Meet Your Therapist: Exploring the Promise and Drawbacks of AI for Treating Digital Addictive Behavior among Adolescents

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Abstract

Within the public health domain, one of greatest concerns is the rise of addictive behavior among adolescents and young adults. Questions have been raised as to how excessive video gaming, social media overuse of misuse, and online gambling, for instance, present deleterious effects to this population's psychological well-being as well as their overall development. In light of these concerns, public health officials, policymakers, and mental health professionals have set out to explore effective interventions designed to address this issue and improve this population's quality of life and health outcomes. Due to its widespread accessibility, low-cost, relative anonymity, and room for personalization and user engagement, artificial intelligence (AI) is one such intervention currently being explored. This paper therefore joins the ongoing conversation on the potential of AI as a mental health tool used to treat addiction behavior, but is also careful to consider areas of concern in its application. Reviewing and synthesizing the existing literature on this topic thus allows this paper to offer the view that although AI should not be used in lieu of human mental health providers, it can serve as an auxiliary resource that complements existing approaches to provide more comprehensive care to those in need.

Keywords: addiction, mental health, artificial intelligence, adolescents

Lede: Addiction to digital technologies is becoming an increasing concern for adolescents. Artificial intelligence-based solutions may represent a viable path for therapeutic intervention.

Introduction

Addiction has been at the forefront of public discourse for some time now. It seems every month, some celebrity or public figure announces that they are checking into a rehabilitation facility. Public service-oriented ad campaigns targeting drug, alcohol, and gambling addictions flood magazines, billboards, and digital media in an effort to lessen what are staggering figures. One in seven Americans reports suffering from an addiction (Volkow et al.). Of this group, people aged 12- 25 represent an especially vulnerable group (SAMHSA). When compared to the population at large, however, this particular demographic may be more susceptible to a different set of addictive behaviors. While the most commonly targeted addictive behaviors (e.g., substance abuse) nonetheless apply to this age group as well, they are often susceptible to other issues related to excessive use or misuse of social media, video gaming, or other overreliance on digital technologies (Twenge & Campbell).

The prevalence of these addictive behaviors is moreover often overlooked or dismissed as relatively harmless, meaning that their deleterious effects may go unaddressed. That is why this article aims to investigate these addictive behaviors, specifically. This review begins by defining addictive behavior and detailing the impact it holds for young people aged 9-18. From there, the article details traditional treatment methods in order to better understand how an AI-based approach compares. It proceeds to discuss the AI treatment options currently being developed, acknowledging both accompanying challenges and possibilities for future applications.

Addiction in the Digital Age

While addiction far preceded the advent of the internet, there is little doubt that the rise of digital technologies may have exacerbated some addictive tendencies and created others. An important question to introduce here, however, asks, “But what is addiction?” And furthermore, "When do certain repetitive behaviors or preferences turn into addictions?" The American Psychological Association (APA) defines addiction as "a state of psychological and/or physical dependence on the use of drugs or other substances, such as alcohol, or on activities or behaviors." One of the most widely referenced set of guidelines for identifying and assessing addiction is outlined in the Diagnostic and Statistical Manual of Mental Disorders (DSM-5). For a particular behavior to be deemed an addiction, it is (1) often recurrent, despite negative consequences; (2) the individual often exhibits preoccupation or obsession with the behavior; (3) the individual may experience withdrawal-like symptoms when refraining from the behavior; and there is (4) a steady increase in the amount of time needed to feel satisfied when engaging in this behavior (APA).

This comprehensive text provides diagnostic guidelines for a variety of mental health issues, but has recently come to tackle addictive internet behavior, such as online gaming. While not offering Internet Gaming Disorder (IGD) as a formal diagnosis, the *DSM-5* does identify it as an area warranting further study. In many ways, researchers are finding that behavioral addictions are just as powerful as substance-based ones (drugs, alcohol) in that they operate on shared neurological pathways. For example, Grant et al. found that behavioral addictions like social media misuse, online gaming, and so on shared many of the same features of substance abuse disorders. These include reported cravings, a loss of control, and persisting with the activity despite the knowledge of negative consequences. The authors point out that both types of addiction involve a dysregulation of the reward circuitry by which the brain operates, particularly with respect to the mesolimbic dopamine system. In fact, these two forms of addiction present in similar ways in neuroimaging, with the same areas of an online gambler's brain being activated as a cocaine addict's.

These findings are further supported by a review conducted by Kuss and Griffiths. For their systematic review, the authors consulted 58 empirical studies on internet gaming addiction, and found that anywhere from 2 to 12% of adolescents demonstrate hallmarks of addiction (i.e., symptoms of withdrawal, negative impacts to their mood, and interpersonal conflict) when their gaming habits exceed healthy levels. The researchers also emphasized that studies in neuroimaging and genetic analysis showed parallels between online gaming addiction and substance addiction, as both involved dopaminergic pathways. The authors concluded that across the studies they surveyed, however, there was a pronounced lack of validated diagnostic tools, which prompts them to call for standardized and scalable assessment measures—a gap AI tools are uniquely suited to fill.

In adolescents, specifically, those same dopamine pathways the authors describe mature before the prefrontal cortex, which is responsible for exerting the cognitive faculties of control. These differing rates of development among various areas of the brain thus creates an imbalance between reward-seeking behavior and the ability to regulate impulses (Casey et al.). The design of various online games and platforms taps into this imbalance by offering the users several opportunities for dopamine hits in the forms of likes, follows, and video recommendations. This element present in the various online platforms available today capitalizes on adolescents' and young adults' peer reward drive. From the age of approximately 10 years old onward, adolescents become especially attuned to peer feedback, which can be provided through these online applications and drive further consumption/engagement. With this engagement, a feedback loop is created, where existing inclinations towards impulsivity are exacerbated by continued online usage in such a way that it eventually leads to a lack of inhibitory control (Crone & Dahhl).

Another reason why this age group is worth examining in depth when discussing online addictive behavior stems from their exposure to digital platforms. Individuals in this age group are often referred to as “digital natives,” meaning that they have grown up in an era where the internet was already established and thriving. The widespread availability of the internet thus set the stage for the ubiquity of online gaming and social media use among this generation. One study conducted by the Pew Research Center found that 85% of U.S. teens played digital video games and nearly 4 in 10 did so daily (Gottfried & Sidoti). On a global scale, the World Health Organization (WHO) presents similar figures, reporting that 34% of adolescents play digital video games daily, and 22% of these individuals spend four or more hours per day gaming. When such a large part of one’s waking hours are spent engaged in gaming, that leaves less time for commitments like academics, lessens the likelihood of exercise, and can lead to sleep deprivation (Health Behaviour in School-Aged Children Collaborative Group).

Yet, these potential side effects of increased online engagement pale in comparison to some of the more serious health outcomes correlated to addictive online behavior. Several studies have shown an association (though not a definitive causation) between compulsive online media use and suicidal ideation or behavior. For example, one study surveyed 4,300 adolescents aged 9-10 and found that 49% demonstrated addictive mobile phone use, 40% did the same when it came to video games, and 10% did for social media. Compulsive users of these media, however, were 2-3 more likely to experience suicidal ideation and behavior (Xiao et al.). In another study of Chinese adolescents, the researchers found that spending more than two hours per day interacting with an electronic device led to higher scores along depression and anxiety indices. And consistent with the findings of previous studies, these researchers also found that excessive time spent online led to other negative behaviors, such as sleep deprivation, which collectively compounded mental health symptoms (Xu et al.). Again, while screen use and online engagement of this kind did not predict psychological issues in all cases, the association between this behavior and certain mental health outcomes may nonetheless be cause for concern.

Where Traditional Treatment Approaches Fall Short

Traditionally, addictive behavior is treated through a combination of psychotherapeutic strategies, including cognitive behavioral therapy (CBT), family systems therapy, and methods for encouraging a “digital detox” (Ding & Li). Regardless of the technique, though, what these therapies share is a desire to uncover and understand the motivations behind this addictive behavior, instruct on self-regulation, and build healthier habits in the long-term (Young). Another quality that many of these therapies have in common is their high associated cost. The average cost of one CBT session in the U.S. averages over $100 per session (Ross et al.). When one considers the fact that the median household income in America is approximately $75,000 (U.S. Census Bureau), even a single CBT session may be financially out of reach for most families. And with all of these therapies—CBT, talk therapy, or something altogether different—the key to their success lies in sustained commitment to the practice (Bennion et al.). This means that the individual attending the sessions must plan to afford multiple sessions over the course of several weeks, months, and even years.

Outside of the financial accessibility, there is also physical accessibility to take into account. Popular digital apps like Better Help, for instance, have brought mental health services to areas that were previously underserved. Yet, the premise of apps such as these is that a real professional therapist will be available to provide advice. In this regard, these platforms can be thought of more as a matching service that pairs those in need with mental health counselors. However, ever since the COVID-19 pandemic, there has been an ongoing shortage of qualified personnel in this area within the U.S. Wait times average 48 days for a new client to be seen (National Center for Health Workforce Analysis), leaving one to wonder, “What happens to the individual in the interim?”

A final point of consideration pertains to stigma. Despite increased social acceptance when compared to the previous decades, mental health issues remain highly stigmatized. In their meta-analysis of 52 studies examining the reasons that people do not participate in help-seeking behavior, Radez et al. reported that 92% of the studies surveyed had identified social factors related to embarrassment and stigma as a reason for not pursuing mental health services. As this particular age group is, as previously established, highly motivated to seek social acceptance, the potential for bullying those seeking mental health support may be a deterrent. In fact, with bullying being such a grave public health concern for this demographic (Armitage), one can see how the perceived stigma attached to mental health issues can be seen as grounds for dissuading young people from getting the help they need due to a fear of peer rejection.

The perceived stigma attached to seeking mental health services for addictive online behavior may be worsened for certain genders and cultural backgrounds. For instance, cultural norms that dictate that masculinity necessitates self-reliance may discourage male-identifying individuals from seeking help. This becomes further complicated when one considers culture here as well. Cultural constructs like the Latin concept of “machismo,” which asserts masculinity as dominant to what is seen as the “weaker” sex (i.e., women), may prevent male-identifying persons from this cultural background from seeking help. In Asian cultures, too, there is often a stigma surrounding mental health issues, in part due to the widespread prevalence of cultural narratives like the “Model Minority Myth.” The Model Minority Myth asserts that Asian immigrants and those of Asian descent are the “ideal” minority within U.S. society, primarily due to their self-reliance and self-sufficiency (Poon et al.). Admitting that one needs help may be seen as running counter to this social narrative and may thus deter this particular demographic (and others) from receiving the care they need, thereby worsening health outcomes for an already vulnerable population (Yi).

While these reasons represent the primary barriers to therapeutic intervention for online addictive behaviors, the good news is that AI is uniquely suited to address each of these. The next section details how, exactly, AI can overcome these limitations by discussing how it is already being enlisted in healthcare contexts. By detailing its current applications, the reader is better able to envision its future possibilities.

AI Interventions: Accessible, Affordable, and Anonymous

The term "AI" encompasses a broad range of digital assistive technologies. For the purposes of this article, however, it is meant to signify natural language processing (NLP), machine learning algorithms, and conversational agents (i.e., chatbots). All of these different types of AI are capable of analyzing patterns in speech or text, and to detect and flag signs of distress, depression, or addictive behavior (Miner et al.). Since AI is algorithm-based, it can analyze user data derived from gaming platforms, smartphones, and social media to determine if such engagement qualifies as addiction. This helps to address the subjectivity characterizing human-only therapeutic approaches, as what qualifies as addiction for one provider may not for another. Such discrepancies not only leave mental healthcare susceptible to bias, but result in inconsistencies for the client. At least partially as a result of its ability to aggregate and interpret large datasets, AI, on the other hand, can provide informed yet objective care recommendations. These qualities are what has allowed it to identify an excessive number of hours spent gaming, disrupted sleep patterns, and withdrawal from offline areas of life (Tateno et al.).

In addition to the promise it shows with regard to early detection and screening, AI may also offer more personalized care as it “learns” about the client. The whole premise of machine learning is AI becomes more knowledgeable of the issue with the more information a user feeds it. In this way, the information it is given is not unlike a therapist’s notes, which are taken over the course of weeks and months to better learn about the client, the nature of their addiction, certain triggers, and so on. AI-based applications have been shown to tailor interventions based on users’ past behavior, preferences indicated, and risk factors. Furthermore, as machine learning can adapt therapeutic techniques in real time, it can adjust elements like messaging or pacing to facilitate engagement and thereby the overall efficacy of the treatment (Alasmrai).

Such personalized care taps into a growing body of literature advocating for what is called “precision medicine”—“an emerging approach for disease treatment and prevention that takes into account individual variability in genes, environment, and lifestyle for each person” (National Research Council). What precision medicine contends is that when an intervention is tailored to the individual instead of rooted in a “one-size-fits-all” approach, it is more likely to succeed. Therefore, the personalized treatment plans that may be offered through machine learning suggest the AI-based therapies could see higher efficacy rates than conventional ones.

Another quality that renders AI-based therapies a viable alternative or supplement to in-person ones has to do with the affordability and accessibility concerns mentioned previously. Digital mental health tools like Woebot, Wysa, and Replika have been shown to reduce depression and anxiety among their users through simple conversational engagement (Fitzpatrick et al.). These apps operate 24 hours a day, 7 days a week, meaning that users can access immediate support. While there are dangers inherent in using AI to completely replace human therapists, as will be discussed in the next sections outlining its limitations, this feature would be extremely helpful to those in acute mental health crises. If one were to feel particularly distressed about their addictive behavior—so much so that they consider self-harm, etc.—AI could provide meaningful assistance until the individual can meet with a human therapist. In this way, AI can be thought of not as the only or lone line of defense against acute mental health episodes, but as a helpful first-line treatment option.

Additionally, all of the abovementioned platforms are highly affordable. In fact, the cost for an annual subscription for an app like Wysa is $74.99 (Inkster et al.)—that's much less than the average cost of a single therapy session. Beyond their low monthly cost, many of these apps offer a free trial period or a free basic version, making the overall investment quite low. As a result, those without insurance coverage could still access the care they need, without cost being a significant deterrent.

Another element of these apps' design that makes them an appealing platform for providing mental health services to those struggling with online addictive behavior is that they are engaging. At first glance, this may seem ironic, leading to questions of how gaming could be used to treat issues like gaming addictions. One might reasonably ask, "Wouldn't the gamified features inherent in these apps worsen addictions related to online gaming?" But several of these outlets include gamification features that encourage the user to keep coming back to them—to keep coming back to therapy (Przybylski et al). The most common gamification features embedded in these tools include feedback on user progress, reward-based systems, scoring, and narrative elements, all of which are designed to encourage continued use (Cheng et al).

AI-based mental health apps such as these are also anonymous, which helps address stigma as a barrier to help-seeking behavior. With addictive behaviors like the ones at the center of this article, there can be a significant amount of perceived shame surrounding this condition.

The individual in question might ask themselves questions like, “What will my peers think of me if they find out?” The anonymity of this treatment method precludes having to entertain such questions. Those in need do not physically visit an office or sit in a public waiting room; they can access mental health services from the privacy of their own home. That said, not all data is guaranteed to remain private—a consideration that will be discussed at greater length in the section that follows.

Future Directions in the Digital Frontiers of Mental Health

Admittedly, these applications of AI are not without several drawbacks. However, these limitations may best be regarded as opportunities for further improvement that will render this use of digital technology more efficacious as a whole. One of the greatest limitations (and area for future improvement) of AI for such purposes has to do with data protection. While these platforms are somewhat anonymous, as already stated, users still supply the app with sensitive personal data. Additionally, data breaches are increasingly common in the digital era, meaning that this data could be accessed by third parties without the client’s consent. To overcome this drawback, app designers should strive for full transparency with regard to how clients’ data is collected and stored. And because the services being offered qualify as healthcare services, they would need to comply with Health Insurance Portability and Accountability Act (HIPPA) guidelines (Vayena et al).

Beyond the data the AI is being fed from the user, there is also a concern for the data it is trained on. Incomplete or biased datasets may reinforce stereotypes or provide ill-informed recommendations for clients from marginalized groups. Therefore, in order to mitigate these potential risks with algorithmic bias, it is important to incorporate diverse and comprehensive datasets into AI training protocols (Obermeyer et al).

Finally, while AI as a treatment option for adolescents and young people struggling with online addictive behavior offers much promise, there are dangers in using it as a stand-in for a human therapist. Uniquely human qualities like empathy and relational depth are not something AI can replicate, but are central to the success of the therapeutic encounter. That is why scholars like Luxton call for a more hybridized version of this approach, one that integrates artificial intelligence with human intelligence.

Despite these concerns, AI nonetheless represents a promising avenue for addressing what the research has shown to be an ever-increasing public health concern among adolescents. Unlike traditional therapies, which are marked by barriers related to accessibility, affordability, and privacy, AI is poised to reach broad audiences, but especially those who grew up (or are currently growing up in the digital era). Additionally, because these individuals are fully immersed in the digital landscape, this therapeutic intervention may resonate with them due to its inherent engagement and design. With deliberate adherence to ethical standards, clinical and regulatory oversight, and recognition of its limitations (i.e., that it should not substitute all care provided by an experienced human/in-person practitioner), artificial intelligence-based mental health platforms are poised to offer an inclusive, innovative, and above all, *intelligent* solution for combating behavioral addictions among young people throughout the world.

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