaneous affordances that can be explained by individual predispositions. Users with a more severe symptomatology especially turned to content that went beyond health information that they would most likely have already obtained through professional help (such as a diagnosis, medication, and/or therapy). However, increased interest in combined causes or detailed descriptions of the experiential facets of depression seem to attract their attention more. Thus, it would be interesting to further explore to what extent an exchange option with other users could be another beneficial affordance of such apps. It would be a worthwhile next step to systematically assess the growing number of smartphone health apps with a focus on their user interactivity levels, and to what extent the averaged experiences of other users are accessible within such apps. Such apps could profit from their "birds-of-a-feather" community that naturally forms around them (e.g., diabetes patients all using the same monitoring app) both regarding a functionality discussion, but also anonymously sharing average, live community information among app users, for example, by informing them that others also feel jaded during a certain time of the year or in their region. Of course, such claims need further empirical exploration.

Future studies will also have to investigate more in detail to what extent other informational sources for facts, for example, Wikipedia entries about depression, or online health forums (Scherr & Reinemann, 2016) are used rather than or in addition to depression apps (Laurent & Vickers, 2009). It remains unclear at this point whether smartphone apps directed at affective disorders (e.g., Shen et al., 2015) are – from a user-experience perspective – a convenient tool for target audiences to teach them about health facts, especially when the main purpose of the application is different (e.g., monitoring symptoms). However, additional analyses also showed that users with key depressive symptoms generally sought more information about different facets of depression per week. Hence, our findings indicate that smartphone apps for monitoring depression operate in more complex ways, and they could enhance mental health literacy as a function of the severity of depression, depression stages, or the phases of depression.

Limitations

This study has several limitations that have to be kept in mind. The analyses were based on aggregate data with no further sociodemographic information being available, in line with the terms of use. Hence, among subgroups of users, observed patterns of the smartphone app usage to monitor depression and to inform themselves about depression might be different. The first studies that used online self-diagnosis tools reported sociodemographic and health-related differences in the self-monitoring of mental health status and treatment-seeking behaviors (e.g., Ameringen, Simpson, Patterson, & Turna, 2015). Moreover, there is no information about why users decided to install and use the app in the first place. The affordances of media technology might vary, shape user needs in different ways, and give rise to new gratifications; they might shift over time and through new media features (Sundar & Limperos, 2013). Consequently, the motivations behind monitoring depressive symptoms might vary widely and we cannot completely rule out to what extent our results were affected by that. It has been shown across a wide range of countries that especially younger adults are reached by depression self-monitoring smartphone apps, and that this also depends on which of the two different app platforms (App Store; Google Play) the apps are available (see BinDhim et al., 2015). It is therefore important to explore to what extent beneficial app effects apply especially for some users, as this would contribute to technological health disparities (Scherr, Haim, & Arendt, 2019). Future studies will have to address these important shortcomings. Finally, differentiating between depression severity levels using smartphone apps has to be evaluated across different instruments to screen depression. Future studies should explore the psychometric properties of depression-monitoring apps relative to clinical instruments.

Conclusions

Our study supports the notion that depressive symptoms link with a slight increase in weekly depression-related health information seeking. As opposed to the concerns that reduced activity in depression might be an obstacle to information-seeking behaviors, our data are promising: Among the strongest observed correlations were those between depressive symptoms and seeking self-help and depression-diagnosis information. Hence, a smartphone app to self-monitor depression might be a helpful tool for patient empowerment in terms of self-help, on the one hand, but, on the other hand, it might also motivate users to seek professional help when facing depressive symptoms.

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