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Digital Life Data in the Clinical Whitespace

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Abstract

In our increasingly digital world, aspects of our lives are encoded in the routine interactions we have with technology. Over the past few years, psychologists and technologists have been exploring what possibilities these *digital life data* might hold for improving mental health and well-being. Here I examine some of the recent advances in this field, particularly in the use of language data; consider the ethical and pragmatic implications of this technology; and examine a few areas where I believe these advances could significantly alter the way in which mental health and well-being are approached. This technology holds special promise for providing information about a patient's life in between clinical encounters, in the *clinical whitespace*.

Keywords

clinical psychology, machine learning, mental health, natural language processing, social media, well-being

Traditionally, much of what is understood about mental health and well-being has come from patients' interactions with the health-care system. Tremendous research has gone into learning as much as possible from those clinical encounters, but the information they provide is limited. The relatively recent emergence of abundant *digital life data*—data generated through everyday interactions with digital devices—provides the opportunity to complement information gained from clinical interactions with information about what takes place between those encounters, in the *clinical whitespace* (see Fig. 1). Digital life data are generated frequently in modern life, such as through posts on social media, wearables, the movement and screen time of smartphones, website browsing, GPS coordinates, and financial transactions. Taken together, these sources of data can provide signals relevant to our psychological functioning, well-being, and mental health. Digital life data are already used in entertainment and advertising, for example, and have the ability to augment patient care by providing important signals related to clinical outcomes. These signals could be useful in many ways, such as for the objective, passive assessment of depression or for alerting practitioners to changes in behavior that might indicate a manic episode or the onset of a psychotic break. For example, GPS coordinates can indicate if someone is staying home or moving about, and measurements of a smartphone's movement can indicate whether a person is resting or engaging in doomscrolling while stationary.

How Are Digital Life Data Complementary to Clinical Data?

Digital life and clinical data complement each other, in both timing and the nature of the signals captured. To optimize the usefulness of both the patient's and the therapist's time, approaches to gathering clinical data are aimed at obtaining as much clinically relevant information in as short an amount of time as possible. Clinical data collection is generally *active, focused*, and *reactive*. Active engagement and participation of the patient (and often the therapist) is required, and thus patient-therapist interactions are focused and narrowed to capture what has been found to be clinically useful information. In addition, they occur in reaction to an event or complaint. In contrast, digital life data are inherently *passive*, *broad*, and *naturalistically longitudinal*. Because digital life data are generated for some other purpose, the collection of such data generally requires no additional effort from the patient and is thus passive. In the case of many digital-life-data sources, retrospective analysis is possible because recordings occur in the moment and not well after an event, providing a source of naturalistically occurring, longitudinal data. Furthermore, digital life data are broad because they encompass a more full context from

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Fig. 1. One person's interaction with the health-care system over 3 years. Each red hash represents a visit to a doctor, an outpatient facility, or an emergency room. The space between the red hashes, which is sometimes referred to as the *clinical whitespace*, accounts for most of the person's life, as it does for most people. The blue hashes indicate the person's posts on a single social-media platform in the same time frame. Other digital life data, such as those recorded by wearables, provide even more continuous information.

across a patient's day-to-day life, and they are not solely focused on what is presently known to be clinically relevant. Information about phenomena both temporally transient (e.g., a manic episode or emotional crisis) and routine (e.g., daily mood) is often not recorded or made usable in therapy because it does not occur within a clinical encounter. Recently, there has been significant progress in technology to sift out clinically useful signals from broad digital life data. So although data from a patient's life may have been previously available to clinicians in some form, only recently has such data become available, though not widely, in a clinically useful form.

Incorporating passive data into more traditional data-collection paradigms holds potential to address some core challenges of measurement in psychology, and mental health specifically. Every clinical encounter is at least somewhat artificial, removed from the patient's life. Oftentimes, patients want to present themselves as their "most adherent" selves during these encounters. Current methods for collecting data about symptoms and well-being during clinical encounters require that the patients disclose their symptoms, either directly in conversation or indirectly through clinical rating scales. Some patients are even further disincentivized to disclose their symptoms because such disclosure may have consequences that they perceive as negative (e.g., hospitalization or consequences for their jobs). A concrete example of data-collection mechanisms used during clinical encounters is the Patient Health Questionnaire (PHQ-9; Kroenke et al., 2001), the most commonly referenced measure of the severity of a patient's depression. Although it is widely accepted, this measure is based on the patient's self reflection and responses to nine specifically crafted and well-studied questions, so its usefulness ultimately depends on the patient's capacity for introspection, ability to accurately and objectively recall the events of the recent past, and willingness to answer truthfully. Another common data-collection technique involves asking patients to record in a journal relevant aspects of their life as part of treatment. These journaling approaches have notoriously poor adherence and compliance rates, and this is particularly true for patients exhibiting the decreased cognitive and memory functions associated with symptoms of depression (Burt et al., 1995). Furthermore, shifting paradigms to include more varieties of data will allow researchers and clinicians, over time, to learn about unexpected signals relevant to patients' mental health and successful outcomes. Incorporating passive, broad data will allow capture of more complex phenomena, such as volatility, and separation of states and traits (e.g., Geiser et al., 2015).

Digital life and clinical data are also complementary in their inherent biases. Digital life data are recorded objectively (which prevents confirmation bias) and as they occur (which prevents hindsight bias). The two kinds of data are subject to different versions of self-presentation bias, given the different audiences involved. On social media, some users have a tendency to show their most exciting selves, and in a therapy session, people are more likely to demonstrate their most adherent selves.

Language as a Lens

The richness of social media will continue to evolve and change, but central to its definition is the creation and sharing of content by individuals, be it via text, image, audio, or video. Social media capture a partial reflection of the cognitive and emotional state that a person is in at a specific point in time. The reflection of that state remains well after the person has moved on from that state. The tradition of using language (both written and spoken) as a lens into the thoughts and emotions of the author is centuries old; social media have just made all aspects of that process—creation, consumption, and analysis—more accessible.

From this realization has emerged a line of research focused on analyzing the language in digital life data for what it can say about psychology. In part, this was inspired by Pennebaker's work with Linguistic Inquiry and Word Count (LIWC), which was designed and deployed to analyze texts in the time before social media (Pennebaker et al., 2001). Pennebaker and his colleagues have spent decades analyzing social phenomena through the lens of language. The first finding linked subtle language patterns, such as the relative frequency of words like "I" and "we," to depression (Chung & Pennebaker, 2007). Since then, these findings have been replicated and expanded to cover a wide range of psychological variables, including personality (Park et al., 2015) and mental-health conditions (Coppersmith et al., 2015; De Choudhury et al., 2013).

Computational techniques such as machine learning are often employed to guide researchers in sifting through large volumes of data and extracting relevant signals. Researchers in psychology and mental health have now begun to use these same techniques. To find signals relevant to clinical outcomes, these techniques require training data: input data with potential signals (e.g., language posted on social media) paired with clear outcomes to be predicted, such as scores (e.g., PHQ-9 assessment) or labels (e.g., "diagnosed with schizophrenia"). With training data in hand, robust machine-learning tools can find signals and predictive patterns in input data that correlate with an outcome of interest. Furthermore, there are well-established techniques to turn these correlations and predictive patterns into a model or algorithm, which can then be used to estimate that outcome (e.g., a novel person's PHQ-9 score) from input data (e.g., the person's social-media language). The perennial challenge, then, is the creation of these training data sets to power this machinery.

Much of the work in this area has been centered around using social-media language to assess the risk that a person has, or will get, a diagnosis for a certain mental-health condition, or to estimate what a person's score on a clinical instrument (e.g., PHQ-9) might be (De Choudhury et al., 2013). There is a dearth of similar work looking at the relationship between social-media language and positive aspects of psychology, such as resilience, life enrichment, and well-being, although there are notable exceptions (e.g., L. Mitchell et al.'s, 2013, work on happiness). This dearth is due, at least in part, to the fact that although there are some scales relevant to positive psychology and well-being (e.g., Angel et al., 2020; Swarbrick, 2006), they do not have the same ubiquity and acceptance as clinical measures of dysfunction (Ong et al., 2021). Consequently, there have been fewer data sets available for training algorithms that can link signals in digital life data to positive aspects of well-being. This shortcoming does temporarily limit the utility of this technology to preventing and treating pathology rather than increasing well-being.[1]

Pragmatic Near-Term Applications and Their Ethics

How the technology for analyzing digital life data ought to be used is a subject of great discussion and debate (e.g., Benton et al., 2017; Conway et al., 2019), but experts in the field generally agree that its use is acceptable when the end user provides explicit informed consent. For brevity, I consider only such *opt-in* applications here.

Privacy

Thoughtful application of this technology starts with consideration of who should have access to what information derived from digital life data, and under which circumstances. Although a full, nuanced discussion of this topic is beyond the scope of this short article, it is important to emphasize that information should be provided only to people who are adequately trained to interpret it and translate it into actions likely to improve the health of the patient. In some circumstances, these people may be the patients themselves, who are reasonably expected to be able to implement clear, actionable suggestions with a strong evidence base. An example might be a simple, timely text message to nudge a person to stay hydrated, which is a simple method to improve mood and cognition (Masento et al., 2014). In many other circumstances, though, information should be delivered only to a trained health-care professional formally engaged in the patient's care because training is required to interpret the information and/or the path to action is unclear. This is the case, for example, with information about increased risk for adverse outcomes, such as mania or suicide.

Considerations of bias

The reliance on training data to create machine-learning algorithms means that in order for researchers and developers to understand and mitigate biases in the resulting technology, careful attention to the creation of data sets is required. In essence, the technology will learn from the data it is given, so in order for the technology to reveal how mental health and well-being are manifest in different groups, those groups must be represented in the training data used. Indeed, Aguirre et al. (2021) found that algorithms designed to identify depression were less accurate for members of underrepresented groups than for members of majority groups and that this difference was not explained simply by there being fewer data from underrepresented groups in the training set. This suggests that depression in these groups is manifested differently on social media. This bias in the algorithms, if left unchecked, would likely result in individuals with nonmajority racial, ethnic, cultural, and other identities failing to benefit from these technologies and subsequent research supported by them. Notably, there is active work within the machine-learning and artificial intelligence communities to build and implement frameworks that address and prevent such bias (e.g., M. Mitchell et al., 2020).

Improving outcomes through personalization

Some aspects of digital life data have traditionally been used for marketing purposes, such as for optimizing experiences with commercial entities by personalizing content. The health field is starting to see the benefits of personalization both for increased adherence and for improved outcomes (Finitsis et al., 2014). There is even preliminary evidence that presenting the same therapeutic content but customizing the order of presentation for a given patient can speed up improvement. In a small-sample study of individuals with an emotional disorder, treatment modules were ordered such that they first addressed either individuals' pretreatment strengths or their pretreatment weaknesses, and the strengths-first group demonstrated an improvement in outcomes earlier in the course of treatment (Sauer-Zavala et al., 2019). Tailoring and adapting clinical best practice to each individual patient's life is an important part of therapy and a prized skill of a good therapist. This is hard for a human clinician to do with the static content that makes up existing automated and online resources even though they are increasingly employed while patients are waiting for (or receiving) traditional clinical care.

One implementation of these concepts that would be feasible in the near term is the following. Personality can be assessed by analyzing the language a person uses on social media (Park et al., 2015). Personality, in turn, has been observed to mediate the efficacy of interventions (e.g., extraverts benefit less from mindfulness-based cognitive therapy than introverts do; Nyklíček et al., 2016). Thus, with no additional clinical time, the analysis of digital life data could change the expected efficacy of a particular therapeutic approach for a particular patient. In isolation, this benefit may seem small, but with similar information available across a wide range of treatment approaches, system-wide increases in efficacy might be possible.

Improving outcomes through just-in-time adaptive interventions

One exciting possibility is that more frequent observations will offer the ability to use just-in-time adaptive interventions (JITAIs; Klasnja et al., 2015) to improve mental health and well-being. JITAIs are aimed at bringing the right intervention to the right person at the right time. They have been embraced by the wearable industry, deployed to support physical outcomes, and backed by physical data. For example, someone who has not taken any steps in the previous hour may receive a JITAI reminder to "get up and move" (e.g., Thomas & Bond, 2015). Critical to supporting mental-health-related outcomes, though, is the ability to measure mental health and well-being in real time in order to provide timely information to such interventions.

One potential use of JITAIs is detecting people at risk for suicide using their digital life data (e.g., Coppersmith et al., 2018). Notably, most of the steps between thinking about taking one's life and taking action on those thoughts progress quickly, often across hours or days, but typically weeks or months pass between health-care visits (Millner et al., 2017). Precursor signals leading up to a suicide attempt, such as lack of sleep (Bernert et al., 2017) and changes in emotional affect, as assessed by traditional clinical approaches (Bagge et al., 2017), can be captured in digital life data using methods similar to those described here (Coppersmith et al., 2016). Thus, one can imagine an application in which patients at risk for suicide opt in to monitoring, JITAIs are deployed as needed to improve thoughts or behaviors that are precursor signals, and a care team is notified when precursor signals are detected. Such an application would have potential to allow proactive action on two fronts, through addressing the precursors and through proactive outreach from the care team (e.g., outreach when a patient has not slept well).

Improving outcomes through measurement-based care

Patients undergoing therapy have better outcomes when a review of measurements is incorporated into the interaction between patient and clinician. This approach is termed *measurement-based care* (MBC; for a review, see Scott & Lewis, 2015). Current evidence supporting MBC centers around traditional clinical methods of data collection (e.g., clinical scales, repeated sampling of behavior and experiences in real time and in natural environments, and journaling), but digital life data can complement these data sources meaningfully. Research to date indicates that information sharing between patient and therapist requires the patient to engage in relatively onerous protocols in the form of homework, which raises the question of MBC's feasibility on a large scale (see Millner et al., 2017, for a review, or Foreman et al., 2011, for a case study). Analysis of digital life data may be a part of the solution here, through supplying some or all of the data needed for MBC, while also simultaneously lessening the burden on both patient and clinician to capture these data.

Caveats

There are some important caveats to keep in mind regarding the clinical application of digital life data. First, not everyone will have meaningful digital life data, and there is work to be done to fully understand who would be excluded from participating. That said, if even 5% of the population had relevant data for this technology, it would still have potential to be very fruitful, both in the lives directly improved and in what could be learned from the emergent findings. Second, although the technology can robustly detect some mental-health and well-being phenomena, a great many questions remain about construct validity, that is, how the phenomena measured map to theoretic constructs. This is not a new challenge, but is perhaps exacerbated by the variety of methods involved and wide aperture of data collected, as compared with measurement in more controlled clinical environments. Notably, clinicians face different challenges (i.e., ecological validity), which suggests that the combination of digital life data and data collected in traditional clinical encounters can provide complementary perspectives. Third, although the analysis of digital life data is well understood from a computational perspective, the integration of such data into people's lives and health care is still nascent. There are many people interested in using this kind of data as part of their clinical practice or research, but the pragmatic reality of integrating it into their workflow while they are already overburdened is challenging. Similarly, there are many users who want more information about their well-being, but establishing the most effective way to provide such information in an ethical and effective way is not yet a solved problem.

Recommended Reading

Chancellor, S., & De Choudhury, M. (2020). (See References). An excellent critical review of the use of machine learning to extract clinically meaningful signals from social-media data, including discussion of the difficulty posed by the complexity of clinical psychology generally.

Coppersmith, G., Dredze, M., Harman, C., & Hollingshead, K. (2015). (See References). Early work describing, in an accessible manner, the techniques used to create models from language data relevant to 10 mental-health conditions.

Hardeman, W., Houghton, J., Lane, K., Jones, A., & Naughton, F. (2019). (See References). A review of just-in-time adaptive interventions, particularly for physical conditions.

Transparency

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Declaration of Conflicting Interests
The author is an employee of and has stock in SonderMind, which is not currently selling any products using digital life data. The author declared that there were no other potential conflicts of interest with respect to the authorship or the publication of this article.

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Note

1. The proceedings of the Workshop on Computational Linguistics and Clinical Psychology (https://aclanthology.org/venues/clpsych/) present papers describing the advances that make the applications discussed in this review feasible. These papers are written to be accessible by psychologists and computer scientists alike.

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