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Social-Ecological Measurement of Daily Life: How Relationally Focused Ambulatory Assessment can Advance Clinical Intervention Science

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Abstract

Individuals' daily behaviors and social interactions play a central role in the diagnosis and treatment of psychological disorders. Despite this, observational ambulatory assessment methods—research methods that allow for direct and passive assessment of individuals' momentary activities and interactions—have a remarkably scant history in the clinical science field. Prior discussions of ambulatory assessment methods in clinical science have focused on subjective methods (e.g., ecological momentary assessment) and physiological methods (e.g., wearable heart rate monitoring). Comparatively less attention has been dedicated to ambulatory assessment methods that collect objective, relational data about individuals' social behaviors and their interactions with their momentary environmental contexts. Drawing on extant social-ecological measurement frameworks, this article first provides a conceptual and psychometric rationale for the integration of daily relational data into clinical science research. Next, the nascent research applying such methods to clinical science is reviewed, and priorities for further research organized by the NIH Stage Model for Clinical Science Research are recommended. These data can provide unique information about the social contexts of diverse patient populations; identify social-ecological targets for transdiagnostic, precision, and culturally responsive interventions; and contribute novel data about the effectiveness of established interventions at creating behavioral and relational change.

Keywords

ambulatory assessment, ecological assessment, naturalistic observation, social processes, intervention science

Imagine an initial psychotherapy session with John, a 43-year-old cisgender male who presents for outpatient treatment for moderate depression. Most evidence-based treatments will assess John's social context—in other words, his social interactions and behaviors in his typical daily environments. With whom does John reside, and what are John's relationships with these individuals typically like? What is his occupation, and how is he faring at work? What does John do to relax at the end of the day? What are his social experiences in his broader local community like? Many of these factors will also play an important role in John's treatment, as either goals of treatment or indicators of John's progress. John's therapist may try a range of interventions, including scheduling activities or interactions through Behavioral Activation (Martell et al., 2013); identifying value-congruent actions John can take in the context of his current circumstances through Acceptance and Commitment Therapy (Hayes et al., 2011) or Cognitive Behavioral Therapy (Beck & Beck, 2011); or examining worthwhile changes to how John approaches his interpersonal relationships through Interpersonal Psychotherapy (Weissman et al., 2008) or Brief Psychodynamic Psychotherapy (Lemma et al., 2011). Arguably, most evidence-based psychotherapeutic approaches converge on the importance of how individuals interact with their environments on a moment-to-moment basis. To date, however, surprisingly little clinical science research has incorporated a comparably explicit focus on measuring daily social-ecological variables in the development and evaluation of clinical interventions. This article aims to illustrate the added value of this research approach to clinical science,

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and in doing so, suggests research priorities that leverage observational ambulatory assessment methods to advance clinical intervention science in novel ways.

Advances in ambulatory assessment technologies—defined as self-reported, observational, or physiological methods that collect data from participants in their natural daily environments—have provoked a paradigm shift for clinical science (Harari et al., 2017; Nugent et al., 2019; Reichert et al., 2020; Wright & Zimmermann, 2019). Prior reviews of ambulatory assessment in clinical psychology have focused on methods for collecting self-reported data about patients' subjective thoughts and feelings in daily life, such as ecological momentary assessment (EMA; Armey et al., 2015; May et al., 2018; Smyth & Heron, 2014; Trull & Ebner-Priemer, 2020), or on methods for collecting physiological biomarkers during daily life, such as ambulatory physiological monitoring and actigraphy (Bertz et al., 2018; Izmailova et al., 2018; Kim et al., 2019). Other impactful discussions have focused on mobile sensing methods, which comprise smartphone applications and wearable devices that collect sensor-based data about a wide range of health-relevant and quantifiable behaviors including sleep (Sano et al., 2020), exercise/activity (Dobbins & Rawassizadeh, 2018; Weiss et al., 2019), ambient light, and GPS locations (Harari et al., 2016) that can be extracted from participants' smartphones to create "digital phenotypes" of patient populations (Torous et al., 2017). Far fewer discussions have focused on observational ambulatory assessment methods for collecting naturalistic data about relational processes—that is, people's social relationships and interactions with their momentary environmental contexts—and how these can be brought to the fore to further advance the science of clinical interventions.

This article begins by presenting a conceptual and psychometric rationale for using observational ambulatory assessment to study person–person and person–environment interactions in the context of clinical intervention science. An overview of existing methods that facilitate this research approach (e.g., naturalistic audio recording methods, mobile picture acquisition, social proximity sensors, and mobile sensing methods) is provided. Drawing on a review of recent literature, this article then proposes three areas of clinical intervention science to which the measurement of daily social-ecological data is already beginning to have a novel impact. These include: a) providing new understanding of the social-ecological contexts and daily relational behaviors of diverse patient populations, b) identifying novel targets for precision, transdiagnostic, and culturally responsive interventions, and c) evaluating the effectiveness of established interventions at creating enacted social and behavioral changes during daily life. Future directions for research are mapped onto the NIH Stage Model for Clinical Science Research (Onken et al., 2014), which provides a useful organizing framework for novel clinical science research approaches and methodologies.

Social-Ecological Measurement in Clinical Science Research: A Conceptual and Psychometric Rationale

The value of studying objectively observable person-person processes (e.g., social interactions and social proximity), and person-environment processes (e.g., interactions with objects, places, computers, organizations, animals, and wildlife) is well-recognized in many subfields of psychological science. Prior work in social and personality psychology has established a foundation for "situations research" (Rauthmann et al., 2015, 2016), which operationalizes the scientific study of psychological situations by delineating situational cues (e.g., social interactions, objects, and activities), situational characteristics (e.g., subjective psychological aspects of a situation), and situational classes (e.g., social situations vs work situations) that can be observationally assessed in daily life (Harari et al., 2015, 2020a). The term "social sensing" has also been used to describe the ambulatory assessment of real-world social interactions (Harari, et al., 2020b; Schmid Mast et al., 2015). Observational measures of "social climates" have a long history in educational research (Noonan, 2004; Thapa, 2013) and in organizational-industrial psychology (Klumb et al., 2009). Discussions about the importance of assessing daily "relational processes" and "relationality" have a long history across the social sciences, including in sociology (Bottero, 2009; Roseneil & Ketokivi, 2016), environmental psychology (Casas et al., 2021), organizational-industrial psychology (Cooper, 2005), as well as psychotherapy research (Mitchell, 2014). The measurement of such processes has also been foundational to relationship science, informing key interpersonal theories such as dyadic coping (Falconier et al., 2015) and basic research on numerous interpersonal processes such as forgiveness and relational repair (Rusbult et al., 2007).

This article examines priorities for further research in clinical science that emerge when these social-ecological frameworks are applied to the science of developing evidence-based psychological treatments. As will be discussed, methods that measure naturalistic person–person and person–environment interactions have applications across all stages of clinical intervention development and implementation. Two terms used throughout this discussion benefit from explanation. The term "*social-ecological measurement"* is used to refer to the focus of this article, which is *naturalistic and passive assessment of person-person and person-environment behaviors that signify how an individual is interacting with their momentary surrounding environments during ordinary daily life*. Perhaps owing to the multi-disciplinary nature of the extant literature on measuring social-ecological phenomena, the literature suffers from a plethora of closely related terms, including (but not limited to) those noted in the preceding paragraph. The use of the term "*social-ecological measurement*" was selected for the present discussion in order to draw upon one widely used term already adopted by other applied public health contexts (e.g., violence prevention; CDC, 2022). The term "*observational* *ambulatory assessment methods"* (Hofmans et al., 2019) is used to refer to the overarching set of methods that includes those which can be used for social-ecological measurement.

A Conceptual Rationale: Daily Social-Ecological Processes in Clinical Science

Social-ecological processes are a central component of our understanding of psychological disorders and how to treat them. Numerous etiological, maintenance, and treatment mechanisms are operationalized in behavioral and relational terms, with illustrative examples found across classes of disorders. Social and behavioral disengagement are key maintenance factors in depression, as well as many anxiety disorders (Choi et al., 2020; Heimberg et al., 2004; Hirschfeld et al., 2000). Avoidance and social withdrawal are defining features of social anxiety disorder, post-traumatic stress disorder, panic disorder, and agoraphobia, among others (American Psychological Association, 2013). Expressed emotion within family environments is understood to be a crucial maintenance and treatment factor to schizophrenia spectrum and other psychotic disorders (Hooley & Gotlib, 2000; López et al., 2004). In rehabilitative psychology, behavioral engagement and social support are recognized as critical to rehab outcomes following a stroke (Salter et al., 2010). Across diagnostic categories, functional impairment as a result of a mental disorder is operationalized in terms of dysfunction in social and occupational domains (American Psychological Association, 2013; Üstun & Kennedy, 2009).

Correspondingly, most evidence-based psychotherapeutic treatments target social-ecological processes. Child, family, and couples psychotherapy interventions frequently focus on daily interactions and the relational patterns that these interactions create (Bradbury & Bodenmann, 2020; Carr, 2012; 2014; Finkel et al., 2013; Wiebe & Johnson, 2016). As illustrated by the opening case example, individual psychotherapy interventions also incorporate an explicit focus on creating sustainable changes in how people relate to and interact with their environments. Examples of evidence-based interventions that typically address patients' behaviors and relationships include Cognitive Behavioral Therapy (Beck & Beck, 2011), Interpersonal Psychotherapy (Weissman et al., 2008), Acceptance and Commitment Therapy (Hayes et al., 2011), Dialectical Behavioral Therapy (Linehan, 2014), and Brief Psychodynamic Interventions (Lemma et al., 2011). In behavioral medicine contexts (e.g., chronic pain management and pulmonary clinics), psychosocial treatments often focus on altering relational behaviors such as social engagement, or how one paces their activities (Morley et al., 2008). A crosscutting goal of psychological interventions is to help patients alter undesired, and often habitual, patterns of behavior and interaction.

Despite the fact that most evidence-based psychotherapies target change in how people interact with their social and physical environments from moment to moment, clinical science research has infrequently incorporated objective measurement of these daily processes and outcomes. Yet, objective tracking of treatment mechanisms and outcomes is increasingly regarded as the gold standard for assessment in clinical research (Clark & Watson, 2019; Cuthbert & Insel, 2013). For example, behavioral sleep interventions pursue the outcome of increased sleep efficiency and quality, which are objectively measured through actigraphy (Sadeh & Acebo, 2002). Similarly, weight loss interventions aim to increase activity and alter eating patterns, outcomes which are both objectively assessed (Turner-McGrievy et al., 2017). The objective assessment of daily social-ecological processes makes it similarly possible to empirically examine when, how, and under what circumstances changes in patterns of relational response unfold, as well as which components of treatments are most effective in this regard.

Incorporating social-ecological measurement into clinical science research designs may also help address shortcomings on issues of diversity, equity and inclusivity. Although the links between social-ecological variables (e.g. cultural norms, systemic oppression) and clinical outcomes for established treatments are well recognized, the development and implementation of culturally competent interventions remains a recognized gap across the field (Bernal, 2006; Castro et al., 2010; Johnstone et al., 2018). Designs that assess social-ecological variables as key variables rather than as extraneous variables contributing to error variance are a vital step in advancing a more diverse and inclusive clinical science. As one example, the best approach for treating social anxiety may differ between a patient who is experiencing daily discrimination and microaggressions in their social context than one who is not (Asnaani et al., 2015; Hofmann et al., 2010). No single method is a panacea for addressing issues germane to cultural competency in research, and as will be discussed later, the methods discussed in this article confer their own unique shortcomings in this regard (see "Diversity and Inclusivity in Social-Ecological Measurement"). However, social-ecological measurement can work alongside other methodological efforts for improving the diversity and inclusivity of clinical science (e.g., the incorporation of community advisory boards and community-based participatory research designs; Newman et al., 2011) by bringing the social and environmental dimensions of patients' experiences into focus.

A Psychometric Rationale: Objective Versus Subjective Measurements of Social-Ecological Processes in Clinical Populations

It has long been possible to study people's *subjective* assessments of their social-ecological processes through self-report measures, and, more recently, daily diary and EMA designs. EMA has led to important advances in the clinical literature in this regard; for example, by making it possible to measure momentary impulsivity (Griffin et al., 2020) and its role in alcohol use behaviors in daily life (Griffin & Trull, 2020). However, as others have pointed out, subjective assessments have several limitations in the information they can provide about daily behaviors and interactions (Boswell et al., 2020; Haeffel & Howard, 2010; Mehl & Conner, 2011; Wrzus & Mehl, 2015).

First, self-report measures are filtered through what people can actually remember, making them vulnerable to recall biases and hindsight biases (Schwarz, 2011). Few people can accurately recall how many times they laughed today, when and how frequently they discussed plans for the future with others in the past week, or what proportion of their total conversations were spent complaining of a headache. Relatedly, human attention during daily life does not always register the constructs that are of the greatest interest to clinicians and researchers. For example, a patient may be able to recall the most salient features of an argument with their partner (e.g., the location, topic, and words exchanged during the most heated moments), but not the more subtle and perhaps impactful ones (e.g., duration, variations in tone, interruptions, body language, and other expressive behaviors). Further, although EMA addresses some aspects of memory bias, the frequency of prompts is limited by participant burden and measurement reactivity concerns. Even ten prompts per day would be insufficient to capture representative data on low-frequency interactions such as those just described. By contrast, because many observational ambulatory assessment methods make use of automated passive assessments that do not require action on the part of the participant, they are able to use much higher sampling rates without increasing participant burden.

Second, self-report assessments are further filtered through self-perceptions and what people are willing to report on, making them vulnerable to biases such as social desirability effects, demand characteristics, confirmation biases, and distortion through schemas about the self (Graham, 2014; Schwarz, 2011). A patient who strongly identifies with the statement "I am shy" may differently report on their momentary social behaviors than one who believes "I am an extrovert." After witnessing a disagreement between two executives at work, an employee who was raised in a conflict-avoidant home may provide a very different account of the event than one raised in an environment where differences of opinion were readily expressed.

Third, subjective reports often become more clinically useful when grounded in objective data (Sechrest et al., 1996). The best approach for treating subjective loneliness, for example, may differ between a patient who spends most of their time alone and one who spends most of their time interacting with others. A patient who claims to "never laugh" or "always fight with my spouse" may benefit from objective information about the degree to which these statements are true. Further, many clinical interventions (e.g., dialectical behavioral therapy, acceptance, and commitment therapy) explicitly aim to help individuals' decouple their subjective experience from the behavioral expression of that experience (Hayes et al., 2011; Linehan, 2014). Designs that only utilize subjective assessments of social-ecological processes are unable to examine meaningful discrepancies between subjective experience and what a third-person observer would see, a juxtaposition that often has clinical relevance. In some sense, this is the psychosocial equivalent to using a pedometer for the ground-truth measurement of actual physical activity.

The sole reliance on subjective assessments of social-ecological processes leads to empirical blind spots that are clinically meaningful, with diagnostic and treatment implications. Objective methods for examining people's daily social environments and their interactions with these environments shed light on processes that subjective assessments are simply unable to capture. In doing so, the incorporation of this assessment approach is poised to make novel and useful contributions to clinical intervention science.

Overview of Observational Ambulatory Assessment Methods for Measuring Social-Ecological Processes During Daily Life

The methods reviewed in this article utilize observational (as contrasted to self-reported) ambulatory assessment to measure aspects of people's daily social relationships and interactions with their momentary environments. Figure 1 illustrates these social-ecological measurement methods, as well as the constructs and variables they assess.

Audio and Image-Based Observational Ambulatory Assessment Methods

Electronically Activated Recorder (EAR) and Language Environment Analysis System (LENA). To date, most social-ecological measurement research has used variants of wearable audio recording technologies. One such observational ambulatory assessment method, the Electronically Activated Recorder (Kaplan et al., 2020; Mehl, 2017) makes short, periodic audio recordings of the wearer's momentary environment at intervals prescribed by the researcher, yielding an "acoustic diary" that elucidates meaningful relational patterns while still leaving the majority of participants' lives private. The resulting data can then be behaviorally coded for a wide range of social behaviors and interactions, or transcribed for analyses of real-world speech using linguistic analysis software such as Linguistic Inquiry and Word Count (Pennebaker et al., 2015). The EAR has been employed in a wide range of range of both clinical and healthy populations, in age groups ranging from early childhood to old age (Alisic et al., 2016; Demiray et al., 2020). Interested readers are directed to other detailed

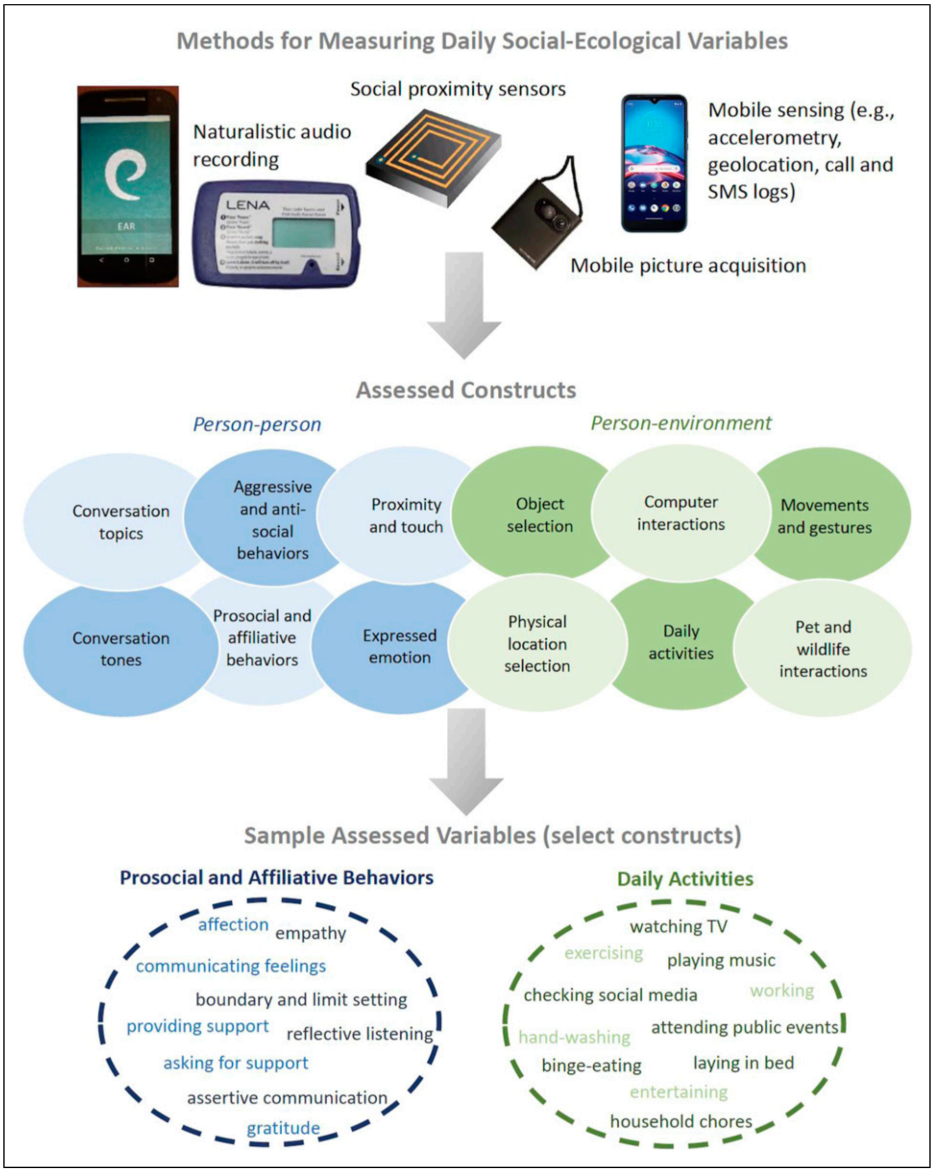

Figure 1. Social-ecological measurement of daily life: Methods, constructs and variables.

resources about the EAR method, including a detailed overview of the method (Mehl, 2017), a methodological guide to the coding and processing of EAR data (Kaplan et al., 2020), and a recent evaluation of EAR obtrusiveness and compliance (Manson & Robbins, 2017). Another novel audio recording method, the Language Environment Analysis System (Izmailova et al., 2018; Woodard et al., 2019), combines a daylong audio recorder with an automated algorithmic analysis that aims to assess children's language environments. LENA enables the objective assessment of the speech overheard and produced by the child, using child vocalization counts, conversational turn counts, and adult word counts as key metrics. Interested readers are directed to a recent review of the LENA method (Cristia et al., 2020).

Mobile picture acquisition. Other observational ambulatory assessment methods make use of portable technologies that capture visual images. The Microsoft SenseCam is a digital camera worn around the neck of the user that takes 2000 images over the course of the day, generating a "visual lifelog" of the wearer's day, from the visual perspective of the wearer (Byrne et al., 2008). Although initially conceptualized as a supplementary method to other traditional observational methods, to date the SenseCam has primarily been used as an intervention tool for supporting memory rehabilitation (Dubourg et al., 2016; Mair et al., 2019). Mobile picture acquisition differs from audio recording in that it does not capture the content of conversations and interactions. It does, however, have the potential to capture clinically relevant visual stimuli from the wearer's environment that audio recording technologies would miss (e.g., the presence of cigarette paraphernalia for an individual who is trying to quit smoking).

Mobile Sensing and Smartphone-Based Methods

Conventional smartphones are an excellent and widely accessible source of behavioral, social, and even physiological data (Ben-Zeev et al., 2015; Harari et al., 2017). A full review of the array of existing mobile sensing technologies is beyond the scope of this article, which focuses specifically on methods that capture social-ecological information. Thus, mobile sensing methods that capture other types of data (e.g., actigraphy, respiration, Bluetooth activity) are largely omitted from this discussion. Readers interested in a comprehensive review of all presently available mobile sensing methods and their utility across the health sciences are directed to other excellent works on this topic (Baumeister & Montag, 2019; Harari et al., 2017).

Most relevant to the present discussion, movement (accelerometry) and GPS location can be used to capture naturalistic behavioral data about participants' locations and frequency of movement. These and other detectable social patterns have clinical relevance for mood and anxiety disorders (Gong et al., 2019; Saeb et al., 2015). Although less directly relevant to the development, refinement and implementation of clinical interventions, call logs and SMS logs may also be important useful social data for certain clinical populations (e.g., social anxiety disorder and agoraphobia). These logs, which provide information about the quantity, length, and frequency of smartphone-mediated social interactions, may also have context-specific relevance (e.g., during the COVID-19 pandemic and computer-mediated interactions represented the sole source of social interactions for many).

Other smartphone-sensed variables such as app use logs and battery status logs (Harari et al., 2017) provide less direct data about the social-ecological variables that are most commonly the focus of clinical science interventions. However, they may have relevance when putative clinical mechanisms or outcomes concern smartphone use itself, such as for the development and evaluation of mobile health interventions, or when changing smartphone usage patterns is an explicit mechanism or outcome of treatment. Prior research in personality psychology has found that individual differences such as personality and fluid intelligence predict smartphone usage (Stachl et al., 2017); correspondingly, smartphone usage has also been found to be a significant predictor of extraversion, openness, and conscientiousness personality domains (Stachl et al., 2017). The degree to which smartphone usage data leaves a digital footprint with translational applications to psychodiagnostics and/or intervention science remains an open empirical question (Torous et al., 2017).

Social Proximity Sensing Methods

Newer technologies have recently expanded smartphone sensors into more sophisticated social sensors that can also detect social proximity. These methods provide data about how close a participant places themselves relative to others, and how long they stay, indicating the presence of substantive social interactions as well as the participants' comfort with different degrees of physical closeness in a range of settings. One recent proof-of-concept study found that RFID badges are sufficiently sensitive to measure social proximity, making them a promising measure for the study of social interactions in workplace environments (Elmer et al., 2019). Relatedly, the TotTag is a wearable device that assesses real-time physical proximity between children and their caregivers throughout the day, making it possible to examine naturalistic patterns in proximity between parents and children (Salo et al., 2020). Another new wearable technology, the Effortless Assessment of Risk States (EARS) Tool (Lind et al., 2018), combines passive collection of geolocation and accelerometry data with an active prompt to the wearer to record a daily two minute video, combining objective and subjective approaches.

Social-Ecological Measurement in Clinical Science: Extant Research and Suggested Future Directions

The measurement of social-ecological processes during daily life enables an explicit focus on person–person and person–environment processes—not just what a participant is doing, but how they are cumulatively interacting with their world. Through a review of recent literature, three facets of clinical science to which this assessment approach is already beginning to yield novel and impactful insights are suggested, and promising directions for further research are discussed. These directions for further research are mapped on to the NIH Stage Model for Clinical Science (Onken et al., 2014), which provides a useful organizing framework for the application of these methods across stages of clinical intervention science.

Providing New Understanding of the Social-Ecological Contexts and Behaviors of Diverse Clinical Populations

The health sciences field increasingly recognizes the importance of methodologies that provide a lens into patients' lived experiences. These methods can enhance and refine knowledge derived from laboratory research, as well as identify solutions to implementation and dissemination obstacles (Weissman et al., 2008). To date, incorporating patients' lived experiences into research has most commonly been achieved through hermeneutic-phenomenological approaches such as qualitative interviews, or self-reported methodologies such as EMA or daily diary designs. While these methods are well suited to characterizing patients' subjective experiences, they are unable to capture the behavioral "transcription" of private experiences (i.e., what people do and don't do throughout the day), or the family systems and broader sociocultural influences that shape lived experience. Social-ecological measurement, by contrast, enables direct inquiry into these dimensions of psychology. This measurement approach also facilitates the assessment of aspects of lived experience that are beyond what people can describe themselves—for example, a microaggression that would be noticed by a third-person observer but feels too "normal" for the person on the receiving end to report, communication that would be perceived by most objective others as "passive" but feels "assertive" to the subject, or solicitous responses to complaints of pain that are perceived by the subject as beneficial. By providing a lens into the aspects of lived experience that elude first-person description, objective social-ecological measurement approaches provide an ideal complement to subjective assessment approaches such as self-report questionnaires and ecological momentary assessment.

Although few studies have used social-ecological measurement to examine the social contexts of patient populations to date, the limited existing literature hints at what is possible. One mobile sensing study used GPS and accelerometry to map behavioral dynamics of social anxiety disorder, and found that individuals higher in social anxiety exhibit more movements around the time of phone calls, particularly when in public and unfamiliar locations (Gong et al., 2019). Another mobile sensing study applied a similar approach to depressive symptoms and found that depressive symptom severity was negatively associated with location variance, mobility between favorite locations, and regularity in movements across a 24-hour period (Saeb et al., 2015). Together, this research suggests there are differences in overall movement across the day among individuals with anxiety and depressive disorders, setting the stage for potential technology-mediated interventions that can interrupt patterns in movement (or lack thereof) that may be subtly contributing to disorder maintenance.

Studies using naturalistic audio recording methods have extended these findings by more closely examining the social interactions of patient populations. One illustrative study used the EAR method to examine family interactions following pediatric injury (Alisic et al., 2015). Researchers found that the objectively recorded daily lives of children following a serious injury remain largely characterized by typical child behaviors and activities—laughing, crying, playing, watching TV, and struggling with parents about things like homework and bedtime. Children were only involved in talking about the injury for an average of 46 minutes per day, and the emotional tone of injury talk tended to be more positive than non-injury conversations. Further, direct talk about the injury with parents was positively associated with emotional wellbeing three months after the injury, setting a foundation for the development of a family-focused intervention strategy (Alisic et al., 2017). Finally, the research approach allowed researchers to draw comparisons between data collected via self-report instruments and objectively recorded data from daily life (Mangelsdorf et al., 2019a). In some cases, objective and subjective data were congruent, and provided researchers with a window into the environmental context of subjectively reported distress. In other cases, objective data were inconsistent with self-report, providing researchers with a more accurate depiction of family environments than what families were able to describe. The approach also provided a window into important familial dynamics that evade self-report, such as emotional "alliances" between family members that are stronger when compared with relationships in the rest of the family unit (Mangelsdorf et al., 2019a).

Another study employing a similar design examined social predictors of psychosocial adjustment to a breast cancer diagnosis among breast cancer patients and their spouses (Robbins et al., 2018). The authors found that couples talked about cancer very little—cancer-related conversations comprised only 5 percent of conversations between the couple. This did not appear to be a function of avoidance, as there were no associations between conversations about cancer and self-reported assessments of cancer-related avoidance or intrusive thoughts (Robbins et al., 2014). Researchers further found that the frequency of overall substantive conversations (i.e., conversations about meaningful topics such as hobbies, interests, or the news of the day) between patients and their spouses positively predicted psychosocial adjustment for patients. This provides a foundation for the development of a couples intervention focused on enhancing mutual (and non-cancer-related) interests and activities.

It is notable that both of these observational ambulatory assessment studies found that conversations and activities related to the focal health event itself comprised very little of daily life for patients. Objectively assessed daily life was noted as sounding "normal" to researchers (Alisic et al., 2017; Robbins et al., 2014), composed largely of the typical sounds of work, play, and relating that make up modern living. Subjective assessment designs may be more likely to inadvertently overemphasize the role of health event-related activities by probing explicitly about them (potentially eliciting measurement reactivity) and by failing to adequately capture the rest of life (oversampling for health event-related thoughts and activities specifically). Observational ambulatory assessment methods are, therefore, potentially better suited for identifying intervention approaches that integrate readily with the broader picture of patients' lives. This approach is also well-aligned with models of psychotherapy such as Acceptance and Commitment Therapy (Hayes et al., 2011) that emphasize the broader values and actions that patients want to move towards, rather than focusing on the symptoms that patients want to resolve or move away from.

Audio recording-based social-ecological measurement is also an optimal approach for investigating normative and disordered language development processes. For example, one recent study piloted use of the LENA system to examine language environments in preschools that serve children with autistic spectrum disorders (Dykstra et al., 2013). Researchers were able to collect data throughout the school-day on adult vocalizations, child vocalizations, and adult–child interactions and concluded that this method was feasible for implementation in schools. The authors noted that in the future, LENA could be used for naturalistically observing progress in child communication, as well as for systematic investigations of differences in child language environments that occur during different activities throughout the school day. In another recent pilot study, researchers used the LENA to examine the home learning environments of children with hearing loss. Parent participants in the study reported finding the device to be easy to use and unobtrusive, and researchers recommended future implementation of LENA as a research tool for characterizing optimal language learning environments, as well as a clinical tool for coaching families about their child's learning environment (Charron et al., 2016).

These methods also make it possible to understand the social lives of patient populations that are difficult to access using traditional laboratory designs. One recent study tested the acceptability and feasibility of using observational ambulatory assessment to gain new insights into the psychosocial challenges faced by post-partum women (Metcalf & Dimidjian, 2020). The authors found that because this method is passive in nature and places almost no burden on participants beyond wearing the data collection device, it circumvents many of the challenges typically associated with collecting data from post-partum women. Further, observational ambulatory assessment may outperform laboratory-based measures of caregiving during infancy in predicting toddler psychopathology, as evidenced by stronger associations between naturalistic measures of caregiving with toddler psychological symptoms than associations observed for laboratory-based measures (King et al., 2020). These pragmatic advantages apply across many patient populations and across the lifespan. Other reviews have highlighted the promise of observational ambulatory assessment methods like the EAR in geriatric populations, noting that this method enables examination of the social and emotional processes that are part of healthy aging (Berke et al., 2011; Demiray et al., 2020). These methods can provide a new window into the social-ecological contexts of individuals with neurocognitive disorders who are unable to accurately recall and report on their subjective experience. Further, these methods can be used to better understand the role of cultural variables in significant life experiences such as the birth of a child or the decline of one's health, providing important data for culturally responsive interventions.

Social-ecological measurement holds promise for illuminating aspects of patients' daily contexts and interactions that have thus far been inaccessible to researchers. These research methods make it possible to address questions that subjective assessments alone are unable to. It is now possible to study, for example, the daily social-ecological processes of patients with medical conditions such as cancer or lupus, psychological disorders such as depression or schizophrenia, or complex comorbidities involving medical and psychological symptoms. Researchers can examine how momentary behaviors and social contexts interact with patients' symptoms and outcomes, which has relevance across all stages of clinical science research. This makes it possible to investigate protective and maintenance factors that are a function of social-ecological contexts, how these processes develop or decompensate over time, and how these variables interact with implementation and dissemination pathways. Moreover, as further discussed in the following section, these methods offer a way to respond to calls for investigations (Johnstone et al., 2018) into the role of social-ecological factors such as systemic oppression in mental disorders such that these data can be translated into culturally responsive interventions.

Identifying Social-Ecological Targets for Transdiagnostic, Precision, and Culturally Responsive Interventions

The publication of the DSM-5 (American Psychological Association, 2013) animated a resurgence of discussion about functional psychiatric diagnoses and the nature of psychopathology. One response, the National Institutes of Mental Health Research Domain Criteria (RDoC), promotes a shift away from classifying mental disorders based on symptom clusters and towards classifying mental disorders based on neurobiological and behavioral systems (Cuthbert & Insel, 2013). For intervention science, this has translated into an increased focus on "precision psychiatry" (Insel, 2014), commonly defined as treatment approaches that take into account "each person's variability in genes, environment, and lifestyle" (Fernandes et al., 2017). More recently, members of the British Psychological Society introduced the Power Threat Meaning Framework (PTMF), which emphasizes relational and social causes of mental distress as an alternative to biomedically centered models of psychiatry (Johnstone et al., 2018). The PTMF has provoked recognition for the urgent need for intercultural therapeutic approaches that can adequately address aspects of social context such as oppression and intergenerational trauma (Dudgeon & Bray, 2016; Johnstone et al., 2018). In clinical practice, social lenses to psychopathology have also prompted an increased focus on transdiagnostic treatment approaches that cut across categorical diagnoses (Choi et al., 2020; Fusar-Poli et al., 2019; Hofmann & Hayes, 2019; Jacquart et al., 2019).

Although there are a number of psychotherapy interventions that focus on social and relational processes directly (e.g., couples and family therapy, interpersonal psychotherapy, and intercultural therapies), these processes have been underemphasized in precision medicine as well as in transdiagnostic treatment protocols. Recent reviews note that "precision medicine" has in practice become "genomic medicine" (Gray et al., 2019), because the field has focused primarily on individual's genetic and biological profiles while neglecting the crucial roles of lifestyle and environmental influences (Phillips et al., 2019). Clinical science transdiagnostic treatment approaches have primarily focused on augmenting facets of patients' internal experience such as emotion (Sakiris & Berle, 2019) and cognition (Kaplan et al., 2018a), rather than on relational and social dynamics. The reason for the dearth of transdiagnostic protocols focused on social-ecological processes may to some extent be pragmatic: until very recently, it has simply not been possible to conduct research about people's daily behaviors and social relationships at a sufficient resolution for the development of evidence-based transdiagnostic behavioral protocols or ecologically-focused precision interventions.

Social-ecological measurement has the potential to help address this. This approach enables research into facets of distress and wellbeing that are, at least in part, either social and ecological processes themselves or downstream consequences of social and ecological processes. In the context of broad ongoing debates in psychiatry, social and ecological pathways towards pathology and wellbeing that were inaccessible only a few years ago are now feasible targets for translational clinical research. Because social-ecological measurement captures concrete processes that cut across diagnoses, it has broad applicability across diagnostic and treatment frameworks. Because data are collected from participants' actual daily ecologies, these methods have the potential to inform a new generation of contextually focused precision and transdiagnostic interventions.

Research employing such a personalized, social context-based approach is nascent and has thus far primarily focused on schizophrenia and other psychotic disorders. In one recent pilot study, patients in active treatment for schizophrenia downloaded an app onto their smartphones that could detect patterns in mobility (e.g., daily distance traveled, daily time spent at home, and daily locations visited) as well as phone-based social patterns (e.g., number of text messages sent, duration of calls, and number of missed calls). Researchers found that among those subjects who had a relapse of symptoms during the study period, the rate of anomalies in these mobility and behavioral variables was 71 percent higher in the two week period prior to relapse than anomalies detected in dates further away from relapse (Barnett et al., 2018). Another recent study recorded samples of naturalistic daily speech in individuals endorsing elevated traits of schizotypy (Minor et al., 2018). Through lexical analyses of these recordings, the authors found that differences in level of social engagement, and differences in verbalized negative affect, both differentiated high versus low levels of schizotypy.

Together, these preliminary studies lay groundwork for the development of personalized, momentary interventions that can alert patients to prodromal behavioral changes that may be below their threshold of awareness. In addition, further research using observational ambulatory assessment methods like those employed by Minor et al. (2018) could build upon laboratory research on expressed emotion (López et al., 2004) by capturing the social feedback loops within families that contribute to the escalation and maintenance of psychotic symptoms. This would allow for an examination of expressed emotion beyond what families are able to describe and report on themselves, extending, for example, research about the role of culture in expressed emotion (Aguilera et al., 2010). This could ultimately translate into transdiagnostic and culturally adapted family-focused interventions.

Social-ecological measurement also makes it possible to collect real-world social data in tandem with real-world physiological data. One of the few studies to attempt this to date examined the interaction between inflammation and family environment in pediatric asthma patients. Researchers collected digital audio recordings of daily family social interactions from participants, as well as NR_3C_1, an anti-inflammatory regulatory gene extracted from peripheral blood. Reduced NR_3C_1 expression is known to increase susceptibility to inflammatory disease over time, and is also linked to glucocorticoid resistance, which increases the frequency of asthma attacks and makes them more difficult to control with corticosteroid medications. The authors hypothesized that lower socioeconomic status (SES) would be associated with reduced NR_3C_1 expression. The study found that there were no direct effects of socioeconomic status (SES) on NR_3C_1 expression; however, there was a significant mediation path such that low SES was associated with a more negative family emotional climate, which in turn predicted reduced NR_3C_1 expression (Farrell et al., 2018). This finding sets the stage for further research investigating family environment variables that can impact NR_3C_1, potentially leading to family interventions that can improve health outcomes for children who have asthma. This study exemplifies how incorporating social-ecological measurement into multi-method designs can inform the development of precision interventions that are able to account for the interconnection between biological, psychological, and social-ecological factors (Borrell-Carrió et al., 2004; Engel, 1981).

These methods could also potentially be used to develop and improve interventions that fit the needs of diverse individuals by providing data that can support culturally adapted interventions (Cabassa & Baumann, 2013; Castro et al., 2010). For example, social-ecological measurement can answer questions that can inform existing precision interventions (e.g., are differences in daily relational experiences of depressed individuals linked to varying culturally-based social norms such as gender roles, and are there different corresponding social intervention targets as a consequence?) Real-world social data also have the potential to make vital contributions to ongoing efforts to improve interventions so that they better meet the needs of persons who experience oppression and/or discrimination. Measuring objective social interaction data can reveal the influences of structural and cultural variables (e.g., microaggressions or culturally affirming words and actions) often unassessed in clinical research. Such measurement is not only vital to understanding the broad social context within which interventions take place, but can also meaningfully contribute to intervention adaptation for diverse populations (Cabassa & Baumann, 2013; Castro et al., 2010). These data can inform targeted approaches that work alongside patients' belief systems, and can inform the development of therapeutic interventions anchored in core values of social justice, liberation, and empowerment (Johnstone et al., 2018).

Finally, social-ecological measurement may be particularly well suited for advancing precision psychosocial interventions for patients with medical conditions. Researchers could, for example, use mobile sensing to track the daily locations, movements, and social interactions of individuals with chronic pain. Using GPS and accelerometry data, researchers could examine patterns in associations between self-reported pain and daily movements and locations (e.g., Are there patterns in activity pacing that are associated with lower pain levels throughout the day? Within pain disorders, is there an amount of daily movement that is optimal?) This assessment approach can be used to develop Just-in-Time Adaptive Interventions (JITAI) for patients, interventions delivered through mobile technologies such as smartphones or wearables that tailor the intervention provided to the patient's real-time circumstances and needs (Nahum-Shani et al., 2015; 2018). In the context of pain, for example, JITAI can potentially help patients detect associations between their pain level and various activities, as well as alert patients to alter their momentary activity level (e.g., sitting down to take a break and getting up for some gentle movement). Observational ambulatory assessment methods that record real-world daily conversations and interactions can also be incorporated to examine a wide variety of social variables relevant to pain. Target variables might include how patients' family members respond to reports of pain, the emotional tone of conversations about pain, the social contexts during which reports of pain increase (e.g., during spousal conflict or withdrawal, after being alone all day), and pain centrality (the frequency and extent to which pain is a focus of daily conversations overall). These data could then inform the development of new couples and family interventions for chronic pain. Such data can also be used to evaluate and improve upon the effectiveness of existing individual interventions that incorporate a social focus (Morley et al., 2008), as will be further discussed.

Evaluating the Effectiveness of Interventions at Facilitating Enacted Change in Daily Life

Implicitly or explicitly, the goal of psychological interventions is to help people facilitate desired, value-congruent change as they go about their days. Assertive communication skills may be practiced in session with a therapist, but the true test of the effectiveness of assertiveness training is what unfolds in the moment the patient has a disagreement with someone in their life. A therapist may elicit a new communication approach during a couples or family session, but the best metric of the intervention's impact is how family members interact during humdrum moments at the breakfast table or respond to one another during stress. Common therapeutic tools such as cognitive reframing, emotional acceptance, family of origin insights, behavioral activation, urge surfing, and relaxation training all aim to increase the automaticity of adaptive psychological responses so that they may be called upon during even the most fraught moments of daily living. In other words, the goal of these therapeutic interventions is that they will generalize outside of the therapy session and into the contexts of patients' daily lives.

Over the course of the last decade, understanding mechanisms of therapeutic change and the intervention dosage required to facilitate change have emerged as sustained priorities in psychotherapy research (Kazdin, 2009; 2014). Observational ambulatory assessment methods have made it possible to examine these efficacy and effectiveness questions with new acuity. In addition to capturing real-world data from participants during moments that may otherwise be difficult to recollect, the resulting data can be analyzed using time-lagged and time-varying effects models that hone in on within-person patterns at the momentary level (Falkenström et al., 2020; Shiyko et al., 2012). Prior reviews have primarily focused on EMA in this regard, pointing out that subjective momentary data shows promise for examining within-person patterns of key processes and for improving existing psychosocial interventions (Falkenström et al., 2020; Smith & Juarascio, 2019; Smyth & Heron, 2014; Smyth & Stone, 2003). In one illustrative example from the EMA literature, Cohen et al. (2008) used nightly electronic diaries to investigate the relationships between daily stressors, negative affect and rate of improvement in a cognitive therapy intervention among depressed patients. The authors found that although within-day negative affect did not predict response to cognitive therapy, patients who had a "negative affect spillover" such that they experienced high levels of negative affect the day *after* a stressor were slower to respond to the treatment. Within-person findings such as these can be used to tailor interventions to best address the needs of patients who have difficulty bouncing back from stressors and may otherwise be slow to show improvement in therapy.

The addition of social-ecological measurement to research designs such as this can add a valuable behavioral dimension to research. Whereas EMA makes it possible to identify components of interventions that most strongly predict *perceived* change in daily life, social-ecological measurement makes it possible to identify components of interventions that most strongly predict *enacted* daily change. In fact, several recent EMA studies have highlighted the integration of momentary behavioral data as a relevant future direction for intervention evaluation, including smoking cessation (Tan et al., 2020), treatment adherence interventions (Baglione et al., 2020), and behavioral activation (Forbes, 2020). Others have also noted that behavioral data can guide the development of JITAI that are responsive to states of opportunity facilitated by the individual's social environment (Nahum-Shani et al., 2018). For example, a number of recent studies have collected accelerometry and GPS data to aid in the delivery and improvement of JITAI for reducing sedentary behavior (Müller et al., 2017; Thomas & Bond, 2015). In behavioral sleep medicine, there have been recent innovative attempts to use actigraphy technologies to develop fully automated digital Cognitive Behavioral Therapy for Insomnia (CBT-I) (Kang & Kim, 2019).

However, to date, there have been very few attempts to employ social-ecological measurement approaches to evaluate psychosocial intervention efficacy (the performance of an intervention under ideal conditions) or effectiveness (the performance of an intervention in real-world clinic settings). There have been two preliminary attempts to do so that this author is aware of. One pilot study used the LENA to establish feasibility for evaluating the effectiveness of parent intervention programs using an audio recorder for the assessment of children's language environments. The authors found that the intervention tested produced minimal effects on parent word count and conversational turns between parents and children. However, they found high levels of participant compliance with the method, suggesting that this naturalistic approach could be used to improve future parent interventions based on real behavioral data (Weil & Middleton, 2010).

In another recent study, researchers used the EAR method to record soundbites of the daily lives of healthy adults before and after they participated in an eight-week mindfulness meditation, compassion meditation intervention, or health education discussion group (Kaplan et al., 2022). In addition to collecting behavioral data, pre and post assessments in this clinical trial also included self-report psychosocial questionnaires and physiological measures of biological stress reactivity that have been commonly used in efficacy trials of meditation interventions. Given the large body of research indicating salutary and prosocial effects of short-term meditation classes, the addition of naturalistically-assessed audio allowed researchers to examine whether meditation facilitates objectively observed social and behavioral changes in daily life, aside from what participants may report. Unfortunately, the meditation interventions used in the study did not produce reliable effects on any of the measures used in the study (including the self-report and physiological assessments), and so the study was unable to address the question of whether meditation interventions that facilitate self-reported change and changes in biological stress reactivity also create measurable changes in daily social life. However, the high rate of adherence to EAR data collection in this study provides a valuable acceptability and feasibility data point for the use of naturalistic audio recording methods in evaluating health and lifestyle interventions.

Finally, social-ecological measurement approaches that objectively capture social interactions also make it possible to investigate how social environments change back in response to individuals' own enacted changes. This has been identified as a future direction for understanding mechanisms of change in family therapy (Mangelsdorf et al., 2019a) and couples therapy (Reblin et al., 2018; Rentscher, 2019) as everyday communication constitutes the vast majority of couple and family interactions and is strongly predictive of relationship health. However, these questions are also relevant to individual treatment approaches. As an individual engages in new behaviors and ways of responding to his or her social context, the social context (family members, friends, partners, colleagues, and the greater community) inevitably responds back, in turn either reinforcing or discouraging the behavior change. These transactional change processes are a current topic of interest in pediatric (Goodman et al., 2019) and addiction literatures (Daley, 2013) but have often been overlooked in other discussions of behavior and psychopathology (Johnstone et al., 2018). Social-ecological measurement makes it possible to examine how, and under what circumstances, psychosocial interventions create change cascades within individual's immediate social environments. These methods also make it possible to objectively assess which components of interventions are most effective in this regard.

Mapping Social-Ecological Measurement onto the NIH Stage Model for Clinical Science Research

This article has proposed three broad contributions that social-ecological measurement can make to clinical science: providing new understanding of the social contexts and daily behaviors of diverse patient populations; identifying social-ecological intervention targets that can inform the development of new precision, transdiagnostic and culturally responsive interventions; and evaluating the effectiveness of established interventions at creating enacted change in daily life. In order to anchor social-ecological measurement within the broader framework of clinical science, the table and figure that follow map these contributions onto research questions following the NIH Stage Model for Clinical Science Research (Onken et al., 2014).

The NIH Stage Model is a model of intervention development that is guided by the assertion that intervention development work is unfinished until an intervention "reaches its highest level of potency and is implementable with the maximum number of people in the population for which it was developed" (Onken et al., 2014 pgs. 8–9). Rather than being a prescriptive and linear model, it is iterative and recursive, advocating for novel research that fills knowledge gaps as they become apparent. The NIH Stage Model is therefore an ideal organizing framework for the application of new clinical research methods and approaches. For example, it has been previously used to guide discussions identifying gaps in the evidence-base for mindfulness-based interventions (Dimidjian & Segal, 2015), as well as for identifying best practices for developing technology-based behavioral treatments (Onken & Shoham, 2015). Here, the NIH Stage Model is used to organize and summarize the clinical science research questions presented in this article (Table 1). Figure 2 then provides a population-based example (comorbid depression and chronic pain) of how social-ecological measurement can fill knowledge gaps across stages of intervention development.

Limitations and Methodological Considerations

Like all methods, the approaches discussed in this article have drawbacks and limitations. Primary concerns that warrant careful consideration include conceptual and methodological issues germane to the study of clinical interventions, diversity and inclusivity in research, data privacy and ethics, and feasibility concerns.

Social-Ecological Measurement in Clinical Science: Conceptual and Methodological Concerns

Although this article has highlighted the centrality of social-ecological processes to clinical science, it is important to bear in mind that such processes are just some of the many clinically important facets of human psychology. Thus, used on their own, the methods described in this article have major limitations. Not all clinically relevant psychological processes have concrete behavioral endpoints, and not all internal experiences are behaviorally expressed. Social behavior is subject to social, cultural, and contextual constraints, as well as to an individual's emotion regulation repertoire and how they choose to respond to internal experience (Kaplan et al., 2018b). Research designs that combine social-ecological measurement with other assessment methods are often necessary for complete examinations of constructs of interest. For example, some clinical interventions such as dialectical behavioral therapy (Linehan, 2014) have the explicit aim of helping individuals' separate their subjective experiences from the behavioral expression of that experience. Optimal research designs for this intervention may be those that combine social-ecological measurement with EMA or daily diaries, in order to investigate meaningful similarities and discrepancies between internal experience and expressed behavior. Combining social-ecological measurement approaches with ambulatory physiological monitoring (e.g., continuously assessed heart rate and daily measures of salivary cortisol) also has novel potential, as this approach makes it possible to investigate how real-world social interactions impact and interact with physiological processes.

A related consideration important to intervention science is that interpersonal change is sometimes regarded as an outcome of treatment, and other times regarded as a treatment mechanism. Relational change is a commonly targeted treatment

Table 1. Social-Ecological Measurement of Daily Life: Research Questions Organized by the NIH Stage Model for Clinical Science Research.

Stage	Research Questions
0. Basic research	-What are the daily behaviors and social interactions of the target patient population? -How do daily behaviors and social interactions of the target population differ from healthy populations (or other patient populations)? -What patterns in person–person and person–environment behaviors predict and maintain symptoms of disorders? -What is the impact of social-ecological influences (e.g., cultural variables, racism, sexism, classism, and ableism) on the development and maintenance of disorders?
I. Intervention generation/Refinement	-What patterns in person-person and person-environment behaviors correspond with remission, resilience trajectories, and recovery? -How do protective social-ecological processes develop or decompensate over time?
II-III. Efficacy (Research Clinics and Community Clinics)	-What components of interventions are most efficacious at promoting *enacted,* observable change in individuals' daily social lives? -What "dosage" of the intervention is necessary to produce measurable social or behavioral changes in daily life? -For Just-In-Time Adaptive interventions, what social-ecological cues (e.g., location, activity, or presence or absence of social interaction) represent ideal intervention points?
IV. Effectiveness	-What social-ecological variables (e.g., discrimination or culturally affirming behaviors) moderate the effectiveness of the intervention, and how can interventions be adapted accordingly? -How do individual's social contexts change in response to behavioral or social changes made by the patient?
V. Implementation and dissemination	-What social-ecological variables are implementation determinants of the intervention?

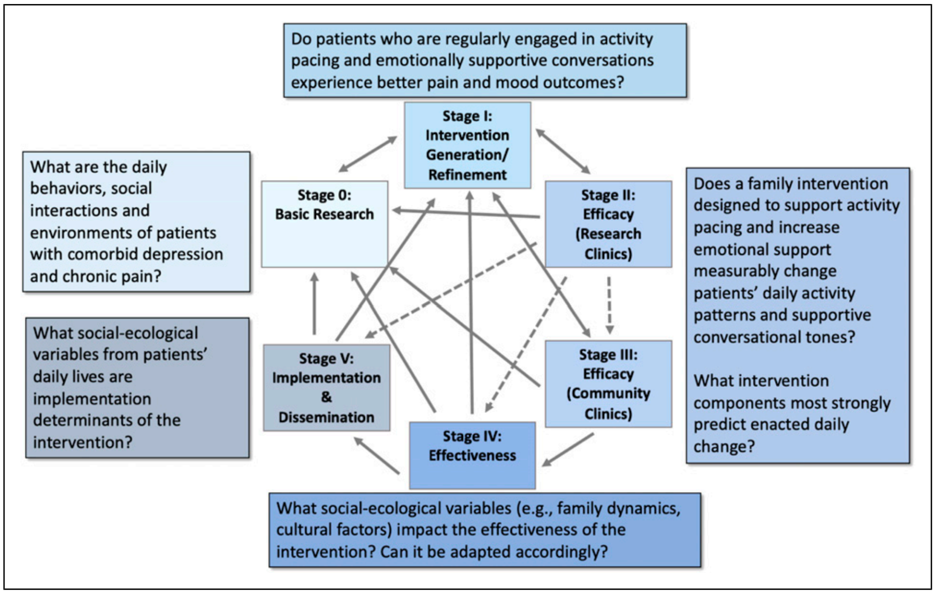

Figure 2. Social-Ecological Measurement of Daily Life Applied Across the NIH Stage Model: A Case Example of Comorbid Depression and Chronic Pain. *Note.* Figure adapted from Onken et al. (2014). Pathways recommended by Onken and colleagues are indicated with solid arrows; pathways that Onken and colleagues recommend should be undertaken with caution are indicated with dashed arrows. The *daily behaviors and social interaction* variables can be assessed using audio recording technologies such as the EAR (for assessments of activities, environments, conversational tones and topics, family dynamics), mobile picture acquisition (for assessments of activities and objects in the physical environment), or social proximity sensors (for assessments of time spent proximal to others). *Activity pacing* can be assessed using mobile sensing methods such as GPS location and accelerometry (for second-level assessments of movement). Wearable accelerometers, such as those found in commercially available activity monitoring watches, may offer superior accuracy to accelerometers built into smartphones. *Social-ecological variables* (e.g., family dynamics and cultural variables such as experiences of discrimination or cultural affirmation) can be assessed using audio recording technologies such as the EAR, which can be coded for social-ecological variables of interest. *Depression and chronic pain*, the dependent variables indicated above, are subjective variables best assessed using self-report measures (e.g., conventional self-report inventories and daily assessments using ecological momentary assessment or daily diaries).

outcome for couples and family interventions and for interpersonal psychotherapeutic interventions. Social changes are better conceived of as treatment mechanisms for interventions such as behavioral activation, which may involve scheduling social activities as a means toward the outcome of a reduction in symptoms of depression (Martell et al., 2013), or behavioral treatments for pain, which aim to create social changes in patients' lives as part of a broader pain management protocol (Morley et al., 2008). Whether social-ecological change is intended to be an outcome or a mechanism of the intervention is an important specification in research design. When such change is conceived of as a mechanism of the intervention rather than the outcome, observational ambulatory assessment methods can help identify the specific person–person and person–environment processes that have the greatest impact on the intended treatment outcome.

Finally, it is important to note that measurable relational and behavioral changes may set a very high bar when specified as an outcome. Longstanding behavioral patterns tend to be ingrained. Making even the most concrete health behavior change such as establishing an exercise routine, modifying one's diet, or increasing treatment adherence is typically hard-won, as evidenced by small effect sizes for many health behavior interventions and variance in intervention efficacy as a function of participant and intervention characteristics (Johnson et al., 2010). Fewer data are available on changing social behaviors and habitual patterns of interpersonal responding, but leading relational theories such as attachment theory (Cassidy & Shaver, 2002) and social baseline theory (Beckes & Coan, 2011) suggest that patterns of interpersonal responding are entrenched and change only with considerable time and effort. Researchers may therefore reasonably hypothesize that longer-term interventions are required to produce measurable relational effects, and that effect sizes will generally be small. These hypotheses warrant empirical investigation, and future social-ecological measurement research can address questions about the "intervention dosage" required to facilitate such changes.

Diversity and Inclusivity in Social-Ecological Measurement Research

Many of the methods described in this article require human coding and processing by a research team. For example, in order to turn qualitative EAR sound files into quantitative data that can be analyzed, coders must listen to each sound file and then make binary decisions based on the coding system for the project (e.g., whether or not a conversation constitutes "conflict"; whether or not a remark directed at a participant constitutes a "micro-aggression") (Kaplan et al., 2020). Similarly, applications of methods such as the mobile picture acquisition may involve coding decisions that parse images into coding system-based categories. Coding systems, by definition, reflect the meaning-making systems of the research teams who design them and the coders who implement them. Thus, although these methods record "objective" data in the sense that the data are observable and traceable, they are still highly vulnerable to subjective researcher biases. Ultimately, researchers make determinations about what information is coded and analyzed, what information is left uncoded, and how these data will be interpreted. The explicit priorities of the research team, as well as researcher implicit bias, can easily seep into data coding and analysis.

To help mitigate these sources of bias, and to maximize the contributions that these methods can make to developing interventions that work alongside individuals' actual social experiences and cultural systems, this article advocates for following the lead of established qualitative methods in adopting a Community-Based Participatory Research (CBPR) approach to the development of coding systems. CBPR methods involve engaging members of the target population in the design of research. In doing so, these methods enhance data quality, contribute to the development of culturally authentic frameworks for research and practice, and minimize gaps between research and translation (Collins et al., 2018; Hacker, 2013; Minkler & Wallerstein, 2011). Applying CBPR to the methods discussed in this article involves recruiting members of the population being studied to contribute to the process of developing of coding systems (e.g., through focus groups), as well as including members of the target population on the research team (e.g., to code data and or to train coders in using the coding system). For methods that making use of automated coding, members of the target population can help researchers contextualize and interpret findings, as well as understand sources of bias that may be inherent to automation. Although the incorporation of a CBPR approach does not eliminate subjective bias inherent to coding social data, it is an important step in deferring expertise about social-ecological variables to the experts themselves: those with actual lived experience of them.

Data Privacy and Ethics

Collecting data from daily life constitutes an intrusion into the private lives of participants that extends beyond concerns that arise in laboratory-based research. The specifics of these concerns and the best practices for addressing them varies by method, and a full treatment of the privacy considerations for all methods discussed in this article is beyond the present scope. Interested readers are instead directed to other comprehensive reviews about navigating privacy considerations in mobile sensing research (Kargl et al., 2019), ethical considerations for research that uses location and accelerometry data (Fuller et al., 2017), research ethics for mobile sensing in vulnerable populations (Breslin et al., 2019), data ethics and privacy considerations for methods that make use of long-form audio recordings, (Cychosz et al., 2020), legal and ethical concerns in research using social environment sampling methods (Robbins, 2017), and privacy considerations germane to the EAR method specifically (Mehl, 2017).

An important consideration that cuts across many (although not at all) methods described in this article, and that warrants further discussion, is the potential of these methods for collecting data from individuals who are not the target participant. By definition, social interactions involve multiple parties, and research methods such as the EAR, LENA, SenseCam, and social proximity sensors therefore may collect data about individuals other than the primary participant who has provided informed consent to participate in research. This creates legal as well as ethical challenges. Legally, within the United States, some states require the consent of one party (the participant only), and other states require "two-party consent"; that is, all parties who are recorded. In the context of research, it is logistically impossible to obtain consent from all individuals that a research participant may encounter (e.g., in a crowded shopping mall). As other discussions have previously suggested, researchers may wish to provide participants with a visual signifier of the nature of the research that they are participating in (e.g., by wearing a button that says "I'm participating in research! This conversation may be recorded") (Manson & Robbins, 2017; Mehl, 2017). It is also critical that, at the level of data processing, researchers take steps to protect the privacy of individuals from whom information is captured but who have not consented to participate in research. These steps can include only coding and transcribing information collected from the target participant, and promptly deleting identifying or other sensitive information captured from non-consented parties (Mehl, 2017).

Feasibility

A final cautionary note concerns the practical feasibility of these methods. Most if not all of the methods referenced in this article require specialized expertise to implement. This includes researcher knowledge of individual apps, software platforms and devices, the Application Programming Interface (API) associated with data extraction, the systems necessary for processing the resulting data (e.g., geocoding algorithms, behavioral coding systems), as well as the statistical expertise in intensive longitudinal data analysis needed to integrate large and complex data streams (see Lane et al., 2019; Yao et al., 2017 for two excellent resources on the latter concern). The rate at which technology evolves—very rapidly when compared with the speed of scientific research—adds to these challenges. Researchers may find themselves in the difficult position of having a generation of a needed device discontinued mid-way through a research study, for example. Operating system upgrades (e.g., to iPhone or Android) can also inject unforeseen bugs into a previously well-functioning smartphone app. For complex multi-method studies, it can be beneficial to collaborate with a computer scientist when possible, who can offer the expertise needed to foresee and address such challenges.

Correspondingly, the methods reviewed in this article are also costly and time-consuming when compared with survey-based methods. Although some of the methods discussed make use of participants' own devices, other methods (e.g., EAR, LENA, TotTag, and SenseCam) require the purchase of devices for participants, which can quickly become expensive for larger studies. Further, methods that require human coding prior to quantitative data processing such the EAR and SenseCam can be very time-consuming, with coding often taking years to complete. Although continued technological advances such as audio signal processing (Sharma et al., 2020) may mitigate the time burden of human coding in the future, at present, adequate technologies for this do not yet exist. The uniqueness and added value of the data yielded by these methods makes them well worth the costs of expertise, funding, and time in the context of clinical science research. However, it is important to acknowledge that the incorporation of these research methods constitutes a non-trivial undertaking.

A related question concerns whether these methods can be feasibly integrated into clinical practice to enhance psychotherapy outcomes. If these technologies pose feasibility challenges to dedicated research teams, can time-strapped clinicians realistically incorporate them into assessment and treatment? Recent discussions have explored the feasibility of incorporating audio recording methodologies (e.g., EAR) into clinical practice (Mangelsdorf, et al., 2019b). To date, one pilot study has attempted to use the EAR to tailor a psychotherapy intervention. Minor et al., (2021) asked patients to wear the EAR for two days following a psychotherapy session, using a sampling rate of 5 minute recordings every 90 minutes (2 hours of audio recorded per week). Captured social interactions were identified using .wav files, and therapists in the study reported that they spent approximately 15–30 minutes per week reviewing sound files for each patient. For a clinician who sees 8–12 patients per day, reviewing this volume of naturalistically assessed data would thus amount to an extra 2–3 hours of work per day.

For data such as these to be feasibly incorporated in psychotherapy practice at-scale, it may therefore be necessary to put the burden of reviewing the collected data and selecting key moments to be discussed during therapy sessions onto the *patient,* rather than onto the therapist. This approach offers several advantages beyond reducing time burden on therapists: keeping the data in the hands of the patient also circumvents some of the potential ethical concerns (e.g., privacy and intrusiveness) associated with incorporating at-home observational assessment into psychotherapy. Further, it ensures that the real-life events focused on in the therapy session remain in line with the *patients'* goals for incorporating these methods into treatment. Finally, such an approach is consistent with findings that psychotherapy "homework" enhances treatment outcomes (Kazantzis & Lampropoulos, 2002).

Conclusion

Most if not all perspectives in modern psychiatry converge on the importance of daily social-ecological processes to health, wellbeing and disease (American Psychological Association, 2013; Cuthbert & Insel, 2013; Johnstone et al., 2018; Lehman et al., 2017). Until recently, the researcher's toolbox for examining the unfolding of these processes during actual daily life has been critically limited. Researchers have largely had to rely on subjective measures, which have a number of recognized drawbacks (Boswell et al., 2020) including recall biases, hindsight biases, social desirability effects, demand characteristics, and distortion through schemas of the self. Our observations of our own social-ecological processes are circumscribed by the lens of our psychological landscape; in some sense, as the writer Jim Harrison put it, "the days are stacked against what we think we are" (Harrison, 2012). The methods reviewed in this article capture patterns in person–person and person–environment processes that elude what people can readily detect and report on. In doing so, the inclusion of social-ecological measurement in clinical science research designs can contribute novel and valuable data to the development and evaluation of evidence-based interventions.

Most clinical science interventions aim to provoke change at the momentary level. What an individual does during this moment, and the next, cumulatively becomes what they are doing. By providing novel and objective data about how people are interacting with their social and ecological worlds, these methods make it possible to better understand the multifaceted complexities of enacted clinical change, which has been a sustained but elusive priority for the field (Nielsen et al., 2018). Observational ambulatory assessment methods can provide insights into the daily social and ecological experiences of diverse patient populations, identify novel intervention targets that account for social context, aid in the development of culturally responsive and culturally adapted interventions, and contribute new data about the effectiveness of interventions at facilitating enacted (as contrasted to perceived) change in daily life. The incorporation of these methods therefore stands to elevate the "social" side of a biopsychosocial clinical science.

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