E-Mental Health: Contributions, Challenges, and Research Opportunities from a Computer Science Perspective

Dennis Becker
Leuphana University Lüneburg

E-Mental Health - Contributions, Challenges and Research Opportunities from a Computer Science Perspective

Author Name

Dennis Becker, Leuphana Universität Lüneburg, dbecker@leuphana.de

Abstract

This chapter discusses some of the challenges in the development of e-mental health applications and points out new directions for further research. It focuses on the technical perspective that is used to deliver the treatments, but also on the supporting part of computer science for the physicians. Problems regarding the quality of the e-mental health applications, the resulting adherence and drop out of therapy are discussed. For the supporting part, data mining algorithms are used, to aid the supervising therapist in its assessment of the client. Sentiment detection and activity recognition are suggested to gain additional knowledge about the client to compensate for the missing face to face treatment within online therapy.

Key words: E-mental health, Virtual Patient, Machine Learning, Sentiment Detection, Activity Recognition, Outcome Questionnaire, Gamification, Dropout, Adherence in therapy

INTRODUCTION

E-mental health is the fusion of computer science and mental health, where the computer science aims at supporting the work of the physicians. It is a recently emerged research field that utilizes information and communication technologies to support and improve mental health. Furthermore, it is an interdisciplinary research topic that contributes to the welfare of society. The use of social media, online and smartphone applications helps to close the large gap between the need and actual treatment for mental disorders (Kohn, 2004). In addition, it aims at the reduction of costs for the society that arises from the direct treatment and the indirect costs, due to the loss of productivity or even the workplace (Fiscal, 2005; Harwood, 2000).

E-Mental health inherits the problems and benefits of clinical mental health, and many research results from mental health also apply to e-mental health. Interventions, screening, and assessment for the treatment of mental disorders can effectively be delivered with Internet-based software. The adherence to therapy and dropout are problems that are linked to the design and implementation of the e-mental health software as well as the provided treatments and interactions with the guiding therapist. Therefore, the development of these applications requires guidelines to guarantee its quality and success.
During the process of treatment, a huge amount of data is collected that contain information that can be unraveled with data mining. Data mining algorithms are useful for the support of the physician's work because it can provide predictions of the client's recovery based on previous patients. In addition, it can be used to extract the mood of the client from a written text or record the activity profile using a mobile phone. Despite the amount of conducted research many questions are still unanswered. Accordingly, this chapter discusses the contribution

of computer science to e-mental health, and suggest directions for further research.

FROM COMPUTERIZED THERAPY TO MACHINE LEARNING

The efficacy of a computerized cognitive behavioural therapy was demonstrated (McCrone, 2004), and online interventions are proven effective for a variety of different mental diseases such as depression (De Graaf et al., 2009), anxiety (Andrews, Cuijpers, Craske, McEvoy & Titov, 2010), eating disorders (Dölemeyer, Tietjen, Kersting & Wagner 2013) and they can be used to improve the medication adherence (Linn, Vervloet, Dijk, Smit & Van Weert 2011).

In the beginning of e-mental health, the quality and success of the e-mental health applications were questionable because this field was lacking development and style guides, which led to a variety of different applications with low user adherence and the results were hardly comparable. This was mostly due to the lack of user involvement in the design of e-mental health applications and missing collaboration between software developers and health service researchers (Pagliari, 2007).
Another major concern was the usability and safety of the clients. The potential of medical errors within the applications has to be minimized, to increase the client's safety. This goal goes hand in hand with the usability of the software and adherence in therapy because a user-unfriendly software can lead to rejection by the customer and is prone to possible medical mistakes (Karsh, 2004). Nowadays still privacy concerns and doubt about the effectiveness of online treatment remain barriers for many patients (Musiat et al., 2014).

Besides the early troubles, currently, many commercial treatment offers exist and even more research studies are conducted within this field. Additionally, many countries invested significantly into the eHealth sector, which enforced the need for development guidelines. This led rise to different proposed frameworks. The suggested frameworks are aiming at including the clients, medical researchers, and stakeholders into the development of the application, to improve the impact and the integration in the health sector (Van Gemert-Pijnen et al., 2013).

Apart from the development of software, the conduction of research studies in this field is under research and about to change. The online technologies develop that quickly that there is the possibility that when a result of a randomized trial is published, the newly studied intervention is already dated and unappealing. To prevent that clients use outdated interventions that are less effective, suggestions to speed up and improve the impact of studies were made (Baker, Gustafson & Shah, 2014).

Another problem within online treatment is early drop-out of therapy. Ineffective treatments or a lack of usability are reasons for a client to drop out of therapy, which endangers their remission. The dropout rate in mental health is a severe problem because the adherence of the clients to the therapy is essential for their remission, and the same applies to e-mental health. The adherence to computerized treatment is even significantly lower than regular treatment (So et al., 2013), and the dropout rate in e-mental health is even higher compared to regular face to face treatment (Melville, Casey & Kavanagh, 2010). This poses challenges on e-mental health, that are yet to research and conquer (Stegemann, Weg, Ebenfeld & Thiart 2012).
Ways to keep the client engaged in the online therapy are under research and fundamental for the success of e-mental health and the remission of the client symptoms. The use of a simple monthly reminder email has already shown to improve the maintenance in therapy (Gill, Contreras, Muñoz & Leykin, 2014). Since mobile phones are widely used and integrated into daily life, mobile applications are extremely useful to deliver mental-health service directly to the customer.

The use of an SMS or a reminder function can also increase the adherence to the therapeutic application and increase the engagement in the overall therapy (Whittaker, Borland & Bullen, 2009). Another benefit of using mobile applications is that they are steadily available. Especially disorders where the symptoms can appear quickly like anxiety, panic disorder or nicotine dependence can be treated effectively with mobile applications because the applications can be used whenever they are needed.

Therapeutic mobile phone applications can also be delivered as a game. The process of transforming a medical intervention into a game is called gamification. Within the gamification of an intervention, the intervention is modified in a way that they require interactions typically found in games. A recent study demonstrated that gamification of an attention-bias modification training leads to the reduction of stress and anxiety (Dennis & O'Toole, 2014). Although the effect of serious games has already been researched, there is still a lack of serious games for additional treatment of mental disorders (Fernández-Aranda et al., 2012). This is a new area of research, where the effectiveness has initially been demonstrated, but the topic still requires more research and still poses unanswered questions.

Despite the effort to improve the clients' condition a deterioration of the client symptoms is possible. Negative side effects of psychotherapy are known but have just recently been researched for the online therapeutic counterpart (Boettcher, Rozental, Andersson & Carlbring, 2014). It is yet unknown what causes the deterioration of the symptoms and what type of clients are affected. Therefore, an early identification of these clients is necessary to prevent their dropout and prevent further deterioration of the symptoms.

MACHINE LEARNING AS SUPPORTING TOOL

A therapist is likely to supervise many different clients, which makes it nearly impossible to take equality care of each client. Therefore, computer science can provide a useful tool to assist the physicians in therapy. This tool is called machine learning. Machine learning uses methods from math and statistics, to identify patterns in previously observed client's data to make predictions for new clients. These predictions can be of various types: the course the disease, the therapy outcome of the individual patient, a recommended therapy, or the identification of a disease.

One is inclined to know the outcome of the therapy beforehand, but the first available data are the demographic data of the client. An outcome prediction from this data is inconclusive and does not allow the prediction of the overall outcome of the therapy. With the beginning of the therapy more and more data of the client is collected that can be used for the assessment of the client and outcome prediction. Usually, an early response to the therapy (Van et al., 2008), the relation to the therapist and special outcome questionnaires (Schibbye, Ghaderi & Ljótsson, 2014) are used for the outcome prediction.

Outcome questionnaires, which can be used for early outcome prediction, can also be used to track the client's improvement. The measurement of the outcome questionnaire allows the estimation of the current state of the therapy for the client and a prediction of the therapy outcome based on previously observed clients (Knaup, Koesters, Schoefer, Becker, & Puschner, 2009). This property can be used to build an early warning system that compares the expected recovery patterns of the client and notifies the supervising therapist about the current recovery rate (Lueger, 1998). Computer science aids in automatically analyzing the data and proving the therapist a recommendation for each client based on previously collected data and therapy outcomes. By proving this kind of information to the therapist, the adherence and outcome results of the clients can be improved (Lambert & Whipple, 2003). In addition, this should make the work of the physicians more efficient, so that they can focus on clients prone to drop-out and therapy failure.

All these analyses can only indicate the direction of improvement or suggest clients for further review. The final judgment of the therapist is always required because the therapist might have more insight into the current situation of the client than the computer system. Nonetheless, the identification of clients that do not respond to the therapy or even deteriorate reduces costs for treating them in an unsuited therapy and these clients can attend another more appropriate therapy, which improves his conditions, earlier.

This leaves the question how could a computer estimate a beneficial treatment for the client.
A method that can be used for the estimation of a beneficial therapy for an individual client is a virtual patient model. The virtual patient is a technology that simulates real-life clinical scenarios that are mainly used for education. A virtual patient system allows the student to train his skills by interviewing the system, making

physical exams, diagnostic and therapeutic decisions. Usually, this training is done with actors that are trained to portray and report symptoms associated with a certain condition (Hubal & Kizakevich, 2000). However, the virtual patient provides standardized feedback and unlimited repetitions. In the context of the client assessment, a virtual patient model can be used to model the course of a therapy beforehand to estimate the therapy with the highest benefit (Both & Hoogendoorn, 2011).

A problem within e-mental health is the lack of visual and audio information in contrast to face to face treatment of the client. Therefore, in the case of online treatment sentiment detection could be a useful tool for the therapist to get additional information about the client's mood and condition.
During the last years, the methods of text analysis are constantly improving and have proven quite powerful. Sentiment detection can be used to extract the emotions out of text or speech samples (Chang, Fisher & Canny, 2011). These tools can assist the physician to obtain the current mood of the client out of text samples from email or chat conversation. Especially, when a diary is used within the therapy, it is sheer impossible for the therapist to read all entries for all the clients. This is where automated text analysis becomes in very handy. All the text samples from the client can be processed automatically. If the system recognizes a deterioration or an abnormality, the system would notify the therapist for further review of this client.
The methods of text analyses have also been used on suicide notes to estimate if the writer is inclined to commit another suicide attempt. The system was able to distinguish between suicide notes from suicide completers and suicide notes from a healthy control group as accurate as mental health professionals (Pestian & Nasrallah, 2010). Methods like these would be useful for the screening of writings from depressive clients.

Mobile phones and machine learning can be used to collect more subtle information about the client's behavior like its activity profile throughout the day. The identification of the daily activities of a client can be of huge benefit for its assessment because many diseases are linked to physical inactivity. The use of activity recognition has been researched for many diseases such as cardiovascular disease, hypertension, diabetes mellitus and depression (Preece et al., 2009). States of depressions are often correlated with a lack of activity. Therefore, mobile phones can be used for activity recognition and tracking of the client's daily activity level. For this measurement, the accelerometers of a mobile phone are used to recognize the current activity of a person. The activities of walking, jogging, ascending and descending of stairs, sitting and standing activities can be successfully recognized (Kwapisz, Weiss & Moore, 2011). By monitoring and processing this type of information, the therapist would have one more detail to assess the recovery process of the client.

After the successful treatment of the mental disorder, the prediction of future relapse is profitable for the estimation of the required after treatment. Relapse is a problem, especially in clients with partial remission and residual symptoms. The data of a 1-year follow-up survey was used with machine learning methods to predict the risk of depressive episodes in the future (Voorhees, Van & Paunesku, 2008). It is suggested that the clients with a low risk continue with an internet-based behavioral therapy, whereas the clients with a high risk require further face-to-face counseling.

All these methods are of great benefit for the therapist, that has to supervise many different clients. If the system provides appropriate feedback and additional information such as the mood development and daily activities, the therapist could have a clearer view on the client's condition. All these algorithms are no guarantee to prevent drop-out or deterioration of a client, but it would definitely improve the overall treatment and alleviate the work of the physicians.

DIRECTIONS FOR FURTHER RESEARCH

Based on the previous section we can define four possible categories for further research: application design, pre-treatment, treatment, relapse prevention.

These different categories are not distinct they are interconnected. Application design phase focuses on the design of e-mental health applications. This incorporates the planning and implementation. Just like in software

planning, the provides functionality has to be defined. This encompasses the front end and back end. Besides the used technologies the back end incorporates the used screenings and interventions, as well as machine learning algorithms. The front end provides the functionality to the therapists and clients. As mentioned in the previous section the usability and has to prevent mistakes by the users.
If the focus lies on the per-treatment phase, there algorithms for the identification of mental illness, outcome and dropout prediction can be researched. For example, text analysis can be used to assist the diagnosis of a patient's disorder based on text samples. The usage of words in a text provides information about a possible disease, like for the diagnosis of schizophrenia (Song & Diederich, 2014). When one plans to incorporate and research such a method within the e-mental health application, one has to go back to application design to incorporate this functionality and feedback to the therapist. The therapist might make better decisions based on the diagnostic help and provide the clients with a more suited treatment, which would require further research.
Now, where we introduced the connection between these different categories, we continue with the treatment phase. The treatment phase might be the most interesting phase because this phase has the highest interaction with the client and the most data is collected. Research studies mainly focus on the approval of a certain therapy type for a certain disease. This neglects the possibility of machine learning algorithms and the individuality of the clients' needs. One therapy design is applied to all clients, this neglects individuality. One could argue that face-to-face treatment provides more individual treatment based on the fact, that human therapists will adapt to the client. But why should an online treatment not also adapt to the requirements of the individual client. One might also argue, that this would endanger the cost-effectiveness and the treatment of more clients, but machine leaning and adequate feedback to the physicians could counter this problem. Research stated that feedback improves the adherence and improvement of the clients (Lambert 2010). Clearly, this also requires the incorporation of the application design phase, and the cooperation of the clients, therapists and financial stockholders, since each one pursues different objectives.
Moving on to the relapse prevention phase. After a successful treatment, the client requires after-care to prevent relapse. The same as in the previous treatment phase applies for the relapse prevention phase, but in addition, this phase also requires some of the results of the pre-treatment and treatment phase. Because typically after-care prediction relies on the initial symptom severity, demographic features and the symptom severity after the active treatment(Domino et al., 2005; Farren et al., 2013; Pedersen & Hesse, 2009; Voorhees, Van & Paunesku, 2008).
Finally, after research on one topic has been conducted the results have to be incorporated into the mental-health application by entering the application design phase again.

The main research opportunity is in successful incorporation of diagnosis support, drop-out, outcome, and relapse prediction into online treatment. Continues assessment of the client with provided feedback for the therapist has been realized in the past (Miller et a., 2006), but it is not established as a standard. By using these techniques, the treatment of the clients could be more individualized regarding their needs.
One could also incorporate these tools into self-help application and provide the feedback to the clients, to aid the clients to steer their therapy. The effect of such methods is yet to research.
After providing such functionality one could incorporate more fine-grained measured of the clients. Usually, questionnaires are used to assess the client, but as mentioned earlier, mobile phones can be used to capture the client's activity and condition without the client even noticing. These more fine-grained measured can further improve the quality of the predictions and could be applied to individualize the treatment.

CONCLUSION

In summary, all the discussed research topics within e-mental health require further research. This can be within the field of developing guidelines for the implementation of e-mental health applications in general, the gamification of existing interventions, the development of new intervention or even the way how research is conducted within this field.

Dropout, engagement in therapy or deterioration of symptoms are problems of e-mental health likewise in clinical mental health. Their solution is essential for the success of mental health and the well-being of the clients. Even though these phenomena are known and well researched, the results are inconclusive and in the case of symptom deterioration due to psychotherapy are not fully understood, as well as the phenomenon that

some patients improve more rapidly than others during therapy. Research has shown that a reminder email or SMS improves the adherence, but there might be more ways to keep the client engaged in therapy and to increase the frequency of interaction with the application.
The prediction of the outcome of the overall therapy for the client is closely linked to these problems. Strategies on the measurement of the client's outcome are the satisfaction of the client, engagement, relation to the therapist and the use of outcome questionnaires. All these topics are from clinical mental health, but they also apply to e-mental health where some have just recently been researched in the context of e-mental health.

Text analysis can be used to gain information about the mood of the client from text or voice samples, to compensate for missing face to face treatments. The use of mobile phones allows activity recognition to record the daily activity profile of the client. These are just two examples of a variety of possibilities for the screening of clients to observe their improvement.

Technologies are constantly evolving and paving the way for better treatment possibilities.
E-mental health is a young research topic that requires much more research, to become an accepted and effective treatment for mental disorders. The interdisciplinarity makes it a thrilling topic that poses great benefits but needs the cooperation of the medical and technical staff to become successful.

REFERENCES

Andrews, G., Cuijpers, P., Craske, M. G., McEvoy, P., & Titov, N. (2010). Computer therapy for the anxiety and depressive disorders is effective, acceptable and practical health care: a meta-analysis. *PloS One*, 5(10), e13196. doi:10.1371/journal.pone.0013196

Baker, B. T., Gustafson, H. D., & Shah, D. (2014). How Can Research Keep Up With eHealth? Ten Strategies for Increasing the Timeliness and Usefulness of eHealth Research. *J Med Internet Res*, 16(2), e36. doi:10.2196/jmir.2925

Boettcher, J., Rozental, A., Andersson, G., & Carlbring, P. (2014). Side effects in Internet-based interventions for Social Anxiety Disorder. *Internet Interventions*, 1(1), 3–11. doi:10.1016/j.invent.2014.02.002

Both, F., & Hoogendoorn, M. (2011). Utilization of a virtual patient model to enable tailored therapy for depressed patients. *Neural Information Processing*, 700–710. Retrieved from http://link.springer.com/chapter/10.1007/978-3-642-24965-5_79

Chang, K., Fisher, D., & Canny, J. (2011). Ammon: A speech analysis library for analyzing affect, stress, and mental health on mobile phones. *Proceedings of PhoneSense*. Retrieved from http://www.cs.berkeley.edu/~jfc/papers/11/AMMON_phonesense.pdf

De Graaf, L. E., Gerhards, S. a H., Arntz, a, Riper, H., Metsemakers, J. F. M., Evers, S. M. a a, … Huibers, M. J. H. (2009). Clinical effectiveness of online computerised cognitive-behavioural therapy without support for depression in primary care: randomised trial. *The British Journal of Psychiatry* : The Journal of Mental Science, 195(1), 73–80. doi:10.1192/bjp.bp.108.054429

Dennis, T. a., & O'Toole, L. J. (2014). Mental Health on the Go: Effects of a Gamified Attention-Bias Modification Mobile Application in Trait-Anxious Adults. *Clinical Psychological Science*. Doi:10.1177/2167702614522228

Dölemeyer, R., Tietjen, A., Kersting, A., & Wagner, B. (2013). Internet-based interventions for eating disorders in adults: a systematic review. *BMC Psychiatry*, 13, 207. doi:10.1186/1471-244X-13-207

Domino, K. B., Hornbein, T. F., Polissar, N. L., Renner, G., Johnson, J., Alberti, S., & Hankes, Effectiveness of a web-based intervention for problem drinkers and reasons for dropout: Randomized controlled trial. *Journal of Medical Internet Research*, 12(4).

Farren, C. K., Snee, L., Daly, P., & McElroy, S. (2013). Prognostic Factors of 2-year Outcomes of Patients with Comorbid Bipolar Disorder or Depression with Alcohol Dependence Importance of Early Abstinence. *Alcohol and Alcoholism*, 48(1), 93–98. doi:10.1093/alcalc/ags112

Fernández-Aranda, F., Jiménez-Murcia, S., Santamaría, J. J., Gunnard, K., Soto, A., Kalapanidas, E., Penelo, E. (2012). Video games as a complementary therapy tool in mental disorders: PlayMancer, a European multicentre study. *Journal of Mental Health* (Abingdon, England), 21(4), 364–74. doi:10.3109/09638237.2012.664302

Fiscal, I. (2005) *President's budget request for NIMH . Bethesda, MD: National Institute of Mental Health*

Gill, S., Contreras, O., Muñoz, R. F., & Leykin, Y. (2014). Participant retention in an automated online monthly depression rescreening program: Patterns and predictors. *Internet Interventions*, 1(1), 20–25. doi:10.1016/j.invent.2014.02.003

Harwood H. (2000) *Updating estimates of the economic costs of alcohol abuse in the United States: Estimates, update methods, and data*. The Lewin Group for the National Institute on Alcohol Abuse and Alcoholism

Hubal, R., & Kizakevich, P. (2000). The virtual standardized patient. Medicine Meets Virtual …, 1. Retrieved from http://spectra.rti.org/pubs/Patient.PDF

Karsh, B.-T. (2004). Beyond usability: designing effective technology implementation systems to promote patient safety. *Quality and Safety in Health Care*, 13(5), 388–394. doi:10.1136/qshc.2004.010322

Knaup, C., Koesters, M., Schoefer, D., Becker, T., & Puschner, B. (2009). *Effect of feedback of treatment outcome in specialist mental healthcare: meta-analysis.* The British Journal of Psychiatry : The Journal of Mental Science, 195(1), 15–22. doi:10.1192/bjp.bp.108.053967

Kwapisz, J., Weiss, G., & Moore, S. (2011). Activity recognition using cell phone accelerometers. *ACM SigKDD Explorations* …. Retrieved from http://dl.acm.org/citation.cfm?id=1964918

Lambert, M. (2010). Yes, it is time for clinicians to routinely monitor treatment outcome. Monitoring Treatment Outcome, 239–266. doi:10.1037/12075-008

Lambert, M., & Whipple, J. (2003). Is it Time for Clinicians to Routinely Track Patient Outcome? A Meta-Analysis. *Clinical Psychology: …*, 288–301. doi:10.1093/clipsy/bpg025

Linn, A. J., Vervloet, M., van Dijk, L., Smit, E. G., & Van Weert, J. C. M. (2011). Effects of eHealth interventions on medication adherence: a systematic review of the literature. *Journal of Medical Internet Research*, 13(4), e103. doi:10.2196/jmir.1738

Lueger, R. J. (1998). U*sing feedback on patient progress to predict the outcome of psychotherapy*. Journal of Clinical Psychology, 54(3), 383–93. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/9545173

McCrone, P. (2004). Cost-effectiveness of computerised cognitive-behavioural therapy for anxiety and depression in primary care: randomised controlled trial. *The British Journal of Psychiatry*, 185(1), 55–62. doi:10.1192/bjp.185.1.55

Melville, K. M., Casey, L. M., & Kavanagh, D. J. (2010). Dropout from Internet-based treatment for psychological disorders. *The British Journal of Clinical Psychology / the British Psychological Society*, 49(Pt 4), 455–71. doi:10.1348/014466509X472138

Miller, Scott D., Duncan, Barry L., Brown, Jeb, Sorrell, Ryan, Chalk, Mary Beth, Miller, S. D., Sorrell, R. (2006). Using Formal Client Feedback to Improve Retention and Outcome: Making Ongoing, Real-time Assessment Feasible. *Journal of Brief Therapy*, 5(1), 5–22.

Musiat, P., Goldstone, P., & Tarrier, N. (2014). Understanding the acceptability of e-mental health--attitudes and expectations towards computerised self-help treatments for mental health problems. *BMC Psychiatry*, 14, 109. doi:10.1186/1471-244X-14-109

Pagliari, C. (2007). Design and Evaluation in eHealth: Challenges and Implications for an Interdisciplinary Field. *J Med Internet Res*, 9(2), e15. doi:10.2196/jmir.9.2.e15

Pedersen, M. U., & Hesse, M. (2009). A simple risk scoring system for prediction of relapse after inpatient alcohol treatment. *The American Journal on Addictions / American Academy of Psychiatrists in Alcoholism and Addictions*, 18(6), 488–493. doi:10.3109/10550490903205983

Pestian, J., & Nasrallah, H. (2010). Suicide note classification using natural language processing: A content analysis. *Biomedical* …, 2010(3), 19–28. Retrieved from http://www.ncbi.nlm.nih.gov/pmc/articles/PMC3107011/

Preece, S. J., Goulermas, J. Y., Kenney, L. P. J., Howard, D., Meijer, K., & Crompton, R. (2009). Activity identification using body-mounted sensors--a review of classification techniques. *Physiological Measurement*, 30(4), R1–33. doi:10.1088/0967-3334/30/4/R01

Schibbye, P., Ghaderi, A., & Ljótsson, B. (2014). Using Early Change to Predict Outcome in Cognitive Behaviour Therapy: Exploring Timeframe, Calculation Method, and Differences of Disorder-Specific. *PloS One,* 9(6). doi:10.1371/journal.pone.0100614

Scott, E. R., & Mars, M. (2013). Principles and Framework for eHealth Strategy Development. *J Med Internet Res*, 15(7), e155. doi:10.2196/jmir.2250

So, M., Yamaguchi, S., Hashimoto, S., Sado, M., Furukawa, T. a, & McCrone, P. (2013). Is computerised CBT really helpful for adult depression?-A meta-analytic re-evaluation of CCBT for adult depression in terms of clinical implementation and methodological validity. *BMC Psychiatry,* 13, 113. doi:10.1186/1471-244X-13-113

Song, I., & Diederich, J. (2014). Speech Analysis for Mental Health Assessment Using Support Vector Machines. *Mental Health Informatics*. Retrieved from http://link.springer.com/chapter/10.1007/978-3-642-38550-6_5

Stegemann, S., Weg, R., Ebenfeld, L., & Thiart, H. (2012). Towards measuring user engagement in internet interventions for common mental disorders. *Ewic.bcs.org*, (2009). Retrieved from http://ewic.bcs.org/upload/pdf/ewic_hci12_pcp_paper7.pdf

Van Gemert-Pijnen, E. W. C. J., Nijland, N., van Limburg, M., Ossebaard, C. H., Kelders, M. S., Eysenbach, G., & Seydel, R. E. (2011). A Holistic Framework to Improve the Uptake and Impact of eHealth Technologies. *J Med Internet Res*, 13(4), e111. doi:10.2196/jmir.1672

Van, H. L., Schoevers, R. a, Kool, S., Hendriksen, M., Peen, J., & Dekker, J. (2008). Does early response predict outcome in psychotherapy and combined therapy for major depression? *Journal of Affective Disorders*, 105(1-3), 261–5. doi:10.1016/j.jad.2007.04.016

Velsen, L. Van. (2013). Designing eHealth that matters via a multidisciplinary requirements development approach. JMIR Research …, 2(1), e21. doi:10.2196/resprot.2547

Voorhees, B. Van, & Paunesku, D. (2008). *Predicting future risk of depressive episode in adolescents: the Chicago Adolescent Depression Risk Assessment (CADRA).* The Annals of Family Medicine, 503–511. doi:10.1370/afm.887.INTRODUCTION

Whittaker, R., Borland, R., & Bullen, C. (2009). Mobile phone-based interventions for smoking cessation. … *Database Syst Rev*, 11(4), CD006611. doi:10.1002/14651858.CD006611.pub3

Machine Learning: Algorithms that allow to identify patterns in data to make predictions on new data based on old data.

Data Mining: Basically the same as machine learning.

Sentiment Detection: Subfield of machine learning and natural language processing that tries to identify the emotions within a text or speech sample.

Activity Recognition: Uses methods from machine learning to identify a person's current activity.

Framework: Describes how the software has to be constructed.

Gamification: Treatments are modified and programmed as a game. The game aims at alleviating the symptoms of the client as the regular intervention would do.

Outcome Prediction: Data from previous clients and machine learning is used, to predict the outcome of the therapy for new clients.