Journal of Engineering Sciences
Vol 13, Issue 01, Jan /2022
ISSN NO:0377-9254

RECOMMENDING ACTIVITIES FOR MENTAL HEALTH AND WELL-BEING: INSIGHTS FROM TWO USER STUDIES

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Abstract—Engaging in daily activities that engender positive affect (e.g., exercise and socializing) is critical for emotional well-being and is effective in reducing clinical depression. However current digital mental health interventions have not exploited recommender approaches to encourage such healthy behaviors. This paper tests the feasibility of recommending personalized healthy activities to users. Using two mobile applications, we collected high-quality data about specific healthy activities from two populations: a clinical sample diagnosed with a mood disorder (n = 318 activities/user) and a non-clinical sample (n = 59 activities/user). Activities were labeled with a type (e.g., social, leisure, work) and rated for their impact on mood. We used a probabilistic multinomial Naive Bayes (NB) Classifier and a Support Vector Machine (SVM) to model the activities as a bag-of-words to predict mood outcome. We separate

the analysis into a generalized model where we pooled all participants, comparing it with a personalized model. In both the clinical and non-clinical samples there was a significant difference between the two models. Both NB and SVM favored the personalized model after collecting 58.92 (SD = 20.96) activities. This research sheds light on recommendations for mental health, showing that personalization is key for recommending the right activity to each user.

Index Terms—Recommendation, Activity, Depression, Well-being, Behavior, Content-analysis, MHealth, Naive Bayes

1 INTRODUCTION

MENTAL health and well-being are major public and personal health issues, being a leading cause of disability and disease burden worldwide [1]. 30% of men and 40% of women experience a major depressive episode at least once in their life with minorities being even more vulnerable [2]. Depression is second only to heart disease as a cause of disease burden [3], and many people remain untreated [4]. As a result, there is a growing research effort to develop personal informatics technologies to alleviate mental health symptoms (see [5], [6] for reviews). These have resulted in innovative mobile (mHealth) solutions [7], [8], [9], [10], [11], [12]. Nevertheless, there are important limitations to these existing applications; they often rely on burdensome manual user tracking of symptoms, and intervention strategies are sometimes based around theoretically unmotivated self-help heuristics. Together these limitations may explain relatively low levels of long-term adoption [13], [14]. The current situation parallels the early era of recommender platforms, which were also driven by simple heuristics. Now, of course, many recommender platforms reduce the analytic burden for users by providing explicit product recommendations, such as books, movies or songs. This not only increases platform usage [15], but also improves user satisfaction [16].

This paper explores the application of recommender techniques to the mental health domain. The key scientific finding that

motivates our work is that when patients regularly enact activities that they rate as pleasant, this has significant positive impacts on mental health [17], [18]. A successful behavioral intervention therefore relies on recommending personal activities that are likely to improve the patient's affective state. For example, walking the dog or meeting friends commonly boost mood. This simple Pleasant Event Scheduling (PES) intervention has been demonstrated to be an effective treatment for depression, with effects that are comparable to standard psychotherapy methods such as Cognitive Behavioral Therapy (CBT) treatment and drug therapies [19], [20].

However, most prior clinical PES interventions rely on non-digital approaches where participants manually log their daily behaviors for several weeks. Patients then collaborate with their therapist to analyze this record, to identify 'pleasant' events. Patient and therapist then generate a treatment plan involving a weekly schedule of those pleasant events. However, there are drawbacks to this approach. First, the process of manually identifying pleasant events may be prone to errors, as the effect of a given event can be specific to an individual. There is also time and cost involved in scheduling therapist meetings. As a result, patients are receptive to computational approaches: with surveys showing 91% of patient respondents are positive about computationally enabled therapies because of the anonymity and control they offer [21]. An app an be accessed privately without needing to disclose personal details or schedule official health services [22]. The goal of our current research is therefore to explore the viability of recommendation methods in the context of PES. Specifically, we examine whether recommender methods might allow us to reliably predict such mood-boosting events. Generating reliable predictions would allow a future system to use these models to recommend positive activities to users.

This study uses data collected from two mobile applications that allow clinical and non-clinical participants to manually log details of personal activities along with mood ratings. We assess whether positive ratings for different activity types can be successfully predicted using automatic methods. We also explore individual differences to determine whether personalized versus general models best predict ratings. If successful predictions can be achieved, these recommendations could be incorporated into well-being apps, enabling recommendations about future activities which – according to PES theory – could improve a user's mental health.

Our main contributions are:

1) Offline analysis of logged activities from patients with a clinical depression and non-clinical users to test the feasibility of predicting activities that are positive for individual users.

2) We ran holdout cross-validation with incremental training size on the logged activities to show the relation between a personalized or general model as a function of the number of activities registered.

3) We performed follow-up evaluations on the trained recommender models to extract key insights about the activity parameters that had an effect on the level of positivity. Furthermore, we make the NB trained general model now publicly available allowing others to build on these insights.

4) Finally, we ran the personalized recommender models through a 4-week app usage simulation to illustrate a novel scenario of applying activity recommendation to technology for mental health.

II. METHODOLOGY

As outlined above, recommender systems for well-being are at an early stage, especially for mental health. Therefore, there is no pre-existing dataset for evaluating recommender model performance. Such a dataset would require detailed activity registration and labeling over an extended period of time, along with detailed information about patient profiles. In this study, we therefore utilize two datasets from two smart phone user studies, which collected data 'in-the-wild' for 3 and 4 weeks respectively. These apps generated high quality data from participants who logged their activities together with labels for activity type and the immediate effects of that activity on mood or pleasure. The dataset possesses two key advantages over typical user-behavior modeling datasets:

1) users provide real-time longitudinal self-generated labels for all attributes without reliance on crowd-sourced annotations, and

2) users log their own perceptions of how activities influence mood and also include textual information, producing a reliable dataset. Both studies have been approved by the relevant Ethical Committees and Internal Review Boards (j. 17018289 and HS2466,respectively). Given the sensitive and personal nature of the

TABLE 1
Example of data collected via the MORIBUS app from P1-P5. *The names have been anonymized for patient protection

Init. time	End time	Activity	Category	Pleasure
01-25 09:00	01-25 10:59	*Bath and breakfast*	Practical	4
08-13 15:00	08-13 20:59	*Collect firewood*	Movement	5
02-21 12:00	02-21 12:59	*Attending a lecture*	Work & Edu.	2
03-25 12:00	03-25 12:59	*Go for a walk with S**	Movement	7
04-12 21:00	04-12 21:59	*Trivial pursuit with family*	Leisure	7

logged data, these approvals required the researchers to sign a con dentiality agreement with the participants stating that their logged activity data would be kept confidential. The two user studies targeted two distinct user groups; the first involved patients with a clinical diagnosis of unipolar (i.e., depression) or bipolar disorder, while the other was a non-clinical sample. In total, the two datasets respectively consist of 1,684 entries from 7 patients, and 6,344 entries

from 134 users.

3.1 Clinical Sample

For the clinical sample, we collected data via the MORIBUS app [39]. It is designed to support BA [40] in which patients log hourly activity information each day, rating each activity with a 'pleasure' score, i.e. the extent to which the activity engenders positive or negative emotion. This detailed information is later used by a therapist to identify activities that influence the depressive symptoms of the patient. Together, the patient and the therapist plan the following week's activities based on recommendations from the therapist, and schedule positive activities that could lead to healthy behavior change. To replicate the BA procedure in the MORIBUS app, each patient was instructed to plan a set of activities for a day or week and evaluate these activities on an hourly basis. This is done using a daily calendar with hour-based timeslots from 8 am (08:00) to 10 pm (22:00). An activity is created and planned using the activity registration page shown in Figure 1 (left). When creating an activity, patients:

(i) select an activity type (e.g., Leisure) as adopted by [41], and

(ii) choose from a precompiled list of typical activities of the chosen type (by pressing the light bulb button), or manually enter an activity. When an activity was marked as done, patients were notified to enter a positivity rating, i.e., how much they enjoyed the activity. This is

shown in Figure 1 (right). Examples of collected data are shown in Table 1.

3.2 Non-clinical Sample

For the non-clinical sample, we collected data using the EmotiCal app [12], [28]. EmotiCal is a mobile application created to help regular people manage their mood and improve well-being using PES. EmotiCal users logged two daily entries in which they manually recorded mood, energy

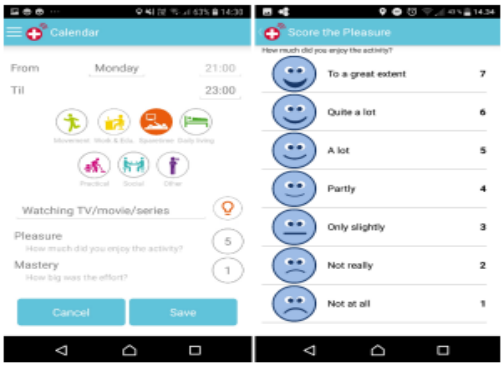

Fig. 1. Two screenshots from the MORIBUS app. The left side shows an example of the activity registration page. After selecting an activity, the user can write text describing it, e.g., *Watching TV/movie/series*. The right side shows the positivity rating page.

level, and activity labels. For example, users can log social interactions (e.g., time spent with a friend or coworker), aspects of physical health (e.g., sleep or exercise), or work activities (e.g. meetings) to track these activities' effects on mood. EmotiCal also prompts users to generate short textual explanations of how and why they think those activities affected mood. Data was collected from Emotical using a slightly different procedure, in which participants first rated their current mood and then assessed which of their recent activities had induced that mood. To generate Mood ratings, participants first reported their current mood on a scale from -3 (very negative) to +3 (very positive). These ratings were generated against a standardized scale where the different scalar values were clearly defined as part of the app registration process. Participants next reported and classified recent activities that contributed to that rating, and finally generated a textual description of those activities. A screenshot indicating how the participants logged relations between Mood and activities is shown in Figure 2. Mood rating is shown on the left side, and activity classification on the right side. Users chose the activities that contribute to their current mood. Participants also rated Energy levels (left hand side), but we did not use these ratings in the current analysis. Examples of Emotical textual descriptions along with their activity labels and mood ratings are shown in Table 2.

3.3 Data Processing

The activity data collected from the two studies were analyzed in MATLAB (vs. R2018B). The processing steps are outlined below:

- In the clinical study, activity entries from Danish-speaking patients were translated by the authors into English.

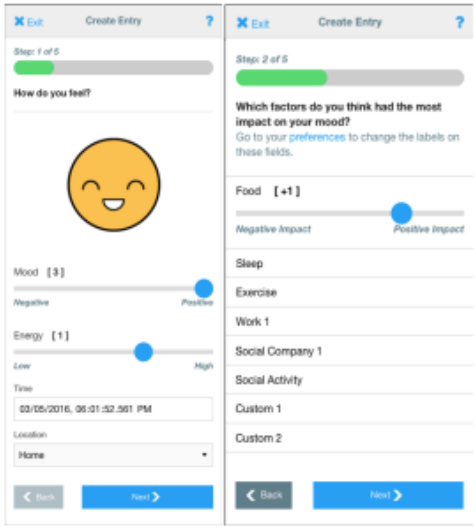

Fig. 2. Two screenshots from the EmotiCal app illustrating the first two steps of registering an activity for the non-clinical sample. The right side shows the activity classes and the left side shows the Mood and Energy ratings. In this case the user has rated current Mood as highly positive, and associated this with a Food activity.

TABLE 2
Example of data collected via the EmotiCal app.

ID	Time	Activity	Label	Mood
S1	08-23 22:04	*I made time to do things I like, watch TV and chat with a friend. So it's been a good day*	Leisure, Social	2
S8	08-27 21:15	*Had delicious chicken dinner with mashed potatoes and broccoli tonight. Will head to amusement park tonight with my family*	Food, Leisure	1
S17	08-08 12:04	*I get to be with my boyfriend*	Social	1
S42	08-04 19:32	*Drinking homebrew with an astronaut*	Work, Leisure, Social	2
S51	08-03 18:45	*Driving home in traffic - not my favorite thing to do*	Work	-1

• A custom script pre-processed textual data into

(i) lower case and

(ii) removed all special characters, dots, commas, trailing and leading spaces from the activity text. Then the dimensionality of unique words was reduced further by

(iii) removing typical words determined by a list of 665 stop-words,

(iv) Porter stemming words (to combine words such as ”cleaned” and ”clean”) and (v) removing long words (n > 15 characters).

• We removed data entries that had empty text strings.

• Data from users who provided fewer than 3 different mood ratings were removed due to low variability in the outcome measure.

• The ratings were transformed to a binary outcome variable (C) indicating a positive activity or otherwise. This was done for each user separately, where the median was used as a cut-off. We transformed the outcome variable to a binary variable to be consistent with existing approaches taken for movie, song, and book recommendations.

• Finally we transformed the activity text and labels to bag-of-words.

To assess the degree of personalization achieved by the trained recommender models, we ran individual subjects models through a public dataset of 320 pleasant activities [17]. An independent researcher manually applied activity labels to all activities in that dataset. Furthermore, we evaluated the impact of two features ‘activity text’ and ‘label’ by assessing their individual information gain on the prior probability through a Kullback-Leibler divergence analysis.

3 RESULTS

An overview of the data collected from the two studies is shown in Table 3. The differences in population, the number

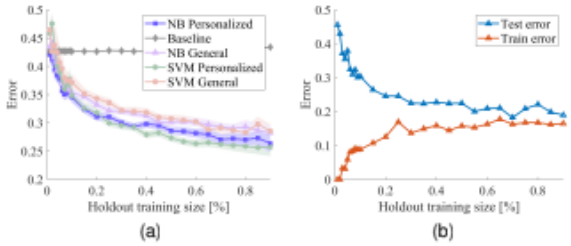

Fig. 3. (a) The error rate as a function of training size for the different models for the clinical sample. SE is shown as a shaded interval. (b) training and test error is visualized for P5 on the NB model.

of activities and the method of activity reporting gave us a unique opportunity to study activity models in two different contexts. Hence, the results from the two studies are presented separately, before we generalize across the two studies.

4.1 Clinical Sample

The error rates of the recommender models, as a function of training size, are shown in Figure 3a. The shaded area represents the standard error (SE). For the personalized and baseline model, we compute the pooled SE instead to represent the SE of each user.

The NB and SVM models seem to converge and stabilize after a training size of 40%. This is

verified by inspecting the test and training error (Figure 3b). Here we see low bias and variance and convergence after a training size of 100 activities (40% holdout).

We supplemented the above error analysis with the F1- score, recall, precision and AUC from the ROC-curve at three different training sizes, for a more thorough comparison between the models. The result is shown in Table 4.

We used the tmax based permutation to test the differ- ence between the general and personalized model for both the NB and SVM models. The result is depicted in Figure 4. The resulting critical t-value is plotted as red horizontal lines on the resulting null-distribution in Figure 4b, 4d. Statistically significant differences between the two models are seen after a 15% holdout (45.65, SD = 16.03 activities). Examples of three holdout samples are shown on the null-distribution as grey-level colored horizontal lines. The benefit of a personalized model was further investigated by inspecting the trained (90% holdout training size) likelihood of the activity labels. The ratio of the likelihood of either recommending an activity label or not was computed and visualized in Figure 5. A value colored in blue indicates a higher likelihood of recommending. Values colored in red indicate the opposite. In both SVM and NB models, we see that the 'Social' activity type has a higher likelihood of recommendation (i.e. has a positive rating) for every subject (P1-P5), while 'Practical' activities do not. This confirms other studies investigating activities and well-being [41]. The other labels show personal preferences when we compare individual models. For instance, 'Spare time' activities are recommended for P1, but not for P3 and P4. Note too that the personal models differ from the general model for one or activity types.

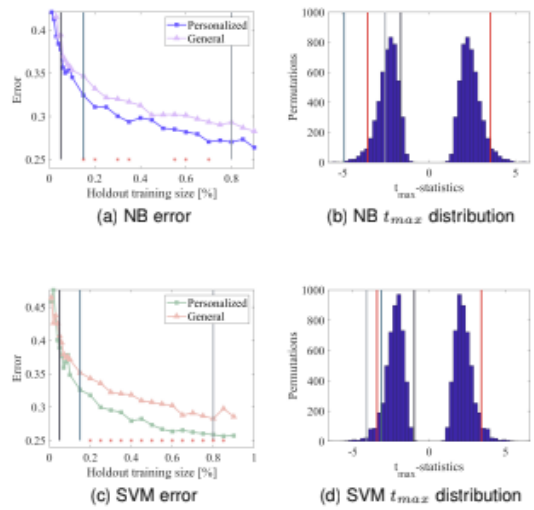

Fig. 4. The results from the t_{max} based permutation test on the clinical sample. Statistically significant samples are indicated by * in (a) and (c). The resulting null-distribution is illustrated in (b) and (d) with the critical t-value shown as a red horizontal line. Three samples at a holdout size of 5, 15, and 80% are high-lighted to show their position in relation to the null-distribution.

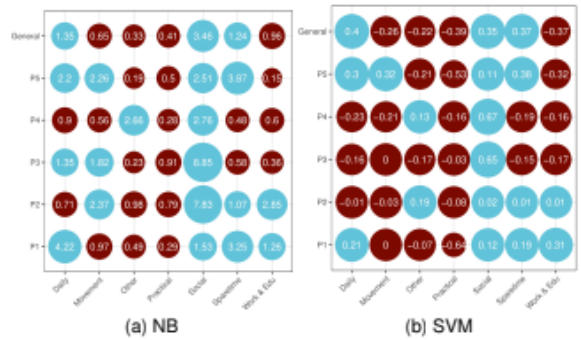

Fig. 5. Matrix showing the weights, trained with 90% holdout, of the activity type feature for each patient and the *general* model for the clinical sample. (a) shows the ratio of the likelihood function for the NB model. Values above one (blue) indicate a higher likelihood for recommendation; (b) shows the beta weights for the SVM model. Values above 0 (blue) indicate weights favoring recommendation in the binary classification.

To compare the information gain of activity text and type features, we ran a Kullback-Leibler divergence analysis on 90% holdout data. For the general model the information gain for the two different features was DKL(P(C|A1)||P(C)) = 0.017 and DKL(P(C|A2)||P(C)) = 0.001 suggesting that activity text carries more information regarding the variability of the posterior probability, while the opposite was true for the

SVM classifier (4.81 · 10−5 and 7.62 · 10−4 respectively).

When inspecting the information gain on a per subject level, we saw contradictory results even within NB and SVM.

TABLE 4
Model results at 1, 10, and 90% holdout training size for the clinical sample. Base: Baseline model, P: Personalized model, G: General model

	1% Holdout training size					10% Holdout training size					90% Holdout training size				
	Base	NB G	NB P	SVM G	SVM P	Base	NB G	NB P	SVM G	SVM P	Base	NB G	NB P	SVM G	SVM P
F1	0.59	0.56	0.54	0.53	0.51	0.59	0.65	0.64	0.61	0.63	0.58	0.71	0.73	0.71	0.72
Recall	0.54	0.55	0.56	0.52	0.51	0.54	0.63	0.64	0.62	0.64	0.53	0.71	0.71	0.70	0.73
Precision	0.65	0.58	0.54	0.55	0.52	0.65	0.67	0.65	0.60	0.63	0.64	0.71	0.75	0.71	0.72
AUC	0.50	0.58	0.55	0.54	0.5	0.5	0.69	0.68	0.65	0.67	0.5	0.74	0.75	0.75	0.74
Error	0.44	0.43	0.43	0.47	0.48	0.44	0.35	0.35	0.37	0.35	0.44	0.28	0.27	0.29	0.26

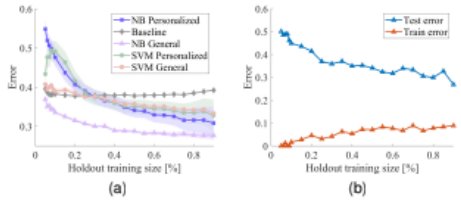

Fig. 6. (a) The error rate as a function of training size for the different models for the non-clinical sample. SE is shown as a shaded interval. (b) training and test error is visualized for S50 in the NB model.

5 CONCLUSION

We have introduced a novel context for recommender systems, to recommend personal activities to improve personal mental health and well-being. We described how we collected high-quality data from two mobile applications and used this to model activity valence based on text and activity type features using two classification methods. In the context of the application, our results show promise given the prevalence of mental illness and the opportunity to contribute to novel forms of personalized treatment discreetly to anyone who has access to a smartphone. In addition, models were reasonably accurate, with personalized models outperforming general models, which argues for the utility of building user-specific models.

We believe the results of this work constitute an important step in developing new technologies that will help the vulnerable user group of depressed patients. We understand the potential ethical concerns that such recommender systems might bring. However, we claim that recommending positive activities can potentially offer valuable benefits to the behavioral therapy process.

REFERENCES

[1] ”World Health Organization”. (2018, Mar.) Depression. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/ depression

[2] M. E. Kruijshaar, J. Barendregt, T. Vos, R. De Graaf, J. Spijker, and G. Andrews, “Lifetime prevalence estimates of major depression: an indirect estimation method and a quantification of recall bias,” European journal of epidemiology, vol. 20, no. 1, pp. 103–111, 2005.

[3] C. J. Murray, A. D. Lopez, W. H. Organization et al., The global burden of disease: a comprehensive assessment of mortality and disability from diseases, injuries, and risk factors in 1990 and projected to 2020: summary. Geneva: World Health Organization, 1996.

[4] P. S. Wang, M. Lane, M. Olfson, H. A. Pincus, K. B. Wells, and R. C. Kessler, “Twelve-month use of mental health services in the united states: results from the national comorbidity survey replication,” Archives of general psychiatry, vol. 62, no. 6, pp. 629–640, 2005.

[5] R. Grist, J. Porter, and P. Stallard, “Mental health mobile apps for preadolescents and adolescents: a systematic review,” Journal of medical internet research, vol. 19, no. 5, p. e176, 2017.

[6] E. Dogan, C. Sander, X. Wagner, U. Hegerl, and E. Kohls, “Smartphone-Based Monitoring of Objective and Subjective Data in Affective Disorders: Where Are We and Where Are We Going? Systematic Review,” Journal of Medical

Internet Research, vol. 19, no. 7, p. e262, 2017. [Online]. Available: http://www.jmir.org/2017/7/e262/

[7] J. E. Bardram, M. Frost, K. Szant´o, M. Faurholt-Jepsen, M. Vinberg, ´ and L. V. Kessing, "Designing mobile health technology for bipolar disorder: a field trial of the monarca system," in Proceedings of the SIGCHI conference on human factors in computing systems. ACM, 2013, pp. 2627–26 36.

[8] K. H. Ly, N. Topooco, H. Cederlund, A. Wallin, J. Bergstrom, O. Molander, P. Carlbring, and G. Andersson, "Smartphone- supported versus full behavioural activation for depression: A randomised controlled trial," PLoS ONE, vol. 10, no. 5, pp. 1–16, 2015.

[9] N. D. Lane, M. Lin, M. Mohammod, X. Yang, H. Lu, G. Cardone, S. Ali, A. Doryab, E. Berke, A. T. Campbell, and T. Choudhury, "BeWell: Sensing sleep, physical activities and social nteractions to promote wellbeing," Mobile Networks and Applications, vol. 19, no. 3, pp. 345–359, 2014.

[10] A. M. Roepke, S. R. Jaffee, O. M. Riffle, J. McGonigal, R. Broome, and B. Maxwell, "Randomized Controlled Trial of SuperBetter, a Smartphone-Based/Internet-Based Self-Help Tool to Reduce Depressive Symptoms," Games for Health Journal, vol. 4, no. 3, pp. 235–246, 2015. [Online]. Available: http://online.liebertpub.com/doi/10.1089/g4h.2014.0046

[11] M. Matthews, S. Abdullah, G. Gay, and T. Choudhury, "Tracking mental well-being: Balancing rich sensing and patient needs," Computer, vol. 47, no. 4, pp. 36–43, 2014.

[12] V. Hollis, A. Konrad, A. Springer, M. Antoun, C. Antoun, R. Martin, and S. Whittaker, "What Does All This Data Mean for My Future Mood? Actionable Analytics and Targeted Reflection for Emotional Well-Being," Human-Computer Interaction, vol. 32, no. 5-6, pp. 208–267, 2017. [Online]. Available: https://doi.org/10.1080/07370024.2016.1277724

[13] S. W. Miyamoto, S. Henderson, H. M. Young, A. Pande, and J. J. Han, "Tracking health data is not enough: a qualitative exploration of the role of healthcare partnerships and mhealth technology to promote physical activity and to sustain behavior change," JMIR mHealth and uHealth, vol. 4, no. 1, p. e5, 2016.

[14] C. Kelley, B. Lee, and L. Wilcox, "Self-tracking for Mental Well- ness," in Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems - CHI '17, 2017, pp. 629–641.

[15] S. Research. (2018, Apr.) Spotify initiation of coverage. [Online]. Available: https://www.stifel.com/research

[16] Y. Yao and F. M. Harper, "Judging similarity: A user-centric study of related item recommendations," in Proceedings of the 12th ACM Conference on Recommender Systems, ser. RecSys '18. New York, NY, USA: ACM, 2018, pp. 288–296. [Online]. Available: http://doi.acm.org/10.1145/3240323.3240351

[17] D. J. MacPhillamy and P. M. Lewinsohn, "The pleasant events schedule: Studies on reliability, validity, and scale intercorrelation," Journal of Consulting and Clinical Psychology, vol. 50, no. 3, pp. 363–380, 1982. [Online]. Available: http: //psycnet.apa.org/record/1982-24797-001

[18] P. M. Lewinsohn and J. Libet, "Pleasant events, activity schedules, and depressions." Journal of abnormal psychology, vol. 79, no. 3, p. 291, 1972.

[19] P. Cuijpers, A. van Straten, and L. Warmerdam, "Behavioral activation treatments

of depression: A meta-analysis," Clinical Psychology Review, vol. 27, no. 3, pp. 318–326, 2007. [20] S. Dimidjian, S. D. Hollon, K. S. Dobson, K. B. Schmaling, R. J. Kohlenberg, M. E. Addis, R. Gallop, J. B. McGlinchey, D. K. Markley, J. K. Gollan, D. C. Atkins, D. L. Dunner, and N. S. Jacobson, "Randomized trial of behavioral activation, cognitive therapy, and antidepressant medication in the acute treatment of adults with major depression." Journal of consulting and clinical psychology, vol. 74, no. 4, pp. 658–70, 2006. [Online]. Available: http://www.ncbi.nlm.nih.gov/pubmed/16881773

[21] C. Graham, A. Franses, M. Kenwright, and I. Marks, "Problem severity in people using alternative therapies for anxiety difficulties," Psychiatric Bulletin, vol. 25, no. 1, pp. 12–14, 2001.

[22] "Beating the blues US". (2014, May) Beating the blues us. [Online]. Available: https://www.upmchealthplan.com/beatingtheblues/

[23] J. Firth, J. Torous, J. Nicholas, R. Carney, A. Pratap, S. Rosen- baum, and J. Sarris, "The efficacy of smartphone-based mental health interventions for depressive symptoms: a meta-analysis of randomized controlled trials," World Psychiatry, vol. 16, no. 3, pp. 287–298, 2017.

[24] D. A. Rohani, M. Faurholt-Jepsen, L. V. Kessing, and J. E. Bardram, "Correlations Between Objective Behavioral Features Collected From Mobile and Wearable Devices and Depressive Mood Symptoms in Patients With Affective Disorders: Systematic Review," JMIR mHealth and uHealth, vol. 6, no. 8, p. e165, aug 2018.

[25] H. E. Payne, C. Lister, J. H. West, and J. M. Bernhardt, "Behavioral functionality of mobile apps in health interventions: a systematic review of the literature." JMIR mHealth and uHealth, vol. 3, no. 1, p. e20, 2015.

[26] D. Bakker, N. Kazantzis, D. Rickwood, and N. Rickard, "Mental Health Smartphone Apps: Review and Evidence-Based Recommendations for Future Developments," JMIR Mental Health, vol. 3, no. 1, p. e7, mar 2016.

[27] F. Wahle, T. Kowatsch, E. Fleisch, M. Rufer, and S. Weidt, "Mobile Sensing and Support for People With Depression: A Pilot Trial in the Wild," JMIR mHealth and uHealth, vol. 4, no. 3, 2016.

[28] A. Springer, V. Hollis, and S. Whittaker, "Mood modeling: ac- curacy depends on active logging and reflection," Personal and Ubiquitous Computing, vol. 22, no. 4, pp. 723–737, 2018.

[29] S. Yang, P. Zhou, K. Duan, M. S. Hossain, and M. F. Alhamid, "emhealth: towards emotion health through depression prediction and intelligent health recommender system," Mobile Networks and Applications, pp. 1–11, 2017.