



Can ChatGPT Be Addictive? A Call to Examine the Shift from Support to Dependence in AI Conversational Large Language Models

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Abstract

The rapid rise of ChatGPT has introduced a transformative tool that enhances productivity, communication, and task automation across industries. However, concerns are emerging regarding the addictive potential of AI large language models. This paper explores how ChatGPT fosters dependency through key features such as personalised responses, emotional validation, and continuous engagement. By offering instant gratification and adaptive dialogue, ChatGPT may blur the line between AI and human interaction, creating pseudosocial bonds that can replace genuine human relationships. Additionally, its ability to streamline decision-making and boost productivity may lead to over-reliance, reducing users' critical thinking skills and contributing to compulsive usage patterns. These behavioural tendencies align with known features of addiction, such as increased tolerance and conflict with daily life priorities. This viewpoint paper highlights the need for further research into the psychological and social impacts of prolonged interaction with AI tools like ChatGPT.

Keywords ChatGPT · Addictive behaviours · Decision-making · Productivity · Personal relevance

1 Introduction

With the launch of ChatGPT in November 2022, this generative AI tool has achieved unprecedented global adoption, quickly becoming one of the most widely used applications of its kind. Within just two months of its release, ChatGPT surpassed 100 million active users, earning the distinction of being the fastest-growing consumer application in history at that time [1]. This rapid growth highlights its significant impact on communication, productivity, and access to information.

Developed by OpenAI, ChatGPT is an advanced generative AI language model designed to process and generate natural language text with a high degree of coherence, contextual awareness, and adaptability. Its primary purpose is to

serve as a versatile conversational agent capable of assisting users across diverse domains. Beyond generating coherent, human-like text, ChatGPT facilitates understanding, learning, and productivity by interpreting user queries, offering tailored responses, and supporting complex tasks such as problem-solving, creative content generation, and knowledge synthesis [2]. In contrast to domain-specific AI systems such as LaMDA, BlenderBot, and Replika, ChatGPT offers broader functionality, making it particularly well-suited for tasks requiring contextual understanding. For instance, unlike Replika, which primarily caters to personal emotional support, or BlenderBot, optimised for open-domain chit-chat, ChatGPT scales effortlessly from casual interaction to high-stakes professional tasks [3]. Furthermore, compared with domain-specific models like LaMDA (focused on dialogue nuances) [4] or Replika, ChatGPT's training data encompasses a wide range of topics, enabling it to perform effectively in fields such as healthcare, education, programming, and customer support [5, 6].

However, not everything that glitters is gold. As OpenAI's Chief Technology Officer pointed out, with increased capabilities comes the risk of designing AI in a way that could make it too central or indispensable, potentially leading to a situation where we become overly reliant on it. It was also stressed that studying the effects of advancing AI technology

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is important, especially to reduce the chances of it becoming addictive or harmful [7]. It is worth noting that these fears lack sufficient evidence or compelling arguments to warrant their validity. They stem primarily from public anxiety about AI. However, we argue that this warning is not merely hypothetical; it reflects growing concerns within technology companies, policy institutes, and the general public, and it has yet to be rigorously investigated within the scientific community.

Several studies have already raised questions about potential addiction to chatbots [8], referring to their negative impact on mental health in adolescents and adults [9–11]. These concerns are further supported by evidence showing that users can develop dependent or addictive behaviours toward AI, including emotional dependence on chatbots, attachment to social chatbots, and reliance on conversational AI [12–14]. What remains unclear is the possible extent of behavioural addiction and the challenges related to ChatGPT, which differs from special-purpose chatbots. This uncertainty raises concerns about the potential psychological, social, and behavioural impacts. It also raises questions about how we can assess, measure, and mitigate the potential for addiction, not just in terms of functional dependence (e.g., relying on AI for daily tasks like drafting emails or translating text) but also in terms of socio-emotional dependence (e.g., seeking comfort, companionship, and social validation from the AI).

While addiction is often associated with dependency on substances like alcohol, nicotine, or drugs, experts in behavioural science argue that addiction can stem from any activity capable of stimulating an individual [15, 16]. Behaviours such as gambling, video gaming, chatting, or browsing the internet can evolve from simple habits into compulsive actions, marking the onset of addiction. This shift occurs when these activities become less about choice and more about an uncontrollable need [17]. There is increasing evidence that behavioural addictions, including those linked to digital tools, can result in significant psychological, social, and cognitive harm [18]. Studies have shown that compulsive use of digital platforms is associated with heightened anxiety, depression, impaired decision-making, and disrupted interpersonal relationships [19–21, 102].

The emergence of generative AI and chatbots introduces a new and largely unexplored area with the potential to foster addictive behaviours. Concerns about these technologies are growing, as reliance on generative AI for decision-making and problem-solving has already sparked debates over its risks and potential negative effects on human cognitive functioning [5, 6, 22, 23]. Over-reliance on these tools also raises questions about their long-term impact, including the potential for users to develop behavioural and cognitive dependencies. The focus of this paper is to discuss the potential inducting and reinforcing features of ChatGPT that may

contribute to the promotion of addictive tendencies beyond other AIs. In the rest of this paper, the terms “addiction” and “addictive behaviour” will be used to highlight the tendency toward dependent behaviours rather than concentrating on formal diagnostic criteria.

2 Can ChatGPT Be Addictive?

2.1 Self-Specificity as a Motivational Factor Facilitating Engagement

Generative AI systems are moving away from their traditional role as information mediators and increasingly taking on the role of direct communicators and active participants in social interactions [24]. As communicators, AI systems can engage users in conversation, provide tailored responses, and display behaviours that mimic human emotions and social cues [13]. As participants, AI systems can influence the dynamics of these interactions, shaping the way how people communicate and make decisions. These dynamics are particularly evident in ChatGPT, where interactions extend beyond basic transactions, involving the level of personalisation and adaptability that makes the communication personally relevant and self-specific. We use the term ‘self-specificity’ following the concept in psychiatry and neuroscience, where self-specificity refers to the unique and fundamental feature of an individual's sense of self providing the foundation upon which personal relevance and subjective experience are constructed, shaping intrinsic motivations [25–28].

When viewed through the lens of human–computer interaction, self-specificity serves as a conceptual bridge for understanding how users engage with systems. Individuals bring their self-concept, driven by unique cognitive and emotional patterns, into interactions with technology. The emotional valence of a system's feedback, for instance, is more likely to resonate with a user when it aligns with self-specific perceptions. A practical example lies in virtual agents that simulate emotional intelligence; users tend to engage more positively when these agents reflect personalised emotional cues, as these interactions feel inherently more relevant to the user's sense of self [29]. Furthermore, the self-specific nature of reward processing suggests that systems offering personalized reinforcement, such as gamified learning platforms, may significantly enhance user engagement. Such platforms tap into the inherent link between self-specificity and reward sensitivity, offering experiences that feel tailored and meaningful [30]. This aligns with the broader principle that individuals are more likely to respond to stimuli that resonate with their cognitive functioning and emotional experiences, whether through social validation, personalized feedback, or meaningful interaction [31, 32]. In this

subsection, we will consider how characteristics of personal relevance and self-specificity may also contribute to patterns of dependency and compulsive use, aligning with behaviours associated with addiction.

ChatGPT has three distinct features fuelling personal relevance and self-specificity. First, it is designed to avoid using hostile or offensive language and to take all user queries seriously, no matter how personal or seemingly minor they may be. This creates a safe space for individuals, encouraging them to ask questions they might otherwise be reluctant to ask in their everyday lives. By consistently offering thoughtful, respectful responses, ChatGPT helps nurture a *sense of self-worth* and can facilitate the user's self-esteem [33].

Second, ChatGPT's ability to "remember" previous conversations allows it to recognise and reference a user's past enquiries, concerns or preferences. This continuity in dialogue can give users the feeling that the AI understands and knows them, which enhances the sense of being part of an ongoing, meaningful interaction. When individuals experience this kind of *familiarity effect*, it fosters trust and reinforces a positive feedback loop of validation [34]. According to the Biased Expectations Theory, the importance of the positive feedback loop to a self-reinforcing cycle in which an initial event or behaviour leads to a subsequent increase in the same behaviour by creating a loop of amplification encouraging further engagement [35].

Third, ChatGPT is a competent assistant in various tasks—from coding, content writing, and learning to entertainment and casual conversations. The interactive, creative process can feel rewarding and stimulate engagement for longer durations because it supports one of the basic psychological needs—the *need for competence*. According to the Self-Determination Theory SDT, competence refers to the experience of mastery and being effective in one's activity as a criterion for psychological growth and well-being [36].

ChatGPT's ability to adapt responses to individual preferences creates a compelling, personalised experience that can easily absorb a user's attention for extended periods. Since ChatGPT provides meaningful, productive engagement in various areas (from work to entertainment), users may lose track of time. This experience aligns with the concept of flow in psychology, where users become deeply absorbed in a task or interaction, often unaware of time passing [37]. For instance, when users engage in problem-solving, creative writing, or learning tasks, ChatGPT can dynamically adapt its responses, maintaining an optimal level of complexity and responsiveness. This alignment mirrors the conditions that research identifies as prerequisites for flow [37]. Flow states are facilitated by a balance between task challenge and user skill, coupled with clear goals and immediate feedback [38]—features ChatGPT inherently provides. While flow is often associated with positive engagement and productivity, prolonged immersion in ChatGPT interactions may blur

the line between beneficial use and compulsive behaviour [108, 109]. Studies on digital engagement suggest that such immersive experiences can foster over-reliance, particularly when users seek to replicate the rewarding sensations linked to flow states [39]. The AI's provision of positive reinforcement may increase the likelihood of users staying engaged longer, sometimes at the expense of their awareness of time—the behaviour was recognised as a symptom of behavioural addiction, i.e. *tolerance* with the increased usage to get the same satisfaction and *conflict* with other life priorities [40]. Over time, this dynamic could foster a habit of interaction with this platform and make it difficult to disconnect from ChatGPT.

2.2 Pseudosocial Bond as a Factor Enhancing Dependence

ChatGPT and other social chatbots are designed to create a sense of social presence, making users feel like they are interacting with an entity that is socially aware, thus fostering a strong connection with the AI. Some research suggests that interactions between humans and social chatbots may mimic the formation of human-to-human relationships [3, 41, 42]. However, the bond created is pseudosocial, imitating social interaction but ultimately remaining a one-sided engagement between the user and the AI. This type of one-sided connection is often referred to as a "parasocial" relationship, where individuals form deep emotional attachments to someone or something incapable of reciprocating their feelings [43]. The concept of parasocial relationships has often been applied to celebrities' fans, where these relationships can be categorised as entertainment-social, intense-personal, or borderline-pathological, depending on the degree of emotional investment and control [44]. This subsection will discuss how the formation of a pseudosocial bond with ChatGPT may contribute to its potential as an addictive feature, particularly through the mechanisms of emotional attachment and perceived social interaction.

Parasocial Interaction Theory suggests that the formation of a parasocial bond with a media personality begins with repeated exposure, which develops a sense of familiarity and trust, allowing viewers to imagine the figure as a friend [45]. This bond is further strengthened if media figures create the illusion of personal interaction, often described as 'intimacy at a distance' [45]. Positive emotions, such as happiness or comfort, further enhance this connection, motivating viewers to engage in activities like planning to watch shows or collecting memorabilia, which imbue the relationship with greater significance and meaning [46].

Researchers have identified parallels between parasocial and interpersonal relationships, noting that both are voluntary, provide companionship, and involve homophily—the tendency to connect with others perceived as similar [47].

These shared mechanisms suggest that parasocial relationship follows a unified psychosocial framework. For instance, studies have shown that parasocial bonds with radio hosts rely on the same processes of familiarity and trust-building as those observed with television personalities, demonstrating the theory's applicability across different media formats [48]. Similarly, the intensity of parasocial bonds with fictional characters in streaming content aligns with mechanisms described by Horton and Wohl [45], confirming the universality of the mechanisms of forming parasocial relationships [49]. Furthermore, recent research has extended this framework to AI-based interactions, showing that parasocial bonds with chatbots mimic these processes, highlighting the adaptability of the theory to evolving digital landscapes [41].

An intriguing question arises about whether *parasocial relationships* could develop with ChatGPT, particularly in more intense forms (i.e., intense-personal or borderline-pathological), where users may begin to lose sight of the fact that the AI is not a real person. Existing frameworks in parasocial relationships and human–computer interaction provide insights into how humans form bonds with non-human entities. For instance, studies in computing have shown that individuals can develop parasocial relationships with AI chatbots, perceiving them as social entities capable of understanding [50–52]. Evidence from cognitive neuroscience indicates a contribution of higher human cognitive functions such as Theory-of-Mind in direct interactions with artificial robots and the tendency to build a model of another's mind linearly increases with its perceived human-likeness [53]. Studies in media psychology suggest that people tend to blur the boundaries between digital and real-world interactions [54, 55] which may be rooted in the human inclination to anthropomorphise or attribute human-like characteristics to non-human entities [56–58]. Although these studies have identified several mechanisms contributing to the formation of parasocial relationships, it remains unclear how these mechanisms operate in the context of ChatGPT. Specifically, it is yet to be determined whether interactions with ChatGPT can facilitate the development of parasocial relationships and, if so, whether these relationships could evolve into forms of dependency.

A key distinction lies in the unique features of ChatGPT that extend beyond traditional chatbots and have the potential to facilitate parasocial bonds. It should be noted that most previous models of human–computer and human–AI interaction have focused on systems designed for specific, narrow purposes, such as customer service chatbots or single-function tools (see [59] for review). Such systems typically operate within predefined boundaries and lack the conversational adaptability of generative AI like ChatGPT. By creating interactions that feel continuous, personally relevant, and highly adaptable, ChatGPT presents unique

challenges. Its features increase the likelihood of users developing a sense of connection or familiarity with the AI, mimicking aspects of human interaction. However, the ability to simulate human-like exchanges carries potential risks. Blurred boundaries between digital and real-world interactions can lead users to overestimate the relational depth of their engagement with ChatGPT, potentially prioritizing these interactions over genuine human relationships.

Such a shift in social preferences may result in greater reliance on ChatGPT for emotional or social needs. Over time, this reliance can contribute to social isolation, diminished interpersonal skills, and fewer opportunities for real-life connections—issues frequently associated with internet addiction [40]. Moreover, unlike human relationships, which typically demand significant effort, emotional investment, and development time, forming a connection with ChatGPT is easier and more convenient. Users can engage with the AI on their own terms, with minimal emotional or personal investment, while still receiving meaningful responses, support, immediate companionship, assistance and emotional validation. According to the Social Exchange Theory of Relationships, people are more likely to pursue relationships where the rewards outweigh the costs and to abandon those where the costs exceed the benefits [60]. In the 'relationship' between an individual and ChatGPT, the rewards for the user are considerably higher than investment, making the connection attractive and sustainable. Furthermore, human relationships are often unpredictable and can be a source of stress or disappointment [61]. In contrast, ChatGPT offers consistent and predictable interactions, which may appeal to many people due to its low-risk, low-effort and controllable options. Several social and psychological theories support this possibility [62, 63]. Over time, people may prefer the ease and predictability of ChatGPT, which comes with the risk of over-reliance on this AI and may lead to unintended social consequences if it begins to replace human interaction altogether.

It is important to emphasise that relying on ChatGPT for companionship does not inherently lead to addiction. However, the potential issue arises when individuals become dependent on ChatGPT to fulfil social needs that could be met through more balanced, real-world interactions. This dependency becomes problematic when users rely on ChatGPT despite the biases it may reinforce, such as self-bias in query selection (e.g., recall bias, selective reporting, minimisation, denial, or cognitive distortion) [64–66]. Particularly, self-bias can emerge when users frame queries to confirm their preexisting beliefs or preferences. ChatGPT's fine-tuning to user prompts and its ability to mirror input, in terms of tone, structure, and style making the interaction feel look more tailored, can create a feedback loop that validates these biases. For example, a user convinced that remote work reduces productivity might ask, "Why does

remote work reduce productivity in teams?” ChatGPT may respond with information highlighting challenges such as communication and collaboration issues, further supporting the user's belief. A follow-up like, “Can you explain why remote work is less efficient than in-office setups?” could elicit additional aligned responses, reinforcing the user's perspective without introducing counterarguments. This cycle of validation can lead to dependence as users increasingly turn to ChatGPT for confirmation and support. Moreover, this dynamic can distort reality by allowing users to strengthen their perspectives without the challenge of real human interaction. For instance, a user researching a controversial topic might frame queries to favour their stance, receiving responses that align with their viewpoint while avoiding critical counterarguments typically encountered in discussions with others. This aligns with research on the problematic use of social media driven by the need for social validation and reassurance [103] and leading to fear of missing out [104] and procrastination [105]. Thus, while ChatGPT offers convenience and predictability, forming a pseudosocial bond may prevent individuals from addressing more profound personal challenges and limit their ability to engage in genuine, reciprocal human relationships—consequences typical of dependency in any form.

2.3 Productivity Boost and Task Automation as Addictive Features

Over the past decade, the concept of work achievement has increasingly become synonymous with productivity, reflecting a shift in success measurements in the workplace [67]. The focus on productivity as a measure of worth has increased pressure to perform constantly, leading many to adopt excessive work habits to meet these demands [68]. Additionally, the widespread adoption of productivity tools to monitor and control progress has significantly reshaped work culture, with employees now expected to be more efficient and output-oriented [3]. This increased focus on productivity can also be linked to evolving social expectations, particularly with the rise of co-intelligence [42]. As AI becomes more integrated into daily workflows, employees may increasingly recognise that differences in outcomes are often due to the use of advanced technologies rather than individual skills alone. This can lead to peer pressure in the workplace, pushing workers to depend more on AI tools not just to enhance productivity but also to keep up with the expectations set by their colleagues. This subsection will explore how ChatGPT's ability to enhance productivity may lead to dependent behaviours, as users increasingly depend on its efficiency to cope with rising demands and expectations.

The introduction of ChatGPT has opened new opportunities to boost productivity by streamlining tasks, providing

real-time support, and offering creative solutions. With its ability to quickly answer questions, summarise documents, and conduct research, ChatGPT saves time and helps users make faster, more informed decisions. It also generates content such as reports, presentations and infographics, allowing users to focus on more critical tasks. For example, recent studies have shown a 40% improvement in writing task productivity and an 18% increase in output quality [69].

However, the substantial productivity benefits of ChatGPT are accompanied by the risk of instant gratification from its rapid and responsive interactions, which can reinforce compulsive usage patterns and increase the likelihood of addictive behaviour. Immediate responses from the AI can be highly rewarding, especially when it effectively meets users' needs or desires. This instant reward can reinforce behaviour, making them more likely to become habitual [70, 71]. The ease of obtaining quick answers may reduce users' tolerance for delays [72], leading them to prefer ChatGPT over other methods of information gathering or problem-solving. The convenience of automating tasks such as writing, scheduling, and information retrieval can also contribute to an over-reliance on ChatGPT. While this feature is not unique to ChatGPT, its efficiency can cause users to raise their productivity expectations, pushing them to complete more work in less time. This escalation can create a cycle where users increasingly depend on ChatGPT to meet these heightened expectations.

Another key factor contributing to addictive behaviour is the potential of escalating the work-reward cycle. For example, completing tasks through ChatGPT's assistance can reinforce feelings of accomplishment, providing a dopamine-driven sense of satisfaction [73]. Over time, users may seek this satisfaction more frequently by taking on more work or complex projects. However, this escalation can become problematic. As the demands increase, so does the reliance on ChatGPT to meet these higher expectations. This can lead to burnout, exhaustion, and a deteriorating work-life balance, much like how addiction leads to *diminishing returns and increased harm over time* [74–76].

It has to be noted that escalating the work-reward cycle can fuel behaviours characterised by an unhealthy preoccupation with work that leads to psychological, emotional, and physical consequences [16]. When ChatGPT helps automate complex tasks, individuals with an addiction to work may increasingly rely on it to maintain high performance. This reliance can become similar to a dependency on substances in other forms of addiction, where the individual feels incapable of functioning without it. For example, it may lead to experiencing *withdrawal-like symptoms* when a person with an addiction to work cannot access the tool, such as frustration, anxiety, or fear of falling behind [77]. Moreover, work-addicted people often struggle to set boundaries between work and personal life [78]. The unlimited availability of

ChatGPT can exacerbate this by enabling continuous work during off-hours or using work as a distraction from other areas of their life, further entrenching the addictive behaviour. This lack of boundaries can result in a detachment from physical, emotional, and relational needs [79]. Just as people with an addiction may neglect their health or relationships, those addicted to work may sacrifice sleep, social interactions, and leisure activities to accommodate their increasing workload, often rationalising this behaviour through the ease of task completion with tools like ChatGPT. This reflects the concept of *escalation of commitment*, where individuals continue to invest excessive time and energy into work, even when it leads to negative outcomes, driven by a desire to justify previous efforts and maximise perceived productivity gains [80].

ChatGPT can also create an endless cycle of searching and re-searching, as its AI capabilities offer numerous novel ways to achieve tasks, leading individuals to compulsively check for better options and results. The cycle can be particularly problematic for idealistic personalities, who may constantly seek perfection. Such behaviour aligns with the concept of *cyberchondria*, where anxiety-driven overuse of online resources exacerbates health concerns, ultimately contributing to stress and mental health challenges [81].

This tendency to rely heavily on AI tools like ChatGPT raises an intriguing question: if generative AI aims to enhance productivity—similar to how the internet transformed problem-solving and efficiency—might this reliance mirror the way people have become increasingly dependent, or even addicted, to the internet. Both ChatGPT and the internet can facilitate productivity but may also lead to dependence. ChatGPT, for instance, can increase productivity pressures by enabling task automation and creating a sense of having a personal assistant. Similarly, internet use can foster “always-on” behaviour, where users feel compelled to stay connected or continuously search for information, a pattern that parallels addictive tendencies. However, there are key differences between ChatGPT-related and internet-related productivity addiction.

Internet use often involves passive content consumption or information searching, whereas ChatGPT fosters active engagement through personalised, conversational interactions. ChatGPT also reduces cognitive effort by automating tasks, whereas internet use typically requires users to independently process and integrate data, demanding greater mental effort to complete tasks. Additionally, ChatGPT’s memory of previous queries simplifies interactions. For example, a query like “Could you tell me the average salary of a schoolteacher in Hong Kong?” can be seamlessly followed up with, “In US dollars, please, and including all benefits,” reducing the cognitive load of starting over. In contrast, tools like Google search do not retain conversational context, requiring users to reframe their queries each

time. Another distinction is that ChatGPT offers direct assistance, akin to having a virtual work assistant, while internet addiction is more centred around content consumption than personalised support. Additionally, ChatGPT may lead users to delegate increasingly complex tasks to the tool, while internet overuse often involves extended time spent online or exploring diverse platforms. These differences need further conceptualisation and experimental research. Nevertheless, they highlight how these tools facilitate productivity in distinct ways while posing unique risks of overuse.

Thus, while ChatGPT can improve productivity and efficiency, it can also inadvertently enable or exacerbate workaholism, particularly for individuals predisposed to compulsive work behaviours. Without conscious awareness and healthy boundaries, over-reliance on tools like ChatGPT can lead to an unsustainable cycle of overwork, similar to other addictive behaviours.

2.4 Over-Reliance on ChatGPT for Decision-Making

ChatGPT has several key features, making it particularly appealing in assisting decision-making. For instance, trained on a vast dataset, it offers suggestions based on many sources and can analyse data, trends, and probabilities, helping individuals make decisions rooted in facts rather than subjective bias. Moreover, ChatGPT is free from personal biases or emotions, providing objective advice based solely on the input it receives. Additionally, ChatGPT’s ability to cover a wide range of topics makes it a versatile decision-making tool capable of adapting to various contexts. How might these features, while enhancing decision-making, also contribute to over-reliance on ChatGPT and reduce users’ confidence in their own judgment?

Decision-making is a fundamental aspect of human cognition, ranging from simple daily choices like deciding what to eat for breakfast to more complex decisions made by business leaders, doctors, and policymakers. The complexity of a decision is often shaped by the cognitive effort required [82], the need for specialised knowledge [83], and the application of decision-making skills and general intelligence [84]. Faced with such complexity, individuals naturally seek ways to manage cognitive load and streamline decision-making. To achieve this, humans have developed a range of mechanisms, including satisficing, cognitive biases, habit formation, and simplification strategies [85, 86]. In behavioural economics, high cognitive load is often mitigated by “heuristics” or mental shortcuts [87]. ChatGPT can be viewed as an external heuristic, providing quick solutions that save time and effort. However, overly relying on these quick solutions can also trigger unwanted processes that potentially can contribute to developing behavioural addiction.

First, it may reduce users’ inclination to assess alternatives or question the validity of AI-generated responses. As

decision-making is increasingly delegated to AI systems, users gradually bypass cognitive processes critical for judgment [88]. For example, there is evidence that individuals tend to over-trust AI-generated recommendations, even when those recommendations are flawed [89]. This phenomenon, known as *automation bias*, causes users to default to AI guidance, diminishing their ability to critically evaluate or question the information presented [90]. Over time, relying on AI recommendations can lead to dependency, where users may start turning to ChatGPT repeatedly for both major and minor decisions, creating a self-reinforcing cycle. This can result in diminished self-confidence and reduced personal agency in decision-making, which are often found in dependent patterns of behaviour [91].

Second, overreliance on ChatGPT can increase uncertainty and indecisiveness. Studies on the use of AI in medical decision-making have shown that individuals who frequently rely on AI systems are more likely to experience *decision paralysis* when those systems are unavailable [92]. Such findings suggest the potential for a behavioural shift towards dependency on AI for decision-making, where the absence of AI induces feelings of uncertainty and anxiety, similar to salience and withdrawal symptoms seen in addictive behaviours [40]. Furthermore, research indicates that as people become accustomed to AI guidance, they tend to delegate more decisions, even when they previously would have felt confident making choices on their own [93]. The escalation of reliance could create conditions where users lose control over the time spent using AI systems like ChatGPT due to its advanced ability to support decision-making processes rigorously.

The growing reliance on AI systems like ChatGPT raises important questions about how dependency on such tools evolves and the broader implications for human decision-making. One of them is whether the dependency on ChatGPT is different from, for instance, other AI tools, such as navigation systems. Navigation systems and ChatGPT both leverage AI to support human decision-making, yet their functions, contexts of use, and implications differ significantly. One key distinction lies in the nature and extent of dependency. Navigation systems are situational tools, primarily limited to route planning. In their absence, users often revert to traditional methods such as maps or memory. In contrast, the dependency potential of ChatGPT is more complex. Its ability to simulate human-like interactions, provide emotional validation, and personalize responses introduces the possibility of behavioural addiction. Furthermore, while utility-focused software such as navigation systems and e-commerce platforms typically rely on rule-based logic and filtering to meet situational needs, ChatGPT represents a paradigm shift toward “co-intelligence,” a concept explored by Mustafa Suleyman in *The Coming Wave* [106]. This shift transforms AI from a tool that automates predefined

tasks into a cognitive partner capable of engaging users in complex, collaborative processes. This evolution aligns with Ackoff’s Data, Information, Knowledge, and Wisdom (DIKW) Pyramid, which traces the progression from data to information, knowledge, and ultimately wisdom [107]. Unlike utility-focused AI, ChatGPT transcends task automation by acting as a thoughtful collaborator, supporting users in areas where clear reasoning may not always be required. Its role as a “cognitive partner,” however, hints at how easily overreliance on ChatGPT can develop, as its personalized and adaptive interactions simplify complex decision-making processes.

In conclusion, ChatGPT, with its advanced capabilities for generating personalised, context-aware interactions, not only transforms productivity and decision-making but also introduces risks of dependency that may diminish users’ critical thinking and personal agency. This raises significant concerns about the psychological, social, and cognitive impacts of generative AI, which remain largely unexplored. Section 2 addresses the need for new scientific inquiry into these issues and proposes research questions to guide future studies and mitigate potential risks.

3 Addressing the Risks of ChatGPT: A Call for Multidisciplinary Scientific Inquiry

3.1 The Dual Nature of ChatGPT and the Need for New Research

Speaking at the launch of the Leverhulme Centre for the Future of Intelligence in Cambridge, Professor Stephen Hawking stated, “Success in creating AI could be the biggest event in the history of our civilisation. But it could also be the last—unless we learn to avoid the risks.” His warning highlights the dual nature of AI, presenting both unprecedented opportunities and significant risks.

One such risk is the widespread use of AI-driven systems like ChatGPT, which has raised ethical, legal, and psychological concerns [94–96]. We argue that a remarkably under-explored issue is the potential for behavioural addiction to AI tools like ChatGPT. Only a few studies have mentioned this concern [97, 98]. Despite these growing concerns, there is still a lack of comprehensive literature systematically examining the behavioural, cognitive, or psychological impacts of frequent interaction with ChatGPT. Although these are still in the early days, this gap points to a broader issue: we do not yet fully understand the mechanisms that could lead to addiction to this AI.

The features that make ChatGPT appealing—instant feedback, personalised responses, and human-like interactions—can encourage prolonged engagement and, potentially, behavioural addiction. Assisting in decision-making

and work routines can facilitate productivity, but it also creates over-reliance, reduced critical thinking and overuse of ChatGPT. This creates a paradox where the qualities that make AI beneficial can also result in harmful consequences. Understanding this paradox is crucial for addressing AI-related addiction, especially with tools like ChatGPT. It has to be noted that studying the dual effects of ChatGPT may present several methodological challenges. For instance, simultaneously measuring positive and negative behavioural changes is difficult [99]. Confounding variables, such as the persona factors of perfectionism, need for control, fear of uncertainty and neuroticism, further complicate matters, as the same factors that lead to positive outcomes might also contribute to negative ones, making it hard to establish cause and effect [100].

Additionally, the timing of effects may vary—positive outcomes could manifest immediately, while negative consequences may develop later—introducing further complexity in study designs [101]. These challenges are substantial but not insurmountable. Several approaches can help address them. For example, a framework incorporating continuous monitoring and adaptive analysis could track the evolving nature of user-ChatGPT interactions. Comparative studies between the frequent use of generative AI and traditional AI may reveal unique psychological and behavioural effects of both of them. Additionally, adaptive study designs, such as iterative testing cycles or simulated environments, could provide more accurate and reliable data.

What is needed now is a new scientific inquiry at the intersection of computer science, psychology, sociology, neurobiology, and law to address the risks of ChatGPT-induced addictive behaviours effectively. This inquiry must go beyond traditional research methods and likely requires innovative tools for real-time monitoring of AI-user interactions and new metrics for assessing the psychological impact of ChatGPT.

3.2 Directions for Future Research

The call for a new scientific inquiry into the potential addictive features of ChatGPT is both timely and critical, given its increasing prevalence in daily life and its profound psychological and behavioural implications. However, this inquiry requires research questions broad enough to explore the complex ways ChatGPT's features might encourage and reinforce dependency, while also supporting studies from

multiple disciplines. For example, a neuroscientist might explore how ChatGPT's rapid, tailored responses activate neural reward pathways, potentially fostering habitual engagement. A psychologist could examine how users form emotional dependencies on ChatGPT, blurring the lines between genuine human connection and AI-mediated interaction. Similarly, sociologists might investigate the societal impacts of over-reliance on ChatGPT, including shifts in interpersonal relationships and social cohesion, while computer scientists could study how design features such as adaptive dialogue enhance user engagement to the point of dependency. These examples illustrate the need to examine ChatGPT's features not in isolation but as interconnected mechanisms that collectively shape user behaviour.

Although the current discussion does not delve into classical models of behavioural addiction, such as Griffiths' components model [110] or the Interaction of Person-Affect-Cognition-Execution (I-PACE) model [20], future work might consider how these frameworks could be adapted to capture the unique dynamics of AI-mediated interactions. For instance, the I-PACE model emphasizes the interplay between individual predispositions, affective responses, and cognitive processes in developing addictive behaviours. This model could be expanded to account for the role of highly responsive, personalized AI systems like ChatGPT in facilitating engagement. Future research could also explore whether traditional notions of salience, mood modification, tolerance, withdrawal, conflict, and relapse [110] adequately describe AI-related dependency or if new dimensions are necessary.

To guide this inquiry, we propose an initial set of research questions and future directions, as outlined in Table 1.

In reflecting on the rapid integration of ChatGPT into daily life, we recognise both the immense opportunities and the pressing challenges it presents. The questions proposed in Table 1 are not merely academic exercises; they are a call to action for researchers, policymakers, and designers to grapple with the profound psychological and societal impacts of this technology. If ChatGPT's potential to foster dependency remains unexamined, we risk normalising behaviours that could undermine critical thinking, interpersonal relationships, and even autonomy. However, this also presents a unique opportunity: by understanding and addressing these risks early, we can guide the evolution of this technology to enhance human well-being without compromising our agency.

Table 1 Research questions (RQs) and future directions (FD)

	RQs	FD
1	Is ChatGPT addiction different from other forms of behavioural addiction?	Traditional behavioural addictions, such as those associated with gambling or video gaming, frequently consist of cycles of rewards, obstacles, and gratification. A fundamental inquiry is whether ChatGPT's attributes can establish an avenue to addiction. Does its ability to replicate human connection enhance its addictive potential in ways not seen with other communication AIs?
2	How does ChatGPT addiction compare to social media or internet addiction?	Social media and internet addiction are well-documented, and users can form compulsive habits around checking notifications or feeds. However, ChatGPT provides a more self-specific and interactive experience with less fear of confidentiality breaches and greater openness and availability. Does this deeper engagement foster stronger dependency than the more passive consumption typical of social media?
3	Can ChatGPT's personalisation features amplify addictive tendencies?	ChatGPT's ability to tailor responses based on user inputs and preferences raises new challenges. Does personalisation increase the likelihood of attachment, particularly for users prone to perfectionism, fear of uncertainty, and need for control who may exhibit compulsive ChatGPT reliance and usage behaviours? How does this customisation impact users' decision-making autonomy, and could it promote dependency?
4	How does ChatGPT affect cognitive development and decision-making?	A key question is whether habitual use of ChatGPT alters cognitive functions like critical thinking, problem-solving, and decision-making. Does frequent reliance on ChatGPT reduce users' ability to make independent decisions? Could this lead to cognitive decline, similar to other forms of addiction where the brain becomes less capable of functioning without external stimuli?
5	What are the neurobiological mechanisms behind ChatGPT dependency?	While addiction has been studied extensively in terms of brain function, little is known about how the brain responds to prolonged interactions with AI systems like ChatGPT. Does the continuous stimulation and gratification from these interactions activate the brain's reward system in a way similar to other addictions? Are there unique neurobiological markers or patterns that differentiate ChatGPT-induced addiction from other forms of compulsive behaviour?
6	How does pseudosocial relationships with ChatGPT influence real-world social interactions?	One of the most important questions is how pseudosocial relationships with ChatGPT impact users' willingness and ability to engage in meaningful human relationships. For instance, longitudinal studies could examine whether prolonged use of ChatGPT reduces the frequency and quality of face-to-face social interactions. Additionally, experimental research could investigate shifts in interpersonal skills, such as empathy, active listening, and conflict resolution, among individuals who heavily rely on ChatGPT for emotional support

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Declarations

Conflict of interest Author Raian Ali is a member of the Editorial Board of the Journal Human-Centric Intelligent Systems. The paper was handled by another Editor and has undergone a rigorous peer re-

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