How do substance use and mental health work for me?

Towards personalized communication in the treatment of addiction and common mental health problems with ecological momentary assessment and network models

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CHAPTER 1

General Introduction

Every day most of us produce big amounts of personal data, which in our data-driven society is often used outside of our agency, knowledge, and benefit. What if we could gain literacy and agency towards our data (Mortier et al., 2015), and use them to improve our mental health and behaviors? Technologies allowing the easy collection of personal data, such as intensive biological, physiological and self-reported personalized monitoring, enabled the development of personalized medicine (Goetz & Schork, 2018), and the birth of health self-tracking and the quantified self-movement (Appelboom et al., 2014; Feng et al., 2021; Swan, 2013). This approach also seems promising for use in communication during psychotherapy. Mental health and addiction are highly heterogeneous and dynamic, differing between people and between moments within the same person (Carroll, 2021; Fried, 2017; Galatzer-Levy & Bryant, 2013; Litten et al., 2015; Volkow, 2020; Wichers, 2014). Consequently, the use of intensive monitoring is particularly promising in this context, to understand individual dynamic psychological and addiction problems and personalize treatment (Wright & Woods, 2020).

Given that psychotherapeutic and pharmacological interventions for most mental health problems have been shown to have limited effect sizes (Leichsenring et al., 2022), improvement in treatment is strongly needed. However, in the past decades of research, neither the latent disease model of psychopathology nor the personalization approach based on identifying neurobiological substrates of psychopathology substantially improved interventions (Hofmann, 2020). The network theory of mental disorders (Borsboom, 2017; Borsboom & Cramer, 2013) is an alternative to the latent disease model that provides a promising framework to approach mental health and psychotherapy from a personalized and dynamic perspective. According to this theory, mental health problems arise from the complex interactions of psychological symptoms, contextual, social, emotional, cognitive and physical factors, and not from a latent disease. Intensive data collected by an individual can be used to estimate personalized networks graphing these interactions in the individual (Epskamp, van Borkulo, et al., 2018). Personalized networks could provide a data-driven tool to help patients and practitioners communicate, jointly understand the complex mental health processes of the patient, and consequently select personalized therapeutic approaches. Indeed, personalization based on the study of individual psychological complex dynamic processes through the network approach has been proposed as a promising new strategy to improve mental health interventions (Hofmann, 2020; Roefs et al., 2022). While initial examples of using networks in a clinical setting are available (Frumkin et al., 2021; Kroeze et al., 2017; Robinaugh et al., 2020), what is the best way do this, and whether this is feasible and effective, must be investigated. Furthermore, in

the field of substance use problems, examples of clinical applications are, to the best of our knowledge, missing.

The main aim of this dissertation is to study the feasibility and potentials of using personalized intensive data collection and personalized network models to improve personalized psychotherapy and patient-therapist communication for substance use and co-occurrent mental health problems. In this chapter, I introduce the concepts of personalized psychotherapy, ecological momentary assessment (intensive monitoring), network analysis and theory, and tailored health communication.

The need for personalized psychotherapy

As mentioned above, both psychotherapeutic and pharmacological interventions for most mental health problems seem to have small effect sizes (Leichsenring et al., 2022). Let's take a closer look at some of the most common mental health problems: Depression, anxiety and addiction. In 2015, depression and anxiety were estimated to affect, respectively, 4.4% and 3.6% of the global population (World Health Organization, 2017). Regarding addiction, the most common disorders are alcohol use disorder, estimated to affect 7% of the global population aged 15 years and older (World Health Organization, 2024), cannabis use disorder, estimated to affect 0.2897% of the global population (Degenhardt et al., 2018), and opioid dependence, estimated to affect 0.353% of the global population (Degenhardt et al., 2018). Tobacco dependence should also not be forgotten, with 22.3% of the global population aged 15 years and older using tobacco on a current basis in 2020 (World Health Organization, 2021). Given the high prevalence of depression, anxiety and substance use problems, effective treatment strategies are needed. In depression, research suggests that more than 50% of patients do not respond to psychotherapy and two thirds do not reach remission irrespective of therapy type (Cuijpers et al., 2021). Additionally, when patients do remit after treatment, they are still at risk for relapse or recurrence, with previous studies reporting, for example, 76.5% (Conradi et al., 2017) and 26.8% to 33.5% (Hardeveld et al., 2013) of patients developing a new depressive episode. In anxiety disorders there also seems to be room for improvement, as on average only 49.5% of patients seemed to respond to cognitive behavioral therapy (CBT) after therapy and 53.6% at follow-up (Loerinc et al., 2015), while 14% of patients were reported to relapse after CBT (Levy et al., 2021). In substance use disorders, research suggests that on average 30% of patients drop out from in-person psychosocial treatment, although this varies across substances

and patient demographics (Lappan et al., 2020). Furthermore, half to two thirds of individuals seem to not achieve remission, an estimate that did not significantly change when only including studies where most or all individuals were receiving treatment at baseline (Fleury et al., 2016). A meta-analysis suggested that 15% to 26% of patients with addiction receiving CBT reached better outcomes than the median of patients in a waiting-list or receiving only assessment or referral (Magill et al., 2019), indicating space for enhancement. Relapse rates also seem to be high, with 40% to 60% of patients going back to active substance use within one year after treatment (McLellan et al., 2000). Given that available treatments do work better than no treatment (Leichsenring et al., 2022; Magill et al., 2019), but there is room for improvement, how can we improve these?

A central part of psychotherapy is to make a case conceptualization with patients to understand what their psychological problems are and explain how they work, based on which treatment plans are made (Dudley et al., 2011). In CBT, functional analysis (Kanfer & Saslow, 1965) is used to examine with the patient the personalized, daily-life external (social, temporal and physical context) and internal (emotions, physical sensations, cognitions) antecedents of behavior and its consequences. Even if mental healthcare systems typically work based on categorical diagnostic systems such as the Diagnostic and Statistical Manual of Mental Disorders and the International Classification of Diseases, personalization is an inherent part of psychotherapy, where the individual and their life problems are the protagonists and not the disorder the individual is labelled with. In fact, the approach that assigns a protocolized treatment to patients based on their diagnosis, and the latent disease model of psychopathology, have been criticized to hinder progress in the treatment of mental health problems, as they do not focus on the mental health processes of the individual, how they interact with each other, and which specific psychotherapy processes can impact this complex individual system to improve mental health (Hofmann, 2020). A promising direction to improve treatment is to do all these things, which is, to help therapists to tailor therapy to each patient (Leichsenring et al., 2022). But how can we actualize this tailoring?

The role of ecological momentary assessment

To tailor psychotherapy, patients should be assessed on the variables we can tailor on. Traditional assessment methods in mental health are based on retrospective questionnaires, which can cause recall bias with over- or under-estimation of symptoms and experiences (Van den Bergh & Walentynowicz, 2016). Fortunately, the emergence of new technologies such as smartphones and wearables allows

to collect intensive time-series data, a method called ecological momentary assessment (EMA) or experience sampling method (Shiffman et al., 2008). This consists of asking individuals to answer questions on their smartphones about their current mental and physical health, behaviors, emotions, cognitions and context, usually multiple times per day for multiple days. With this method, we reduce the risk of recall bias and obtain intense time-series data that can capture the dynamic nature of the individual's mental health and its contexts. Indeed, EMA data can be used to estimate personalized models of mental health (Piccirillo & Rodebaugh, 2019; Wright & Woods, 2020). The next question then is: How can we theorize and model mental health in one individual?

Network theory and analysis

The network theory of mental health (Borsboom, 2017) proposes that the mental health of an individual is a complex dynamic network (system) composed of nodes (behavioral, emotional, cognitive, physiological, biological, social, and physical variables) that cause each other at different timescales through direct, mediated, unidirectional, bidirectional, stronger or weaker relationships (represented as edges connecting the nodes). These causal chains can often give rise to feedback loops, for example, a client may come home stressed, drink, feel better, then get tired, fall asleep early, wake up in the middle of the night, have troubles to fall asleep again, take sleeping pills, feel drowsy the next morning, drink too much coffee, get stressed again and start the whole loop again. Furthermore, the value of the nodes and their relationship with other nodes can change over time, precipitating the network into a diseased or healthy state. This provides an alternative to the traditional latent disease model of psychopathology, according to which people with mental health problems have a latent disorder that cannot be directly measured but causes observable symptoms. The network theory of mental health has been recently developed (Cramer et al., 2010), however, we can find its precursors in functional analyses from the 20th century (Haynes & O'Brien, 1990), where the problems of an individual (e.g., depression and insomnia) were investigated through functional analytic causal models (i.e., conceptual vector diagrams). Functional analyses already included characteristics of complex models such as feedback loops. They graphed multiple independent and dependent mental health variables (e.g., negative rumination, marital distrust) interacting with each other through (bidirectional) causal paths and covarying relationships of different strengths (weights), including mediated effects (Haynes & O'Brien, 1990). This may be why the network theory of mental health is so promising and popular: It gives a theoretical backbone to approaches that were

and are already used in the therapy room, supporting the further development of clinical research and practice focused on the individual as a dynamic, complex system, ultimately allowing to match therapy modules to idiographic mental health processes rather than therapy approaches to medical diagnoses.

Moving from theory to empirical research and practice, we can use EMA data to estimate personalized networks graphing the complex interactions between mental health variables in one individual. We can estimate both temporal networks, graphing the relationships between the variables over time while controlling for all other variables in the model, and contemporaneous networks, graphing the relationships between the variables within the same time point while controlling for all other variables in the model and temporal effects (Epskamp, van Borkulo, et al., 2018; Epskamp, Waldorp, et al., 2018). While estimating personalized networks from data is not without challenges, some of which will be investigated in the second chapter of this dissertation, these models could potentially indicate which problematic and protective pathways to examine and address within psychotherapy for each individual. The remaining question to touch in this introduction is: How can we integrate EMA and derived personalized networks into psychotherapy?

Tailored health communication

One could argue that communication lies at the core of most psychotherapy. Case conceptualization, functional analysis, and intervention strategies are co-created and chosen through therapist-patient communication. In fact, cumulative evidence indicates that different therapists and the quality of therapeutic alliance explain variability in therapy outcomes (Flückiger et al., 2018; Johns et al., 2019), stressing the importance of relational factors and communication in mental health care (van Os et al., 2019). Therapist-patient communication could be improved through tailoring. Tailored health communication has been defined as adjusting communication based on the personal characteristics of the individual receiving it (Hawkins et al., 2008; Noar et al., 2011). Based on the elaboration likelihood model (Petty & Cacioppo, 1986), the individual is expected to perceive this information as more personally relevant, thus to have larger attention towards it, more likely cognitively elaborate it, and therefore act on it (Fishbein & Cappella, 2006), compared to generic health communication (Hawkins et al., 2008; Lustria et al., 2016; Noar et al., 2011). Specifically, in content-tailored health communication, the content of health messages is personalized, for example based on the characteristics and determinants of the health behavior in the individual, which can be measured through surveys (Smit et al., 2024). Cumulative evidence indicates

that content-tailored health communication has more impact on targeted behaviors than generic communication (although with small effect sizes), for example in the context of web-delivered tailored interventions for smoking (Lustria et al., 2013). While psychotherapy could in itself be considered a form of interpersonal tailored health communication, the quality of tailoring may depend on the knowledge and skills the therapist has to understand the psychological processes of the patient (Noar et al., 2011; Smets et al., 2024). Measuring a patient's mental health and substance use through EMA and providing personalized information that the therapist can share and interpret with the patient during psychotherapy (e.g., as part of functional analysis) could potentially help the therapist to provide more content-tailored information to the patient, which could improve patient's processing of the information (Petty & Cacioppo, 1986) and patient active participation (Smets et al., 2024). Consequently, the patient may be able to provide more input to the therapist on how to further provide tailored communication, feeding a co-constructive dynamic communication process (Smets et al., 2024). In line with the relevance of active participation (Street & Millay, 2001) for interpersonal tailored communication, is the critical role of user-centered approaches in tailored digital health communication (Bol et al., 2020). For example, with a customization approach, patients (or users) can customize digital tools, such that communication or interventions can be personalized by the patients themselves (Bol et al., 2019; Smit et al., 2024). From the field of clinical psychology, voices also rise in favor of person-centered approaches in mental health treatment (van Os et al., 2019), and a person-centered approach based on fostering patient autonomy and self-efficacy is the core of motivational interviewing, which is a relatively effective intervention for behavioral change and substance use disorders (Miller & Rollnick, 2013). Personalized EMA and derived idiographic networks could be used to increase patients' autonomy, active participation and self-efficacy. This could be achieved, for example, by encouraging patients to select what is relevant for them to measure in the EMA and to actively interpret the resulting statistical models, transforming them into 'scientist-patients' who research their own mental health challenges and ways to improve them. Importantly, examining the patient's problems in CBT is based on empiricism to base the intervention on the patient's reality and experience, and collaborative communication to create active patient participation (Okamoto et al., 2019). In this context, using personalized networks could improve both empiricism by providing data-driven information on how different factors relevant to mental health predict each other in the daily life of the patient, and collaborative communication by introducing personalized feedback, and consequently more tailored communication and active patient participation. We conclude that integrating personalized networks into patient-therapist

communication as a communication tool is a promising strategy to improve personalized psychotherapy.

Thesis aims

This thesis aims to investigate the feasibility and preliminary effects of using personalized EMA and derived personalized networks to improve patient-therapist communication and therapy outcomes in the context of personalized psychotherapy for substance use problems and mental health. As a case study, I focus on cannabis use problems.

In the second chapter of this dissertation, I use simulations to investigate the statistical feasibility of estimating personalized networks. In the third chapter, I apply personalized EMA and network models to improve patient-therapist communication in a proof-of-principle case study in the context of cannabis use problems. In the fourth chapter, I use network analysis to explore gender differences in cannabis use disorder symptoms illustrating how between-subject networks could also give information to personalize interventions. In the fifth chapter, I illustrate a mixed-methods pilot randomized controlled trial integrating EMA and derived personalized statistics, including networks, within a short cognitive behavioral and motivational interviewing intervention for cannabis use problems. I report the applied feasibility of this approach and its preliminary efficacy to diminish cannabis use and mental health problems in young adults. In the sixth chapter, I propose approaches to integrate EMA and personalized networks in cognitive bias modification interventions for addiction. Finally, in the seventh chapter, I connect and discuss the findings of this dissertation.

References

Appelboom, G., Camacho, E., Abraham, M. E., Bruce, S. S., Dumont, E. L. P., Zacharia, B. E., D'Amico, R., Slomian, J., Reginster, J. Y., Bruyère, O., & Connolly, E. S., Jr. (2014). Smart wearable body sensors for patient self-assessment and monitoring. *Archives of Public Health*, *72*(1). Scopus. https://doi.org/10.1186/2049-3258-72-28

Bol, N., Høie, N. M., Nguyen, M. H., & Smit, E. S. (2019). Customization in mobile health apps: Explaining effects on physical activity intentions by the need for autonomy. *Digital Health*, *5*, 2055207619888074. https://doi.org/10.1177/2055207619888074

Bol, N., Smit, E. S., & Lustria, M. L. A. (2020). Tailored health communication: Opportunities and challenges in the digital era. *DIGITAL HEALTH*, *6*, 2055207620958913. https://doi.org/10.1177/2055207620958913

Borsboom, D. (2017). A network theory of mental disorders. *World Psychiatry*, *16*(1), 5–13. https://doi.org/10.1002/wps.20375

Borsboom, D., & Cramer, A. O. J. (2013). Network Analysis: An Integrative Approach to the Structure of Psychopathology. *Annual Review of Clinical Psychology*, *9*(1), 91–121. https://doi.org/10.1146/annurev-clinpsy-050212-185608

Carroll, K. M. (2021). The profound heterogeneity of substance use disorders: Implications for treatment development. *Current Directions in Psychological Science*, *30*(4), 358–364. https://doi.org/10.1177/09637214211026984

Conradi, H. J., Bos, E. H., Kamphuis, J. H., & de Jonge, P. (2017). The ten-year course of depression in primary care and long-term effects of psychoeducation, psychiatric consultation and cognitive behavioral therapy. *Journal of Affective Disorders*, *217*, 174–182. https://doi.org/10.1016/j.jad.2017.03.064

Cramer, A. O. J., Waldorp, L. J., van der Maas, H. L. J., & Borsboom, D. (2010). Comorbidity: A network perspective. *The Behavioral and Brain Sciences*, *33*(2–3), 137–150; discussion 150-193. https://doi.org/10.1017/S0140525X09991567

Cuijpers, P., Karyotaki, E., Ciharova, M., Miguel, C., Noma, H., & Furukawa, T. A. (2021). The effects of psychotherapies for depression on response, remission, reliable change, and deterioration: A meta-analysis. *Acta Psychiatrica Scandinavica*, *144*(3), 288–299. https://doi.org/10.1111/acps.13335

Degenhardt, L., Charlson, F., Ferrari, A., Santomauro, D., Erskine, H., Mantilla-Herrara, A., Whiteford, H., Leung, J., Naghavi, M., Griswold, M., Rehm, J., Hall, W., Sartorius, B., Scott, J., Vollset, S. E., Knudsen, A. K., Haro, J. M., Patton, G., Kopec, J., … Vos, T. (2018). The global burden of disease attributable to alcohol and drug use in 195 countries and territories, 1990–2016: A systematic analysis for the Global Burden of Disease Study 2016. *The Lancet Psychiatry*, *5*(12), 987–1012. https://doi.org/10.1016/S2215-0366(18)30337-7

Dudley, R., Kuyken, W., & Padesky, C. A. (2011). Disorder specific and trans-diagnostic case conceptualisation. *Clinical Psychology Review*, *31*(2), 213–224. https://doi.org/10.1016/j.cpr.2010.07.005

Epskamp, S., van Borkulo, C. D., van der Veen, D. C., Servaas, M. N., Isvoranu, A.-M., Riese, H., & Cramer, A. O. J. (2018). Personalized Network Modeling in Psychopathology: The Importance of Contemporaneous and Temporal Connections. *Clinical Psychological Science*, *6*(3), 416–427. https://doi.org/10.1177/2167702617744325

Epskamp, S., Waldorp, L. J., Mõttus, R., & Borsboom, D. (2018). The Gaussian Graphical Model in Cross-Sectional and Time-Series Data. *Multivariate Behavioral Research*, *53*(4), 453–480. https://doi.org/10.1080/00273171.2018.1454823

Feng, S., Mäntymäki, M., Dhir, A., & Salmela, H. (2021). How Self-tracking and the Quantified Self Promote Health and Well-being: Systematic Review. *Journal of Medical Internet Research*, *23*(9), e25171. https://doi.org/10.2196/25171

Fishbein, M., & Cappella, J. N. (2006). The Role of Theory in Developing Effective Health Communications. *Journal of Communication*, *56*(suppl_1), S1–S17. https://doi.org/10.1111/j.1460-2466.2006.00280.x

Fleury, M.-J., Djouini, A., Huỳnh, C., Tremblay, J., Ferland, F., Ménard, J.-M., & Belleville, G. (2016). Remission from substance use disorders: A systematic review and meta-analysis. *Drug and Alcohol Dependence*, *168*, 293–306. https://doi.org/10.1016/j.drugalcdep.2016.08.625

Flückiger, C., Del Re, A. C., Wampold, B. E., & Horvath, A. O. (2018). The alliance in adult psychotherapy: A meta-analytic synthesis. *Psychotherapy*, *55*(4), 316–340. https://doi.org/10.1037/pst0000172

Fried, E. (2017). Moving forward: How depression heterogeneity hinders progress in treatment and research. *Expert Review of Neurotherapeutics*, *17*(5), 423–425. https://doi.org/10.1080/14737175.2017.1307737

Frumkin, M. R., Piccirillo, M. L., Beck, E. D., Grossman, J. T., & Rodebaugh, T. L. (2021). Feasibility and utility of idiographic models in the clinic: A pilot study. *Psychotherapy Research*, *31*(4), 520–534. https://doi.org/10.1080/10503307.2020.1805133

Galatzer-Levy, I. R., & Bryant, R. A. (2013). 636,120 Ways to Have Posttraumatic Stress Disorder. *Perspectives on Psychological Science*, *8*(6), 651–662. https://doi.org/10.1177/1745691613504115

Goetz, L. H., & Schork, N. J. (2018). Personalized medicine: Motivation, challenges, and progress. *Fertility and Sterility*, *109*(6), 952–963. https://doi.org/10.1016/j.fertnstert.2018.05.006

Hardeveld, F., Spijker, J., De Graaf, R., Hendriks, S. M., Licht, C. M. M., Nolen, W. A., Penninx, B. W. J. H., & Beekman, A. T. F. (2013). Recurrence of major depressive disorder across different treatment settings: Results from the NESDA study. *Journal of Affective Disorders*, *147*(1), 225–231. https://doi.org/10.1016/j.jad.2012.11.008

Hawkins, R. P., Kreuter, M., Resnicow, K., Fishbein, M., & Dijkstra, A. (2008). Understanding tailoring in communicating about health. *Health Education Research*, *23*(3), 454–466. https://doi.org/10.1093/her/cyn004

Haynes, S. N., & O'Brien, W. H. (1990). Functional analysis in behavior therapy. *Clinical Psychology Review*, *10*(6), 649–668. https://doi.org/10.1016/0272-7358(90)90074-K

Hofmann, S. G. (2020). Imagine there are no therapy brands, it isn't hard to do. *Psychotherapy Research*, *30*(3), 297–299. https://doi.org/10.1080/10503307.2019.1630781

Johns, R. G., Barkham, M., Kellett, S., & Saxon, D. (2019). A systematic review of therapist effects: A critical narrative update and refinement to Baldwin and Imel's (2013) review. *Clinical Psychology Review*, *67*, 78–93. https://doi.org/10.1016/j.cpr.2018.08.004

Kanfer, F. H., & Saslow, G. (1965). Behavioral Analysis: An Alternative to Diagnostic Classification. *Archives of General Psychiatry*, *12*(6), 529–538. https://doi.org/10.1001/archpsyc.1965.01720360001001

Kroeze, R., van der Veen, D. C., Servaas, M. N., Bastiaansen, J. A., Voshaar, R. C. O. V., Borsboom, D., Ruhe, H. G., Schoevers, R. A., & Riese, H. (2017). Personalized feedback on symptom dynamics of psychopathology: A proof-of-principle study. *Journal for Person-Oriented Research*, *3*(1), 1–11. https://doi.org/10.17505/jpor.2017.01

Lappan, S. N., Brown, A. W., & Hendricks, P. S. (2020). Dropout rates of in-person psychosocial substance use disorder treatments: A systematic review and meta-analysis. *Addiction*, *115*(2), 201–217. https://doi.org/10.1111/add.14793

Leichsenring, F., Steinert, C., Rabung, S., & Ioannidis, J. P. A. (2022). The efficacy of psychotherapies and pharmacotherapies for mental disorders in adults: An umbrella review and meta-analytic evaluation of recent meta-analyses. *World Psychiatry*, *21*(1), 133–145. https://doi.org/10.1002/wps.20941

Levy, H. C., O'Bryan, E. M., & Tolin, D. F. (2021). A meta-analysis of relapse rates in cognitive-behavioral therapy for anxiety disorders. *Journal of Anxiety Disorders*, *81*, 102407. https://doi.org/10.1016/j.janxdis.2021.102407

Litten, R. Z., Ryan, M. L., Falk, D. E., Reilly, M., Fertig, J. B., & Koob, G. F. (2015). Heterogeneity of alcohol use disorder: Understanding mechanisms to advance personalized treatment. *Alcoholism: Clinical and Experimental Research*, *39*(4), 579–584. https://doi.org/10.1111/acer.12669

Loerinc, A. G., Meuret, A. E., Twohig, M. P., Rosenfield, D., Bluett, E. J., & Craske, M. G. (2015). Response rates for CBT for anxiety disorders: Need for standardized criteria. *Clinical Psychology Review*, *42*, 72–82. https://doi.org/10.1016/j.cpr.2015.08.004

Lustria, M. L. A., Cortese, J., Gerend, M. A., Schmitt, K., Kung, Y. M., & McLaughlin, C. (2016). A model of tailoring effects: A randomized controlled trial examining the mechanisms of tailoring in a web-based STD screening intervention. *Health Psychology*, *35*(11), 1214–1224. https://doi.org/10.1037/hea0000399

Lustria, M. L. A., Noar, S. M., Cortese, J., Van Stee, S. K., Glueckauf, R. L., & Lee, J. (2013). A meta-analysis of web-delivered tailored health behavior change interventions. *Journal of Health Communication*, *18*(9), 1039–1069. https://doi.org/10.1080/10810730.2013.768727

Magill, M., Ray, L., Kiluk, B., Hoadley, A., Bernstein, M., Tonigan, J. S., & Carroll, K. M. (2019). A meta-analysis of cognitive-behavioral therapy for alcohol or other drug use disorders: Treatment efficacy by contrast condition. *Journal of Consulting and Clinical Psychology*, *87*(12), 1093–1105. https://doi.org/10.1037/ccp0000447

McLellan, A. T., Lewis, D. C., O'Brien, C. P., & Kleber, H. D. (2000). Drug Dependence, a Chronic Medical IllnessImplications for Treatment, Insurance, and Outcomes Evaluation. *JAMA*, *284*(13), 1689–1695. https://doi.org/10.1001/jama.284.13.1689

Miller, W. R., & Rollnick, S. (2013). *Motivational Interviewing: Helping People Change* (3rd ed.). Guilford Press.

Mortier, R., Haddadi, H., Henderson, T., McAuley, D., & Crowcroft, J. (2015). *Human-Data Interaction: The Human Face of the Data-Driven Society* (arXiv:1412.6159). arXiv. https://doi.org/10.48550/arXiv.1412.6159

Noar, S. M., Grant Harrington, N., Van Stee, S. K., & Shemanski Aldrich, R. (2011). Tailored Health Communication to Change Lifestyle Behaviors. *American Journal of Lifestyle Medicine*, *5*(2), 112–122. https://doi.org/10.1177/1559827610387255

Okamoto, A., Dattilio, F. M., Dobson, K. S., & Kazantzis, N. (2019). The therapeutic relationship in cognitive–behavioral therapy: Essential features and common challenges. *Practice Innovations*, *4*(2), 112–123. https://doi.org/10.1037/pri0000088

Petty, R. E., & Cacioppo, J. T. (1986). The Elaboration Likelihood Model of Persuasion. In R. E. Petty & J. T. Cacioppo (Eds.), *Communication and Persuasion: Central and Peripheral Routes to Attitude Change* (pp. 1–24). Springer. https://doi.org/10.1007/978-1-4612-4964-1_1

Piccirillo, M. L., & Rodebaugh, T. L. (2019). Foundations of idiographic methods in psychology and applications for psychotherapy. *Clinical Psychology Review*, *71*, 90–100. https://doi.org/10.1016/j.cpr.2019.01.002

Robinaugh, D. J., Brown, M. L., Losiewicz, O. M., Jones, P. J., Marques, L., & Baker, A. W. (2020). Towards a precision psychiatry approach to anxiety disorders with ecological momentary assessment: The example of panic disorder. *General Psychiatry*, *33*(1), e100161. https://doi.org/10.1136/gpsych-2019-100161

Roefs, A., Fried, E. I., Kindt, M., Martijn, C., Elzinga, B., Evers, A. W. M., Wiers, R. W., Borsboom, D., & Jansen, A. (2022). A new science of mental disorders: Using personalised, transdiagnostic, dynamical systems to understand, model, diagnose and treat psychopathology. *Behaviour Research and Therapy*, *153*, 104096. https://doi.org/10.1016/j.brat.2022.104096

Shiffman, S., Stone, A. A., & Hufford, M. R. (2008). Ecological Momentary Assessment. *Annual Review of Clinical Psychology*, *4*(1), 1–32. https://doi.org/10.1146/annurev.clinpsy.3.022806.091415

Smets, E. M. A., Menichetti, J., Lie, H. C., & Gerwing, J. (2024). What do we mean by "tailoring" of medical information during clinical interactions? *Patient Education and Counseling*, *119*, 108092. https://doi.org/10.1016/j.pec.2023.108092

Smit, E. S., Linn, A. J., Nguyen, M. H., Solovei, A., de Looper, M., & van Weert, J. C. M. (2024). Tailored Health Communication in a Digital World. In T. Araujo & P. Neijens (Eds.), *Communication Research into the Digital Society: Fundamental Insights from the Amsterdam School of Communication Research*. (pp. 155–176). Amsterdam University Press. https://doi.org/10.5117/9789048560592

Street, R. L., & Millay, B. (2001). Analyzing Patient Participation in Medical Encounters. *Health Communication*, *13*(1), 61–73. https://doi.org/10.1207/S15327027HC1301_06

Swan, M. (2013). The Quantified Self: Fundamental Disruption in Big Data Science and Biological Discovery. *Big Data*, *1*(2), 85–99. https://doi.org/10.1089/big.2012.0002

Van den Bergh, O., & Walentynowicz, M. (2016). Accuracy and bias in retrospective symptom reporting. *Current Opinion in Psychiatry*, *29*(5), 302. https://doi.org/10.1097/YCO.0000000000000267

van Os, J., Guloksuz, S., Vijn, T. W., Hafkenscheid, A., & Delespaul, P. (2019). The evidence-based group-level symptom-reduction model as the organizing principle for mental health care: Time for change? *World Psychiatry*, *18*(1), 88–96. https://doi.org/10.1002/wps.20609

Volkow, N. D. (2020). Personalizing the Treatment of Substance Use Disorders. *American Journal of Psychiatry*, *177*(2), 113–116. https://doi.org/10.1176/appi.ajp.2019.19121284

Wichers, M. (2014). The dynamic nature of depression: A new micro-level perspective of mental disorder that meets current challenges. *Psychological Medicine*, *44*(7), 1349–1360. https://doi.org/10.1017/S0033291713001979

World Health Organization. (2017). *Depression and Other Common Mental Disorders: Global Health Estimates* (WHO/MSD/MER/2017.2). World Health Organization. https://iris.who.int/bitstream/handle/10665/254610/WHO-MSD-MER-2017.2-eng.pdf?sequence=1

World Health Organization. (2021). *WHO global report on trends in prevalence of tobacco use 2000-2025*. World Health Organization. https://iris.who.int/bitstream/handle/10665/348537/9789240039322-eng.pdf?sequence=1

World Health Organization. (2024). *Global status report on alcohol and health and treatment of substance use disorders*. World Health Organization. https://iris.who.int/bitstream/handle/10665/377960/9789240096745-eng.pdf?sequence=1

Wright, A. G. C., & Woods, W. C. (2020). Personalized Models of Psychopathology. *Annual Review of Clinical Psychology*, *16*(1), 49–74. https://doi.org/10.1146/annurev-clinpsy-102419-125032