Toward Cognition-Aware Digital Phenotyping for Substance Use Disorder

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ABSTRACT

Digital phenotyping has been used in substance use disorder (SUD) research to predict substance consumption and monitor relevant symptoms. While various digital sensors have been utilized in SUD research, there is a lack of consideration for digital phenotypes that reflect cognitive functions. However, previous research has consistently shown the association of cognitive impairments with SUD and the positive effects of cognitive remediation in improving treatment outcomes. Given the role of cognitive functions in SUD, measuring and tracking the cognitive functions of patients can contribute to enhancing the process of intervention and treatment. Thus, this paper aims to facilitate the discussion of identifying and validating cognition-aware digital phenotyping in SUD. As a step toward this goal, this paper suggests the potential of a specific type of digital feature: keystroke dynamics. Keystroke dynamics have been found to be effective in estimating cognitive functions in various clinical domains. Future research needs to investigate if keystroke dynamics can be applied in SUD research and find other digital phenotypes that can measure the cognitive functions of patients with SUD.

CCS CONCEPTS

• **Human-centered computing** → **Ubiquitous and mobile computing**; • **Applied computing** → *Health informatics.*

KEYWORDS

Digital Phenotyping; Substance Use Disorder; Cognitive Functions; Keystroke dynamics; Digital Phenotype

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1 INTRODUCTION

Substance use disorder (SUD) is a mental disorder characterized by compulsive substance use and the loss of control over substance use [32]. SUD is a serious social problem in the United States. According to the 2021 National Survey on Drug Use and Health, around 46 million people living in the U.S. and aged 12 or older are estimated to have had a SUD in the past year [28]. Moreover, the estimated drug-involved overdose deaths increased since 2019, reaching 106,699 in 2021 [23]. Thus, it is important to prevent people from substance abuse and offer interventions at the right time.

Digital phenotyping is a term defined as "moment-by-moment quantification of the individual-level human phenotype in-situ using data from smartphones and other personal digital devices." [31]. This is an emerging approach that aims to measure human behaviors and internal states using digital devices in a minimally invasive manner [9, 18]. By collecting real-time data from people's daily lives, digital phenotyping offers objective measurements of human behavior, cognition, and mood [17, 18]. This approach has also been applied in SUD research. For example, personal data collected by wearable devices [19, 25] and smartphones [4, 21, 30] have been used to detect or monitor substance use behaviors.

However, it has been pointed out that the mobile sensors which have been applied in SUD research tend to be selected based on their availability rather than their benefits [25]. This implies the current practices of digital phenotyping lack consideration and discussion regarding which digital features are effective in the detection and intervention of SUD and the reasons thereof. We posit that the characteristics of SUD and digital phenotypes that can reflect those characteristics should be considered to maximize the benefits of digital phenotyping.

Particularly, this paper focuses on the cognitive aspect of SUD. It has been continuously reported that patients with SUD have deficits in cognitive functions such as attention, memory, and executive cognitive functions [26, 27]. In addition to the high prevalence of cognitive impairments among patients with SUD [8, 10], individuals with impaired cognitive functions are associated with poorer treatment outcomes [7]. However, digital phenotypes measuring cognitive functions have been under-explored in SUD literature [20]. To reduce this gap, this paper aims to facilitate the discussion of identifying and validating cognition-aware digital phenotyping, which means the digital features that can measure cognitive functions.

This paper starts with a discussion of the relationships between SUD and cognitive impairments and the effectiveness of cognitive remediation in improving treatment outcomes. Then, we will discuss how digital phenotyping has been applied in SUD literature and how other clinical domains used digital phenotyping in order to measure cognition functions. Lastly, we suggest keystroke dynamics as a fertile growth area for digital phenotype research that can be utilized to capture cognitive functions in SUD research.

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2 CURRENT LANDSCAPE

2.1 Substance Use Disorder and Cognitive Impairment

SUD is known to develop over time with repeated misuse of substances [32]. Repeated and prolonged substance use lead to changes in brain circuitry that governs reward, stress, and executive functions [22, 32]. In particular, executive functions refer to the ability "to organize thoughts and activities, prioritize tasks, manage time, make decisions, and regulate one's actions, emotions, and impulses" [32]. The impairment in cognitive functions has been reported as one of the effects of substance use on the brain. Cognitive impairments in attention, memory, or executive functions have been continuously reported across patients with different types of substances [7] and impaired cognitive functions of drug users barely improved even after 3 months of abstinence, which suggests the lasting effects of substance use on cognitive function [5]. In addition, it was estimated that about 30% to 80% of patients with SUD have cognitive impairments [10]. Likewise, cognitive impairment is a common experience for individuals with SUD [8].

More importantly, research has shown that cognitive impairments are closely associated with treatment outcomes such as treatment dropout and relapse. Patients with SUD who exhibit cognitive impairments are more likely to have lower treatment retention rates [1] and are less likely to attend all treatment sessions [11]. Cognitive impairments have also been identified as risk factors for relapse [26, 27]. Previous research has shown deficits in cognitive functions are related to relapse or treatment dropout across different types of SUD [27]. Impaired inhibition has been identified to be related to relapse or treatment dropout among individuals with alcohol and cannabis use disorders, while attentional bias has been related to treatment outcomes in opioid use disorder [27].

Given the influence of cognitive impairments on treatment outcomes, cognitive remediation has emerged as a promising adjunct treatment in addition to traditional SUD treatment [22, 27]. Cognitive remediation generally refers to interventions that aim to improve impaired cognitive functions with the goal of enhancing favorable treatment outcomes [22]. Previous research has found the effectiveness of this intervention in improving treatment outcomes among patients with SUD. For instance, past studies [13, 22] have reported the group that received cognitive remediation showed higher treatment engagement, longer days of abstinence, and lesser usage of alcohol and drug compared to the control groups. Likewise, empirical evidence has supported the importance of improved cognitive functions and the potential of cognitive remediation in SUD treatment.

There are several challenges in implementing cognitive remediation for patients with SUD. To offer appropriate cognitive remediation to each patient, their cognitive functions should be measured in the treatment process. However, neurocognitive assessments are not usually included in the patient evaluation for SUD treatment due to financial and practical reasons [11]. Despite the importance of cognitive assessments to plan personalized treatment strategies [6, 27], cognitive functions of patients with SUD are not typically measured and monitored in their treatment process [8]. This can be problematic because early detection and interventions of cognitive impairments can lead to favorable treatment outcomes [8].

Digital phenotyping can potentially be used to measure the cognitive functions of patients with SUD. Furthermore, it can also be helpful to improve the treatment process by enabling real-time cognitive assessments and detecting patients with cognitive impairments. However, there is a lack of literature on SUD that focuses on the cognitive perspective of digital phenotyping. Recently, researchers in other clinical domains have tried to capture the cognitive functions of patients with digital devices [9, 15, 33]. It would be valuable to understand the approach of other clinical domains toward cognitive functions considering the important role of cognition in SUD treatment.

2.2 Digital Phenotyping in Substance Use Disorder

Digital phenotyping has been applied in substance use research in order to detect substance use [4, 21] and monitor relevant symptoms [25, 30]. Various types of digital devices have been utilized including smartphones, smartwatches, and wearable devices. Smartphones have been used to collect physical mobility/activity [4, 30], phone usages, psychomotor functionings [4], or gait-related features [3, 14, 29]. In addition, ecological momentary assessments (EMA) were also collected to obtain self-reported substance use using smartphones [4, 30]. Similarly, smartwatches were used to collect data such as physical activities, sleep patterns, device usage related features, and EMA [19]. Other types of wearable devices like chest bands or wristbands have been widely used to collect physiological data like heart rate, skin temperature, blood pressure, and so on [25].

Previous studies have shown the benefits of digital phenotyping in substance use research. Specifically, the data collected by digital devices has been found to be effective in detecting high-risk drinking periods [4], blood alcohol level [14, 21, 29], and alcohol consumption [3]. Previous studies also showed the potential use of smartwatches and smartphones as a tool for recording individuals' substance use behaviors and self-monitoring [19, 30]. Digital phenotyping has been acknowledged for its potential to enhance substance use treatment by improving relapse prediction, detection, and intervention [16].

However, digital phenotypes that can capture cognitive functions have been rarely discussed and investigated in SUD literature [20]. To the best of our knowledge, there are only a few studies that tried to measure cognitive functions with digital devices. For example, there is a study that developed smartphone-based tasks in order to assess motor coordination and cognition [21]. This study showed the performance of those tasks can be used to estimate participants' blood alcohol level. However, those tasks mainly focused on measuring motor skills and it was not validated whether those tasks are capable of measuring the cognitive functions of individuals with SUD. Given the important role of cognitive functions in the SUD treatment process, future research needs to identify digital sensors which can be used to measure neurocognitive functioning.

3 TOWARD COGNITION-AWARE DIGITAL PHENOTYPING

Human-computer interaction data have been investigated for their ability to measure cognitive functions. For example, a prior study

Table 1: The Examples of Keystroke Dynamics Features

Study	Feature	Description
Chen et al [9]	Typing speed	The median interkey delay
	Autocorrection rate	The total number of autocorrection events offset by a log-transformed character count per session
	Backspace rate	The total number of backspace events offset by a log-transformed character count per session
Holmes et al [15]	Keystroke data	The timing of key-press and release events in a typing stream
	Key type data	The key-content category of each keystroke event (e.g. space, enter, etc)
	Tap precision data	The distance of the center of a tap to the center of the target key
	Assisted typing events	The autocorrection events and usage of word suggestions
	Typing session context	Details about typing session (e.g. session start time)
Zuluete et al [33]	Keypress data	The number of keypresses
	Interkey time	The time difference between consecutive keypresses
	Autocorrection rate	The number of autocorrect events / total number of keystrokes
	Backspace rate	The number of backspace events / total number of keystrokes

showed that smartphone touchscreen interactions such as the patterns of swipes, taps, and keystroke events can predict the scores of traditional neurocognitive assessments for the five domains (e.g. working memory, memory, language, dexterity, and intelligence) [12]. This finding suggests that human-computer interaction data can be used to measure cognitive functions in daily lives.

In particular, keystroke dynamics have been getting attention for their strengths over other types of digital phenotyping. Firstly, keystroke dynamics are "content-free" [18]. This is because keystroke dynamics collect the way people type, not the actual content they type [18]. Thus, keystroke dynamics are less intrusive compared to other digital sensors which collect the content (e.g. messages). At the same time, keystroke patterns are involved with various cognitive aspects such as fine motor skills, executive cognitive functions, and visuospatial components [2, 15, 24]. Recently, keystroke dynamics have been investigated in various clinical domains, especially to test their feasibility in estimating cognitive functions. For instance, previous research utilized keystroke patterns of patients with bipolar disorder [33], multiple sclerosis [9], and cognitive impairments [15] in order to estimate patients' cognitive functions.

Specifically, Chen et al [9] found patients with multiple sclerosis typed slower than the healthy control group and the relationship between typing patterns and cognitive functions. One of their results showed that faster typing speed was related to better neuropsychological test performance on speed, attention, and executive functioning. Holmes et al [15], showed machine learning models built with keystroke patterns can be used to estimate cognitive subdomains such as executive function, verbal, and non-verbal memory. Lastly, Zulueta et al [33] predicted participants' brain age by using keystroke dynamics. Table 1 shows the examples of keystroke dynamics features used in these studies [9, 15, 33]. Overall, typing speed, autocorrection, and backspace uses were commonly used while there were some differences in details.

Considering the findings in other clinical domains, keystroke dynamics can be a promising digital phenotype for SUD research. As discussed, SUD often accompanies cognitive impairments as repeated and prolonged substance use affects brain functions [32]. It is also important to improve impaired cognitive functions in order to enhance the treatment outcomes [22, 27]. Since keystroke dynamics have estimated the cognitive functions of different patient groups, the cognitive functions of individuals with SUD can potentially be estimated with keystroke dynamics. Additionally, previous research found that keystroke patterns can estimate cognitive functions related to SUD such as executive functions, attention, and inhibitory functioning [9, 15]. Thus, we suggest keystroke dynamics have the potential to offer new opportunities in monitoring and intervention of SUD by measuring relevant cognitive functions.

There are several studies that used keystroke dynamics in substance use research. For instance, keystroke dynamics were used with other digital phenotypes to estimate the blood alcohol level of users [21] or high-risk drinking periods [4]. However, these studies focused on psychomotor or communication-related aspects of keystroke patterns [4] or missed features that are found to be related to cognition. Thus, future research needs to further investigate the usability of keystroke dynamics in measuring the cognitive functions of patients with SUD.

4 CONCLUSION AND FUTURE WORK

This paper suggested the future direction for SUD research toward investigating cognitive-aware digital phenotyping. To facilitate this discussion, we suggested keystroke dynamics as the potential digital phenotypes that can be applied in SUD research based on the results in other clinical domains. This type of digital phenotyping may offer new opportunities by enabling the measuring and tracking of cognitive functions of patients with SUD. Furthermore, we expect this paper contributes to the discussion of maximizing the potential of digital phenotyping for safer lives and well-being for the population.

Future research needs to identify digital phenotypes which can measure cognitive functions and be applied in SUD research. For instance, researchers can test keystroke dynamics or other digital phenotypes whether they can be used to estimate the cognitive functions of patients with SUD. There are several potential scenarios using cognition-aware digital phenotyping to enhance the interventions of SUD. For example, future work can collect keystroke patterns (or other types of cognition-aware sensors) to monitor the cognitive functions of SUD patients in their daily lives. Their keystroke patterns can be analyzed in order to determine the priorities of patients to receive cognitive remediation. This practice is expected to contribute to improving treatment outcomes by conducting real-time assessments of cognitive functions and offering cognitive training at the right time.

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