Is there evidence for attentional bias to social media stimuli in social media users?

Technology bringing us closer together or pulling us further apart?

Natasia K Lawrence

University of Strathclyde

MPhil in Psychology

Abstract

The rapid proliferation of social media has prompted critical inquiry into its psychological consequences, particularly its potential to foster addictive behaviours. Grounded in cognitive and addiction frameworks—most notably Incentive Sensitisation Theory (IST)—this thesis explores whether social media users exhibit attentional biases towards social media-related stimuli and whether these biases are moderated by factors such as screen time, craving, and problematic use. Across three experiments, different attentional paradigms were employed: Experiment 1 utilised the Flicker-Induced Change Blindness (FICB) paradigm to assess selective visual attention to Instagram-related images; Experiments 2 and 3 implemented the Dot Probe paradigm, with the latter introducing temporal variations to distinguish between initial orienting and sustained attention. Findings provide partial support for the presence of attentional biases to social media cues, particularly under short display durations, aligning with IST's assertion that repeated cue exposure enhances motivational salience. However, the results also highlight methodological and conceptual complexities—such as stimulus timing, task sensitivity, and individual differences—that challenge the consistency of these effects. This thesis contributes to the emerging field of behavioural addictions by offering nuanced insights into the cognitive mechanisms underpinning problematic social media engagement, and by critically evaluating the ecological and theoretical validity of commonly used attentional bias paradigms. Implications for diagnostic models, intervention development, and future research directions are discussed.

Keywords: attentional bias, social media addiction, behavioural addiction, cognitive mechanisms, Incentive Sensitisation Theory, dot probe, flicker change blindness, screen time

Contents

Chapter 1 The Growing Use of Social Media and Addictive Tendencies

The predominant utilisation of social media as a contemporary means of communication occurs through online platforms. Social media encompasses platforms where users directly engage and communicate. Currently, there are 3.8 billion active social media users (Statista, 2020). Prominent social media platforms include Facebook, YouTube, Twitter, WhatsApp, Instagram, TikTok, LinkedIn, and Snapchat (Brevers & Turel, 2019). These platforms can be accessed through various mediums such as websites, blogs, or mobile applications. Accessibility to social media only necessitates internet access and internet-enabled devices like computers, smartphones, and tablets (Nesi, 2020). Equipped with features facilitating real-time connections, these devices contribute to the popularity of social media due to its perceived convenience, cost-effectiveness, and reliability (Aksoy, 2018). Key characteristics of social media usage include staying updated on news, discovering engaging content, and sharing ideas, videos, and images (Ryan et al., 2014; Whiting & Williams, 2013).

Social media can offer advantages to individuals by fostering positive community and connecting them with peers who share similar identities, abilities, and interests (Weinstein, 2018). It serves as a platform for accessing crucial information and creating a channel for self-expression (Bekalu et al., 2019). Positive effects of social media use include the ability to establish and sustain online friendships, enabling social connections with more diverse peer groups than offline interactions. This can be particularly beneficial for marginalized individuals, such as those from racial, ethnic, sexual, and gender minorities, as online social support can function as a buffer against stress (Charmaraman, 2022; Tibber & Silver, 2022). For instance, studies indicate that social media plays a role in supporting the mental health and well-being of LGBTQIA+ youths by facilitating peer connections, identity development, and social support (Berger et al., 2022). Furthermore, majority of individuals report feeling more accepted, emotional support, having a platform for creative expression, and being more connected to their friends' lives through social media (Kose & Dogan, 2019; Moretta et al., 2023; Vogels & Gelles-Watnick, 2023). However, increased social media use has also been associated with higher levels of loneliness (Hunt et al., 2018; Marttila et al., 2021).

Although there are positive effects to using social media, recent research has explored the potential negative impacts of excessive usage on mental health (Kırcaburun & Griffiths, 2018; Shensa et al., 2017; Woods & Scott, 2016). Excessive use of social media has been associated with issues such as anxiety, depression, and sleep disturbances (Lervik-Olsen et al., 2023; Olasina & Kheswa, 2021; Zafar & Mobin, 2024). Excessive social media users are more likely to experience feelings of social isolation and depression (Klinger et al., 2024). Despite its popularity, social media has been linked to adverse effects, leading to excessive use (Brevers & Turel, 2019). Problematic social media use involves an individual's increasing desire to be on social media, often neglecting responsibilities in other areas of life due to excessive time spent on these platforms (Griffiths et al., 2014). This excessive use is harmful, disadvantaging users in numerous ways (Andreassen et al., 2017).

Nevertheless, although excessive social media use is often described as addictive, the DSM-V and ICD-11 classification systems do not officially recognise it as such (Kuss & Griffiths, 2017; Kırcaburun & Griffiths, 2018; WHO, 2018). Currently experts are finding a connection between the utilisation of digital media and mental well-being which has sparked debates and discussions. Both the DSM-V and ICD-11 currently focus on gaming disorder to classify internet addiction, as it exhibits characteristics such as excessive use, withdrawal symptoms, tolerance, and adverse consequences—patterns reminiscent of substance abuse disorders. This excessive use is particularly prevalent among adolescents and young adults (Allahverdi, 2022), and it is referred to by various terms such as social media addiction, social networking addiction, problematic social media use, or internet addiction. Individuals are not addicted to the internet itself but to specific online activities (van den Eijnden et al., 2016). The problem arises from exposure to social media, with the time spent on it influencing individual behaviours (Rømer Thomsen et al., 2014). Continued usage can lead to an obsession and an inability to disengage. Several studies have increasingly characterised extensive social media engagement as a form of addictive behaviour (Griffiths, 2000; Kuss & Griffiths, 2017; LaRose et al., 2010; Ryan et al., 2014). As social media becomes an integral part of daily life, it can impact individuals' lifestyles and communication, potentially leading to excessive use (Uyaroğlu et al., 2022), thereby posing a threat to mental health (Kanwal et al., 2024).

The modern understanding of addictive behaviour has evolved beyond the traditional focus on substance-related dependencies like alcohol (Enoch & Goldman, 2002), smoking (Brown et al., 2014), and illicit drug use (Sofuoglu & Kosten, 2006). Problematic behaviours such as gambling (Gainsbury, 2015), gaming (Kuss & Griffiths, 2012), and internet use (Kuss & Lopez-Fernandez, 2016) are now seen as sharing similar underlying biological, psychological, and social mechanisms of addiction (DSM-V, ICD-11 & WHO), including elements like salience, mood modification, tolerance, withdrawal, conflict, and relapse, as seen in chemical addictions (Paschke et al., 2021). With the rise of social media, there is an argument that excessive usage can exhibit behaviours meeting the criteria for addiction (Griffiths & Kuss, 2017; Ryan et al., 2014), when looking at the same criteria for substance-use addictions (Banyai et al., 2017). Despite varied support for identifying excessive social media use as a potentially addictive behaviour with negative mental health consequences, research findings on its association with anxiety, lower self-esteem, and increased depression have been inconsistent (Keles et al., 2020; Andreassen et al., 2017; Lin et al., 2016; Shensa et al., 2017; Coyne et al., 2020; Heffer et al., 2019; Houghton et al., 2018). Unlike substance-related addiction literature, there has been limited exploration of whether excessive social media use can be identified through cognitive mechanisms like selective attention. The current research investigates whether an 'attentional bias' to social media-related stimuli exists among a group of social media users (Anderson, 2013). This exploration lays the foundation for a deeper discussion on the conceptualisation of behavioural addictions.

Conceptualisation of Behavioural Addictions

The conceptualisation of addictive behaviours is gaining increasing societal and scientific attention, though there is ongoing debate regarding its accurate classification and limitations. The term 'addiction' is contentious, with challenges in defining it, but a crucial element involves dependence on an activity or substance (Alavi et al., 2012). The categorisation of behavioural addiction sparks debates on distinguishing it from other mental disorders, particularly as technology, such as smartphones, becomes ingrained in daily life (Petry et al., 2018). Research indicates that addictive behaviours, including behavioural addiction, exhibit parallels with compulsive behaviour and are increasingly prevalent in society (Grant et al., 2010). The common thread in behavioural addiction consequences is impaired control, manifesting as neglect of relationships, deterioration of health, obesity, and somatic symptoms (Konkolÿ et al., 2015). Currently, efforts are underway to establish common ground for ongoing research, with Kardefelt-Winther et al. (2017) proposing an operational definition of behavioural addiction based on their collective understanding of problematic behaviours. Notably, the elements of 'tolerance' and 'withdrawal' in non-substance abuse situations involve a unique psychological process that distinguishes behavioural addiction from other categories of addiction (Kraplin, 2017). Consequently, a typical response to a common problematic situation may not be considered indicative of behavioural addiction. We will explore the identifications of behavioural addiction, examining how they are defined within medical and psychiatric frameworks, behavioural and substance addiction can be two sides to the same coin, and then delve into various models of addictive behaviours to better understand their complexities and implications.

Identification of Behavioural Addiction. Efforts are currently being made to establish a framework for understanding behavioural addictions, which involves defining and explaining this concept. At present, the potential candidates for this framework are medical and psychiatric. The traditional concept of 'addiction' primarily focused on dependencies related to substances such as nicotine, alcohol, and cocaine (Brown et al., 2014; Enoch & Goldman, 2002; Sofuoglu & Kosten, 2006). According to the DSM-V, addiction is characterised by risky usage, impaired control, pharmacological aspects, and impairment. Recently, both the DSM-V and ICD-11 introduced a category for "non-substance related behavioural addiction," encompassing various behaviours like video game playing, eating disorders, gambling, sex addiction, internet use, exercising, and pathological working (APA, 2013; WHO, 2018; Paschke et al., 2021). Stating that these activities can have addictive tendencies and qualities. Behavioural addiction is broadly categorised into medical and psychiatric classifications. The DSM-V includes 'impulse control disorders' under behavioural addiction, involving excessive behaviours related to the internet, games, pornography, food, compulsive shopping, and gambling (Grant et al., 2010). Other types of behavioural addictions, such as love, exercise, tattoos, and work, are also recognised. Internet Addiction, particularly associated with compulsive disorder, is prevalent in contemporary society, and DSM-V explicitly addresses the adverse psychological consequences of Internet Addiction (IA) (Block, 2008). However, despite the recognition of internet addiction, social media addiction has not yet been classified as a distinct disorder within these frameworks. The surge in social media use has sparked debates on whether its excessive use qualifies as addictive behaviour (Griffiths & Kuss, 2017; Ryan et al., 2014). The primary reason for this ongoing debate lies in the difficulty of distinguishing between high engagement and addiction. While some researchers argue that excessive social media use shares many characteristics with recognised behavioural addictions, such as impaired control, tolerance, withdrawal, and significant impairment or distress, others contend that the current evidence is insufficient to classify it as a formal addiction (Chamberlain et al., 2016; Kuss & Lopez-Fernandez, 2016; Griffiths et al., 2014; Griffiths & Kuss, 2017; Ryan et al., 2014). This is partly due to the variability in social media use patterns and the context-dependent nature of its impact on individuals' lives. Thus, while social media use can exhibit addictive qualities similar to other behavioural addictions, it is not yet formally recognised as a distinct addiction in major diagnostic frameworks like the DSM-V or ICD-11. This ongoing debate highlights the need for further research to better understand the implications of excessive social media use and its potential classification as a behavioural addiction.

Over the past few decades, there has been significant growth in the study of behavioural addictions (Grant et al., 2010). Similar to research on gambling and internet gaming, studies have also focused on other compulsive behaviours that are considered behavioural addictions. These behaviours include compulsive buying, sex addiction, binge eating, work addiction, exercise addiction, and smartphone addiction (Grant et al., 2010; Goslar et al., 2020; Devoe et al., 2022; Redish et al., 2008; Roberts et al., 2014). The common characteristic of all behavioural addictions is the inability to resist an impulse or urge, resulting in persistent engagement in the behaviour despite recurring negative consequences (Grant et al., 2010).

Despite the similarities between behavioural and substance addictions, there is ongoing debate in the literature about whether behavioural addictions should be classified as new psychiatric disorders (Billieux et al., 2015). However, when examining the relationship between behavioural and substance addictions, the similarities are more notable than the differences. Both types of addictions share common etiological, phenomenological, and clinical features (Grant et al., 2010). For example, behavioural addictions like gambling and internet gaming disorder often begin in late adolescence or early adulthood and follow a variable course of lapses and recoveries, similar to substance use disorders (Chambers & Potenza, 2003; Slutske, 2006). They also share common risk factors, such as adverse childhood experiences or trauma, and similar neurobiological dysregulation, particularly involving the dopamine reward system, as well as executive functioning deficits (Grant et al., 2010, Konkolÿ et al., 2017; Gainsbury, 2015; Kuss & Griffiths, 2012; Thomas et al., 2023).

The significant overlap between addictive disorders has implications for treatment. Both behavioural and substance addictions share common clinical processes that can be targeted in treatment, such as impulsivity, compulsivity, and emotional dysregulation (Grant et al., 2010). For instance, impulsivity is a key characteristic in many behavioural addictions, including gambling (Gainsbury, 2015), video games (Kuss & Griffiths, 2017), sex (Goslar et al., 2020), and shopping (Muller et al., 2015). Compulsivity (Blanco et al., 2009; Everitt & Robbins, 2005) and emotional dysregulation (de Castro et al., 2007; Williams & Grisham, 2012; Schreiber et al., 2013; Poole et al., 2017) are also present in both types of addictions, with emotional dysregulation being linked to increased severity of addictive behaviours. Lack of social support and interpersonal conflicts negatively affect both substance use disorders (McCrady et al., 2006) and various behavioural addictions (Petry & Weiss, 2009; Wartberg et al., 2017).

Despite these similarities, there are important neurological differences between behavioural and substance addictions. For example, while neurotransmitters, particularly dopamine, play a significant role in substance use disorders, their role in behavioural addictions like gambling is less clear (Potenza, 2018). A meta-analysis found increased activation in the ventral striatum during reward outcomes for substance use disorders, whereas gambling addiction was associated with decreased activation in the dorsal striatum (Luijten et al., 2017). Differences have also been observed in internet gaming disorder, which shows stronger functional connectivity in the left ventromedial prefrontal cortex compared to alcohol use disorder (Yoon et al., 2017). Nonetheless, engaging in both behavioural and substance addictions activates the dopamine reward system, leading to structural and functional changes (Grant et al., 2010). In this way, behavioural addictions closely mimic the key characteristics of substance use disorders (Diana, 2011).

Models of Addictive Behaviours. The conceptualisation of addictive behaviours has sparked considerable debate, leading to the emergence of a comprehensive definition. Marlatt et al. (1997) characterise addictive behaviour as a repetitive habit pattern that increases the risk of disease and personal/social problems. The behaviour is often subjectively experienced as a 'loss of control,' persisting despite attempts to abstain. Although the classification of behavioural addictions is a topic of debate, theoretical models from research on substance-related addictions have been frequently applied to understand specific behavioural addictions. These models, along with those developed specifically for behavioural addictions, outline the psychological (and partially neurobiological) mechanisms that might explain addictive behaviours. Generally, these models do not align strictly with the principles of various psychotherapeutic schools but rather concentrate on the processes underlying the development of symptoms.

Widely recognised models in addiction research fall under the term Dual-Process Models (Bechara, 2005; Everitt & Robbins, 2016). These models propose that addiction involves an increasing imbalance between the strengthening of impulses (primarily linked to limbic structures and the reward-processing ventral striatum) and the weakening of control processes (mainly associated with the lateral prefrontal cortex). Control processes, components of the reflective system, enable the regulation of cravings and impulses processed within the impulsive system. According to Dual-Process Models, controlling these intensifying impulses becomes progressively harder during addiction, leading to a significant loss of control over addictive behaviour, a core symptom of addiction. Recently, these models have been expanded to include a third component, which places interoceptive mechanisms as a link between impulsive and controlling processes, representing an awareness of cravings (Noël et al., 2013). Other theoretical approaches examine specific processes in greater detail, such as the reduced influence of control and steering processes on addiction-related impulsive behaviours (Volkow et al., 2016), mechanisms contributing to heightened sensitivity to rewards (Berridge & Robinson, 2016), or the idea that individuals with addictions generally have a diminished ability to process natural reinforcers, leading them to seek exogenous reinforcers (Blum et al., 2014). However, all these theories share the notion that affective-impulsive and cognitive-control processes interact, with progressive habituation during the addiction process sustaining addictive behaviour.

The component model of addiction identifies six key criteria, including salience, tolerance, mood modification, withdrawal, conflict, and relapse, all of which must be present for a behaviour to be labeled as addictive (Griffiths, 2019). According to this researchers' views, in this model addiction is argued to result from a complex interplay of factors, including social environment, psychological constitution, biological predisposition, and the nature of the activity (Griffiths, 2019). However, critics argue against applying substance-use disorder criteria to behavioural addictions, suggesting the need for exclusion criteria to avoid overdiagnosis and inappropriate pathologization (Kardefelt-Winther et al., 2017; Starcevic, 2016; Billieux et al., 2019; Kim & Hodgins, 2018). Moreover, the components model is criticised for relying on symptoms of substance addiction in defining behavioural addiction, particularly challenging with behaviours, raising questions about the accuracy of including symptoms like withdrawal and tolerance (van Rooij & Prause, 2014). Advocates of the component model propose important exclusion criteria, suggesting that behaviour should not be considered a behavioural addiction if it can be better explained by an inherent disorder, arises from a deliberate decision despite potential harm, lacks notable functional impairment or distress, or is a coping strategy (Kardefelt-Winther et al., 2017). Specifically, they propose that behaviour should not be labeled as a behavioural addiction if it can be better explained by an existing inherent disorder, such as a mental health condition. Additionally, if behaviour results from a conscious and deliberate choice despite potential harm, it should not be considered an addiction. Furthermore, the behaviour should not be seen as an addiction if it does not lead to significant impairment in daily functioning or cause notable distress. Finally, if the behaviour serves as a coping mechanism for dealing with stress or other issues, it should not be classified as an addiction. These criteria aim to ensure that behaviours are accurately classified and not mislabeled as addictions when they are better understood through other frameworks or explanations (Kardefelt-Winther et al., 2017).

The models previously discussed are not comprehensive, either within a specific behavioural addiction (e.g., there are additional models for internet addiction and computer game addiction) or across all the behavioural addictions (e.g., problematic use of social networks). Nonetheless, even in these brief and illustrative explanations, it is evident that specific core assumptions are consistently repeated across individual models for various behavioural addictions. Differences certainly exist in predisposing features and situational characteristics that can favor particular behavioural addictions. For instance, materialistic values significantly impact shopping addiction (Villardefrancos & Otero-López, 2016; Dittmar et al., 2007), while the experience of rewards (e.g., receiving positive comments or "likes") and negative reinforcements (e.g., fear of missing out) can be a specific vulnerability factor for excessive social network use (Sherman et al., 2018; Wegmann et al., 2015). These factors can explain why one person is particularly responsive to shopping-related stimuli while another has the urge to be online by social media stimuli. The common thread is that individuals have strong affective reactions to certain stimuli, which appear to intensify during the addiction process, a pattern seen across different behavioural addictions (Starcke et al., 2018). The goal of cross-disorder theoretical models is to summarize the processes underlying behavioural addictions.

The Interaction of Person-Affect-Cognition-Execution (I-PACE) model, originally designed for internet use disorders and later generalized, offers a comprehensive framework for understanding addictive behaviours (Brand et al., 2019). This model synthesizes established theories, especially those pertinent to substance addictions, incorporating the latest empirical data. Unlike a purely dual-process model, I-PACE emphasises the dynamic interaction between affective-impulsive tendencies and executive control processes (Brand et al., 2019; Kumalaratih & Margono, 2023). Central to the model is the notion that affective and cognitive processes interact in ways that can either amplify or mitigate each other. The core premise is that through interactions between the individual and their environment (such as engaging in computer games), cyclically reinforcing mechanisms emerge, making the behaviour increasingly automatic and potentially leading to problematic or addictive patterns with corresponding symptoms.

The models discussed share a common focus on the similarities between different addictions, but they also have significant differences. Dual-Process models are more psychological and neurological, emphasising brain systems and cognitive processes (Bechara, 2005; Everitt & Robbins, 2016). Components model of addictions is more holistic and descriptive, detailing the various facets and experiences of addiction (Griffiths, 2019). I-PACE model integrates multiple perspectives, including psychological, cognitive, and affective components, providing a comprehensive view of the interactions leading to addiction (Brand et al., 2019). Each model has its strengths and weaknesses. For instance, the dual-process models These models can explain a wide range of behaviours, including impulsive actions and habitual behaviours, making them relevant for understanding addiction (Bechara, 2005). On the other hand, these models might not fully account for individual differences in cognitive processing styles or the influence of environmental factors (Everitt & Robbins, 2016). I-PACE model by focusing on affective and cognitive processes, it highlights the role of emotional and cognitive responses in addiction (Brand et al., 2019). However, accurately measuring the interactions between person, affect, cognition, and execution components can be difficult (Brand et al., 2019). The components model of addictions effectively simplifies the similarities of addictions into six core components, but this simplicity might overlook other important aspects, such as compulsivity, that characterise both behavioural and substance addictions (Griffiths, 2019).

Attentional Processing: The Role of Attentional Bias in Behavioural Addictions

Attention functions as a mechanism to filter and simplify the vast and complex information received from our environment. Selective attention is a key aspect of this mechanism, enabling us to concentrate on and process relevant information based on our goals and motivations while ignoring irrelevant data (Klinger, 1996; Panksepp, 2023; Chun & Wolfe, 2001). Research indicates that stimuli are more likely to capture attention if they are pertinent to an individual's current objectives (Folk et al., 1992). Attentional bias, a form of selective attention, occurs when a specific category of stimuli disproportionately influences attentional processes at the expense of other competing stimuli (Chun & Wolfe, 2001; Field & Cox, 2008). In the context of addiction, attentional bias towards substance-related stimuli is observed when experienced users preferentially focus on information related to the substance, neglecting other types of information (Bruce & Jones, 2004). Several theoretical frameworks anticipate the existence of attentional biases related to behavioural addictions. These include the elaborated intrusion theory of desire (Kavanagh et al., 2005), the theory of current concerns (Cox & Klinger, 1988; Cox & Klinger, 2004), negative reinforcement model (Baker et al., 2004), and incentive sensitisation models (Franken, 2003; Robinson & Berridge, 1993). On the other hand, the main focus will be on Incentive Sensitisation Theory which delves into the neurobiological aspects of addiction (Robinson & Berridge, 1993). Together, these perspectives contribute to a comprehensive understanding of behavioural addiction, encompassing psychological, neurobiological, and behavioural dimensions.

Theoretical Perspectives. We will examine the concept of attentional bias and its role in behavioural addictions, examining various theoretical perspectives that shed light on this phenomenon. Attentional bias as stated before, refers to the tendency of individuals to focus disproportionately on addiction-related cues, which can perpetuate and intensify addictive behaviours (Cox & Klinger, 2004; Field & Cox, 2008). The discussion will highlight several key theories, including the Theory of Current Concerns (Cox & Klinger, 1988, 2004), the Elaborated Intrusion Theory of Desire (Kavanagh et al., 2005), the Dual-Process Theory (Wiers et al., 2007), negative reinforcement models (Baker et al., 2004), and the Biased Competition Theory (Desimone & Duncan, 1995). These frameworks collectively provide a comprehensive understanding of how attentional biases develop and sustain addictions by influencing cognitive and emotional processes. Through this exploration, we aim to elucidate the intricate interplay between attentional processing and addictive behaviours, offering insights into the mechanisms that underlie the persistence and relapse of behavioural addictions (Field & Cox, 2008; Robinson & Berridge, 1993).

The Theory of Current Concerns (TOCC) provides insights into why individuals select, pursue, and persist in achieving specific goals, with motivation defined as "the internal states of the organism that lead to the instigation, persistence, energy, and direction of behaviour towards a goal" (Klinger & Cox, 2008, pp. 4-5). TOCC provides a framework for understanding how individuals are more likely to notice, attend to, and be distracted by stimuli that are relevant to their current concerns or goals. TOCC posits that internal processes, or motivation, drive behaviour toward a goal, and current concerns represent a person's commitment to pursue a specific goal (Cox et al., 2006). Current concerns act as mental schemas influencing attention, memory, and priority, creating an attentional bias towards goal-related stimuli, such as anxiety (Klinger & Cox, 2008). This attentional bias, or hypersensitivity to goal-related information, is argued to play a role in various behaviours, including addictive behaviours. Attentional biases, external factors that catch a person's attention and remind them of their goal, play a crucial role in sustaining commitment to pursue the goal (Klinger & Cox, 2008). For instance, individuals committed to losing weight display attentional biases toward food-related stimuli, especially those associated with high-calorie foods. These biases can influence their eating behaviours, either by increasing the temptation to consume such foods or by reminding them of their dieting goals, thereby aiding in self-regulation efforts (Werthmann et al., 2015). Moreover, smokers have shown that they detect smoking-related stimuli faster than non-smokers, indicating a strong attentional bias (File et al., 2024). This bias is linked to higher levels of nicotine dependence, where the disparity between the desire for the substance and the pleasure derived from it is more pronounced (File et al., 2024).The TOCC models addictive behaviour by showing how a person's commitment to pursue a particular objective or goal and ultimately the attainment of that goal or failure to attain that goal depends on the external factors, such as attentional biases (Cox et al., 2006). Attentional biases create cognitive hypersensitivity to cues related to substances or behaviours, leading to subjective craving (Klinger & Cox, 2008). The decision to engage in addictive behaviour is influenced by the perceived value of the substance or behaviour and its expectancy of attainment (Klinger & Cox, 2008). Attentional biases are linked to emotional and motivational states, affecting cognitive, behavioural, and physiological responses (Field et al., 2009a). For instance, positive associations with alcohol or drugs may lead to attentional biases and substance-seeking behaviour (Schoenmakers et al., 2008).

Building upon the insights provided by TOCC, the Elaborated Intrusion of Desire theory (EIT) offers a deeper exploration into the nature of cravings and their impact on behaviour. The Elaborated Intrusion of Desire theory (EIT) suggests that cravings are not just simple urges but complex mental events involving a combination of cognitive and emotional processes (Kavanagh et al., 2005). Subjective cravings for substances like alcohol or nicotine can be 'triggered' by external or internal stimuli that initiate the craving process (Kavanagh et al., 2005). These triggers can be anything from the sight or smell of food, the presence of drug paraphernalia, or even specific emotional states like stress or boredom. Once these cravings arise, individuals tend to dwell on their desired substance, leading to an increased focus on related stimuli (Kavanagh et al., 2005). These intrusive thoughts are typically automatic and involuntary, popping into the mind without conscious effort. This cognitive elaboration strengthens the craving, which in turn heightens the focus on substance-related stimuli, creating a positive feedback loop that drives substance seeking and consumption (Kavanagh et al., 2005). While acknowledging the role of target salience in motivation (Robinson & Berridge, 1993), the theory emphasises the emotional nature of desires and the duality of affective reactions.

By further advancing the understanding of cognitive processes, the Dual-Process Theory complements EIT by highlighting the existence of two distinct cognitive systems: an automatic, fast, unconscious processes and a controlled, slow, conscious processes in managing these cravings and their influence on behaviour (Wiers et al., 2007). Substance-related attentional biases are understood as resulting from automatic processes (System 1) that drive attention towards substance cues, often overwhelming controlled processes (System 2) that might otherwise inhibit use, thus increasing craving, impulsivity and the potential for relapse (Wiers et al., 2010). This imbalance between the two systems can explain why individuals with addictions frequently engage in substance use and behaviour despite being aware of its negative consequences (Wiers, et al., 2007 & 2010). System 1 quickly directs attention to emotionally charged stimuli, such as threats or rewards, often bypassing rational deliberation. Substance and behavioural-related cues can trigger automatic attentional capture, which System 2 might struggle to override, leading to cravings.

By demonstrating how automatic processes (System 1) can overpower controlled processes (System 2), the Dual-Process Theory aligns with the Negative reinforcement model, suggest that substance use persists because it alleviates unpleasant withdrawal symptoms or other negative emotional states (Baker et al., 2004). As negative emotions intensify, the motivational value of substance-related cues also increases (Baker et al., 2004). Consequently, this model implies that when negative emotions rise, the primary motivation of the individual becomes reducing these negative emotions. As a result, substance-related cues become associated with relief from discomfort, capturing attention and perpetuating craving as individuals seek to avoid negative states (Baker et al., 2004).

This interplay between emotional states and attention is further elucidated by the Biased Competition Theory (BCT), which posits that stimuli compete for processing resources, and biases (such as emotional significance of a stimulus) can affect this competition (Desimone & Duncan, 1995). This theory emphasises the role of both bottom-up (stimulus-driven) and top-down (goal-driven) processes. Emotional stimuli are more likely to win the competition for attention, especially if they are relevant to the individual's current state (Desimone & Duncan, 1995). Individuals addicted to a substance may exhibit a biased competition towards drug-related stimuli, leading to enhanced focus on these cues and subsequent cravings. According to BCT, various stimuli compete for limited cognitive resources, and attention biases this competition by enhancing the processing of relevant information and suppressing irrelevant details (Desimone & Duncan, 1995). This selective attention mechanism allows for more efficient and effective cognitive processing, ensuring that the brain focuses on the most pertinent stimuli at any given moment.

Across these theories, several common predictions emerge regarding attentional bias and behavioural addictions. All theories predict that individuals with addictions will show a strong attentional bias towards stimuli associated with their addictive behaviour. This bias reinforces the addiction by constantly reminding individuals of their cravings and increasing the likelihood of engaging in the addictive behaviour (Cox & Klinger, 1988, 2004; Kavanagh et al., 2005; Wiers et al., 2007; Baker et al., 2004; Desimone & Duncan, 1995). Attentional bias is closely linked with subjective craving. The more attention individuals pay to addiction-related cues, the stronger their cravings become, leading to compulsive behaviour despite negative consequences (Berridge & Robinson, 2016; Franken, 2003). Attentional bias and cravings persist even when the actual enjoyment derived from the addictive behaviour decreases (Cox & Klinger, 1988, 2004; Kavanagh et al., 2005; Wiers et al., 2007; Field & Cox, 2008). This can explain why individuals continue their addictive behaviours despite adverse outcome. Environmental cues associated with past addictive behaviours can trigger relapse, even after periods of abstinence (Cox & Klinger, 1988, 2004; Kavanagh et al., 2005; Wiers et al., 2007; Baker et al., 2004; Desimone & Duncan, 1995; Field & Cox, 2008). The theories converge on the idea that attentional biases towards stimuli-related cues are a significant predictor of craving and potential relapse (Cox & Klinger, 1988, 2004; Kavanagh et al., 2005; Wiers et al., 2007; Baker et al., 2004; Desimone & Duncan, 1995; Field & Cox, 2008).

As discussed earlier, various theoretical frameworks suggest that substance-related stimuli are integral to addictive behaviours. The elaborated intrusion of desire theory, the theory of current concerns, and the negative reinforcement model all focus on the substance user's overall motivational state and its impact on substance seeking and consumption, highlighting the role of biased attention towards substance-related stimuli (Kavanagh et al., 2005; Klinger & Cox, 2008; Baker et al., 2004). However, these models fall short in explaining how substance seeking, and substance-related stimuli become motivational targets. The incentive sensitisation model, however, offers a more comprehensive framework with clearly testable predictions regarding the development of attentional biases and their role in behaviours and substance use (Field & Cox, 2008).

Incentive Sensitisation Theory (IST). As noted before, there are several models which have theorised the role of attentional biases in addictive behaviours. However, these models offer limited insight into how substance seeking, and substance-related stimuli become motivational targets. The incentive sensitisation model offers a more comprehensive framework with clear, testable predictions regarding the development of attentional biases and their role in substance use behaviours. According to this model, substance use is sustained due to the incentive motivational properties of substance-related stimuli, acquired through classical conditioning (Franken, 2003; Robinson & Berridge, 1993). Repeated pairings of substance-related stimuli with substance consumption result in these cues becoming associated with the positive reinforcing properties of the substances, thereby acquiring conditioned incentive motivational properties (Berridge & Robinson, 2016). In essence, "motivational properties" refers to the ability of certain stimuli, particularly those associated with drug use or other rewarding experiences, to acquire a heightened motivational value. These properties cause substance-related stimuli to capture and maintain the user's attention, making the substance more 'wanted' and promoting substance seeking and consumption (Franken, 2003; Robinson & Berridge, 1993). It is not surprising that incentive sensitisation models are notably the most encompassing theory (Berridge & Robinson, 2016; Robinson & Berridge, 2008; Rømer Thomsen et al., 2014; Cox et al., 2006; Field & Cox, 2008; Klinger & Cox, 2008). Their popularity is further bolstered by substantial empirical support found in the literature, stemming from both behavioural and neurobiological research. Due to their testable predictions and strong empirical backing, these models will serve as the theoretical foundation for this thesis, which will now be explored in great detail.

The phenomenon of substance addiction is a complex interplay of psychological and neurobiological processes. Attentional bias plays a crucial role in this context, influencing the development and persistence of addictive behaviours. Addiction is a result of progressive neuroadaptations induced by social and repeated drug use (Robinson & Berridge, 1993; Berridge & Robinson, 2016). These neuroadaptations manifest through changes in the nervous system, involving both neurochemicals and behaviour. In particular, sensitisation, defined as a progressive increase in drug effects with repeated treatment, becomes a key ingredient leading to addiction (Robinson & Berridge, 1993). This theory explains how repeated drug use can lead to a heightened sensitivity in the brain, making individuals intensely crave and seek drugs, often to the detriment of other aspects of their lives (González-Marín et al., 2020; Grigutsch et al., 2019; Arulkadacham et al., 2017). More specifically, IST posits that substance use triggers a dopaminergic response in the ventral striatum, a region known to be associated with reward (Bromberg-Martin et al., 2010; González-Marín et al., 2020). With repeated use, this dopaminergic response becomes progressively larger. Supporting IST, research indicates that all drugs of abuse, including tobacco and alcohol, prompt dopamine release in the ventral striatum (González-Marín et al., 2020; Grigutsch et al., 2019; Arulkadacham et al., 2017). Additionally, stimuli associated with substances, through classical conditioning, also induce dopamine release in this area (Fleming et al., 2021; Brevers et al., 2011; Garbusow et al., 2016; Elton et al., 2021; Luijten et al., 2012; Franken et al., 2005). This dopaminergic mechanism, linked to reward, is believed to attribute incentive salience to related stimuli. Transforming the neural representations of otherwise neutral stimuli into significant motivational incentives, making them 'attractive' and 'wanted' (Robinson & Berridge, 1993). Moreover, it has been demonstrated that cue-induced activation of the mesocorticolimbic reward system directs attention toward alcohol-related stimuli in alcohol dependents, consistent with IST predictions (Pennington et al., 2020; Vollstädt-Klein et al., 2011; Knight et al., 2018; Field et al., 2011).

This theory explains how the brain processes “wanting” and “liking”, leading to hypersensitivity to drugs or other obsessions, making it challenging to resist (Robinson &

Berridge, 1993). “Wanting” evolves into an obsessive craving, solidifying addictive behaviour through the sensitisation of incentive salience within the brain (Robinson & Berridge, 2000; Berridge & Robinson, 2016; Olney et al., 2018). The process involves the mesolimbic dopamine system in the brain, which plays a crucial role in reward and pleasure, creating a sense of pleasure and impacting reward-related behaviour (Berridge, 2012). Incentive salience “wanting” is more closely tied to reward cues, making them attention-grabbing and attractive (Anderson & Yantis, 2013; Hickey & Peelen, 2015). These cues can trigger strong urges to obtain and consume rewards (Ostlund et al., 2014; Peciña & Berridge, 2013). This type of “wanting” is largely mediated by brain mesocorticolimbic systems involving midbrain dopamine projections to forebrain targets such as the nucleus accumbens and other striatum parts. The strength of these urges is influenced by both the reward association of the cue and the current state of an individual's dopamine-related brain systems. This interaction allows “wanting” to be amplified by states that increase dopamine reactivity, such as stress, emotional excitement, relevant appetites, or intoxication (Anselme & Berridge, 2020; Berridge, 2012; Robinson & Berridge, 2008). Mesolimbic sensitisation causes the brain's "wanting" systems to become overly responsive (hyperreactive) to drug-related cues and environments, which in turn increases the incentive salience of those cues or contexts. As a result, addicts experience stronger cue-triggered urges and an intense “want” to consume drugs. Stressful states, even positive ones like winning the lottery, can also increase the risk of relapse in addiction and related disorders (Sinha, 2013). Thus, addiction is less about satisfaction, pleasure, need, or withdrawal, and more about “wanting.”

Compared to the robust “wanting” system, the brain’s system for generating intense pleasure or “liking” reactions is much smaller and more fragile. This "liking" system is made up of a network of interconnected hedonic (subjective pleasure) hotspots, which could be shared by different forms of pleasure, including sensory pleasures from food and drugs as well as human cultural and social pleasures (Ahmed & Koob, 1998; Berridge & Kringelbach, 2015). These pleasure-generating hotspots are anatomically tiny, neurochemically specific, and easily disrupted, possibly explaining why intense pleasures are rarer in life compared to intense desires (Castro & Berridge, 2014; Mahler et al., 2007; Peciña & Berridge, 2005; Smith et al., 2011). Each hedonic hotspot is embedded within a larger limbic structure, such as the nucleus accumbens, where the hotspot constitutes only a small fraction of the total volume and the remaining parts primarily enhance “wanting” without affecting “liking.” Unlike “wanting,” “liking” does not necessarily increase with sensitisation and may even decrease. Sensitised “wanting” can persist for years, even if the individual does not cognitively desire to take drugs, does not expect the drugs to be pleasant, and long after withdrawal symptoms have ended (Berridge & Robinson, 2011, 2016; Robinson & Berridge, 2001, 2008). The core idea of the incentive-sensitisation theory is that addiction becomes compulsive when mesolimbic systems become sensitised and hyperreactive to the motivational properties of drug cues (File et al., 2024; Ostlund et al., 2014; Witteman et al., 2015). This theory aims to explain why some individuals have near-compulsive urges to take drugs and remain at risk of relapse even after prolonged periods of abstinence.

It is important to note that while IST suggests an association between attentional bias and subjective craving, these are considered distinct emotional and cognitive outcomes that drive substance seeking and consumption. Therefore, even though the IST posits that both subjective craving and attentional bias are rooted in the same underlying processes, Robinson and Berridge (1993) also argue that substance-related cues can motivate substance-seeking behaviour unconsciously, implying that craving and attentional bias can sometimes be independent (Robinson & Berridge, 1993). The brain's approach mechanism becomes hypersensitised, leading to a desire-related emotional state and reinforcing incentive salience (Franken, 2003). Franken (2003) extended the IST proposed by Robinson and Berridge (1993), who agreed with the IST's explanation of substance-related attentional biases but argued that attentional bias and subjective craving have a mutual excitatory relationship. Craving, as an emotion, results from cognitive processes that amplify dopamine levels, drawing more attention to the addictive stimuli (Franken, 2003). This cognitive process, mediated by attentional bias, reinforces repetitive behaviour by drawing more attention to the perceived stimuli, contributing to the development and maintenance of addiction (Franken, 2003). The model suggests that as subjective craving intensifies, it enhances the attention-capturing properties of substance-related cues, creating a positive feedback loop that contributes to the cycle of addiction (Franken, 2003). This sensitisation process also occurs in behavioural addictions, like the obsessive use of social media (Hellberg et al., 2019).

Studies on the relationship between subjective craving and substance-related attentional biases have shown mixed results. Research has largely focused on tobacco addiction, but there is growing evidence that neutral stimuli repeatedly associated with tobacco can elicit tobacco-related attentional bias, subjective craving, increased physiological responses, and approach behaviours (Austin & Duka, 2012; Waters et al., 2004; Winkler et al., 2011). Similarly, cues paired with low doses of alcohol have been shown to evoke alcohol attentional bias, subjective craving, and physiological responses in social drinkers (Field & Duka, 2002; Field et al., 2013; Ramirez et al., 2015). A meta-analysis found a significant but weak association between attentional bias and craving in substance abuse, which aligns more with Robinson and Berridge's (1993) theory that the two can be decoupled, rather than Franken's (2003) theory of mutual excitation (Field et al., 2009a). Thus, the empirical evidence regarding the relationship between subjective craving and substance-related attentional biases remains inconclusive. Numerous studies have provided evidence of attentional sensitisation across various contexts. For example, research has demonstrated that individuals using tobacco (Field et al., 2009b), marijuana (Field, 2006), cocaine (Liu et al., 2011), alcohol (Duka & Townshend, 2004), or engaging in internet use (Nikolaidou et al., 2019) show enhanced information processing for visual stimuli linked to their addictions. These studies consistently find that addicts, compared to control subjects, exhibit faster detection of changes, quicker response times, and a decreased ability to inhibit distracting visual stimuli when those stimuli are related to their addiction. This phenomenon is observed in tests like the Addiction-Stroop Test and the Change Blindness Task, demonstrating how substance-related stimuli gain incentive motivational salience, leading to attentional bias and, ultimately, repetitive behaviour (Cox et al., 2006; Hobson et al., 2012).

Experimental Evidence of Attentional Bias in Substance-related Users

Understanding the mechanisms behind substance-related attentional biases is crucial in addressing addiction and its impact on cognitive functioning. Research on attentional biases in substance users often employs tasks like the Modified Stroop and Visual Probe are commonly used to investigate attentional biases in substance users (Boskovic et al., 2018; Waters et al., 2013; Ataya et al., 2012; Lopes et al., 2015; Miller & Fillmore, 2010; Spiegelhalder et al., 2011). Another paradigm, the flicker induced change blindness task (Flicker ICB), is also used in the literature (Favieri et al., 2024; Varakin et al., 2021; Kuss et al., 2013). Each of these experimental paradigms reveals distinct facets of attentional biases, highlighting the cognitive processes influenced by substance use. This segment reviews the evidence from these tasks, examining their findings, methodological strengths, and potential limitations, to provide a comprehensive understanding of how attentional biases manifest in substance users.

Modified Stroop Paradigm. A particularly notable method within this field is the Modified Stroop Paradigm. The Stroop task is a widely used method to measure cognitive bias and information processing abilities, originally designed to test inhibition and interference (Stroop, 1935). The Modified Stroop task, a variant of the classic Stroop task, involves assigning colours to words related to substances, requiring individuals to name the colour while ignoring the word's meaning (Cox et al., 2006; Cox et al., 2017). Through various studies, it has been demonstrated that individuals dependent on substances exhibit slower reaction times when naming the colours of substance-related words compared to neutral words (Parris et al., 2019; Langston & Tuhin, 2018; Niziolek et al., 2017). Attention may go to the semantic meaning of the substance-related word, instead of ignoring it because it may be more noticeable to the individual (Lusher et al., 2004). These findings indicate an attentional bias towards substance-related cues, which is more pronounced in heavy users compared to light social users and non-users (DeVito et al., 2018; Heitmann et al., 2018; Ersche et al., 2010). However, the task's reliability and methodological limitations, such as controlling for word frequency and length, as well as the potential for semantic priming effects, have raised questions about its effectiveness in accurately measuring cognitive biases and attentional processes (Tejero et al., 2014; Frings & Wühr, 2012).

Users of alcohol and other substances have indicated that alcohol-dependent, dependent smokers, and illicit drug-dependent individuals are slower to colour-name words related to their relevant substance than neutral words (Parris et al., 2019; Field et al., 2013). Heavy users were slower to colour-name words related to their relevant substance of dependence measured to light social users and non-users (Kennedy et al., 2014; Cousijn et al., 2013; Field et al., 2013; Liu et al., 2011; Drobes et al., 2006; Munafò et al., 2003). The task also reveals attentional bias across levels of substance use (Field et al., 2013; Lusher et al., 2004; Bruce & Jones, 2004). The Modified Stroop task revealed that alcohol-related words distract both social drinkers and alcoholics (Field et al., 2013; Lusher et al., 2004).) Heavy social drinkers are more distracted by alcohol-related pictures than light drinkers in a picture version of the task (Bruce & Jones, 2004). Alcohol abusers show higher attention bias compared to non or occasional drinkers (Cox et al., 2003; Mentzoni et al., 2014; Zamani et al., 2014). However, findings from studies employing the Modified Stroop task have yielded inconsistent and sometimes contradictory results. Participants have demonstrated varying response patterns when exposed to different categories of stimuli—namely, neutral words, general anxiety-related words, and test anxiety-specific words. These inconsistencies suggest that individual differences, contextual factors, or methodological variations may influence how attentional biases are manifested in individuals experiencing test anxiety (Boskovic et al., 2018)." Moreover, attentional bias is identified across different levels of substance use, impacting social and dependent drinkers as well as smokers with varying levels of nicotine dependence (Field et al., 2013; Lusher et al., 2004; Bruce & Jones, 2004).

Possible task and methodological limitations may explain these inconsistencies. One limitation is the need to control various linguistic elements, such as word frequency and length, to ensure the validity of substance-related stimuli (Tejero et al., 2014; Frings & Wühr, 2012). Word frequency and length impact the Stroop interference effect, with less frequent and longer words causing greater difficulties in studying psychological issues (Tejero et al., 2014; Frings & Wühr, 2012; Kahan & Hely, 2008; Burt, 2002). Likewise, words that are semantically associated with each other are considered to strengthen intertrial priming of related concepts, resulting in heightened cognitive interference (Tejero et al., 2014; Frings & Wühr, 2012; Kahan & Hely, 2008; Burt, 2002). This increased interference can skew the results, making it difficult to isolate the specific effects of substance-related stimuli. Additionally, the semantic association between words can lead to unintentional priming effects, where the processing of one word influences the processing of subsequent words, thus confounding the interpretation of data (Tejero et al., 2014; Frings & Wühr, 2012; Kahan & Hely, 2008; Burt, 2002). The arrangement of trials (blocked or unblocked) also influences attentional bias strength, resulting in variability in the outcomes observed. Block trials, where similar types of stimuli are grouped together, may enhance attentional biases due to the repetitive exposure to related concepts, thereby amplifying the observed effects. In contrast, unblocked or mixed trials, where different types of stimuli are presented in a random order, may reduce these biases by disrupting the continuity of semantic associations (Knight et al., 2018; Roy-Charland et al., 2017) This variability complicates the interpretation of results, as it becomes challenging to determine whether the effects are due to the intrinsic properties of the stimuli or the structure of the task itself (Knight et al., 2018; Roy-Charland et al., 2017). Additionally, the theoretical foundations of the Stroop interference effect have been questioned, suggesting that the observed effects might not solely be due to cognitive interference but could also be influenced by other factors such as task demands, participant motivation, and individual differences in cognitive control (Ben-Haim, 2016; Fackrell et al., 2013; Lovett, 2002, 2005; Cohen et al., 1990).

Despite its widespread use, concerns have been raised about the task's ability to provide a comprehensive understanding of selective attention, as it overlooks subcomponents like attention preservation and primary positioning of attention (Field et al., 2004a; Knight et al., 2018). Attention preservation refers to the ability to maintain focus on a particular task or object over time, ensuring sustained attention without distraction. On the other hand, primary positioning of attention pertains to the initial focal point or main focus of an individual's attention when multiple stimuli are present, highlighting how people prioritize different pieces of information. By neglecting these aspects, the task may fail to capture the full complexity of selective attention. Pictures of substance-related stimuli may be more indicative of real-life experiences and elicit a stronger attentional bias than words alone (Bruce & Jones, 2004). Moreover, the emotional and cognitive processes involved in the Modified Stroop task are more complex than just attentional allocation, encompassing impaired inhibitory control and perceived threat (Crunelle et al., 2012; Zhao et al., 2018; Cox et al., 2006; Greenaway et al., 2012).

Furthermore, the task's dependence on response time as a measure of cognitive processing has been critiqued (Wiley et al., 2024; Basu, 2023; Field & Cox, 2008; Ataya et al., 2012; Spiegelhalder et al., 2011). Response time in the task serves as an indirect measure of cognitive processing and may not capture the complexity of behavioural responses to substance-related cues (Langner et al., 2023; Ataya et al., 2012; Spiegelhalder et al., 2011). Slow response time is often interpreted as a consequence of increased cognitive load triggered by the processing of substance-related words. This heightened load may reflect the mental effort required to suppress or regulate attention away from salient stimuli, rather than indicating a direct or specific attentional bias toward them. As a result, reaction time alone serves as a broad indicator of attentional disruption and cognitive interference, rather than a precise measure of attentional bias, thereby limiting its specificity in isolating the underlying mechanisms of attentional processing (Field & Cox, 2008). Taking individuals longer to respond because these words increase their cognitive load, or the mental effort required to process the information. Because slow response time results from increased cognitive load, it reflects a broad measure of attention. It shows that people are paying more attention overall. Additionally, concerns have been raised about the internal and test-retest reliability of the Modified Stroop task, suggesting it may not be a consistently reliable measure (Wiley et al., 2024; Basu, 2023; Langner et al., 2023; Ataya et al., 2012; Spiegelhalder et al., 2011). In light of these concerns, researchers have investigated alternative methods, such as the Visual Probe Paradigm, to achieve more reliable measurements of attentional bias.

Visual Probe Paradigm. The research on attentional bias using the Modified Stroop task identifies three attentional components: avoiding cues, enhanced attention to pertinent cues, and challenges in disengaging from cues (Cisler & Koster, 2010; Cisler et al., 2009). The visual probe task (dot-probe) measures attentional bias by presenting pairs of stimuli (e.g., substance-related and neutral images), followed by a visual probe, often called dot probe (X or +) replacing one of the images (MacLeod et al., 1986). Participants must quickly indicate the probe's location (left or right side of screen), and reaction time differences between neutral and substance-related images across trials indicate attentional bias (Frewen et al., 2008). This task has been utilised in substance-related studies, such as those involving alcohol (Türkoğlu et al., 2022; Monem et al., 2019; Duka & Townshend, 2004) and tobacco (Rehme et al., 2018; Begh et al., 2016; Marks et al., 2016; Bradley et al., 2003).

Attentional bias in substance users is evident in quicker responses to probes replacing substance-related stimuli, indicating sustained attention to these stimuli (Posner et al., 1980; Duka & Townshend, 2004). Attentional bias is measured through reaction time differences, revealing biases in sustained attention or initial orienting (Field et al., 2004a). Another critical factor in examining attentional bias is the exposure duration of the stimuli. The duration for which substance-related cues are presented can significantly influence the nature and strength of the attentional bias observed. Short exposure durations (200ms) are argued to typically capture initial orienting responses, highlighting the automatic, reflexive nature of attentional bias (Field et al., 2004a). In contrast, longer exposure durations (500ms, 2000ms) tend to reveal sustained attention processes, indicating how substance-related stimuli can hold an individual’s attention over extended periods (Cox et al., 2006; Field & Cox, 2008). This distinction is crucial, as it helps differentiate between the immediate draw of substance-related cues and their ability to maintain attention, both of which are important in understanding the cognitive mechanisms underlying substance use disorders (Cox et al., 2006; Field & Cox, 2008).

Different stimulus presentation times (e.g., 500ms, 2000ms) help assess sustained attention, with variations observed based on levels of substance use (Türkoğlu et al., 2022; Fluharty et al., 2016; Field et al., 2004a). Attentional bias was not apparent at shorter intervals of 200ms for social drinkers (Fluharty et al., 2016; Field et al., 2004a). Alcohol-dependent participants only indicated an alcohol-related attentional bias at 50ms (Bradley et al., 2004; Noël et al., 2006). Presentation times ranging between 50ms and 200ms were maintained to measure initial orienting of attention (Mogg et al., 2005; Noël et al., 2006). These results indicate that various elements of attention may play several roles in the various levels of use. Attentional bias can differ between substances, with smokers showing bias towards smoking-related stimuli at 500ms and 2000ms (Rehme et al., 2018; Ehrman et al., 2002; Bradley et al., 2008). Whereby heavy social drinkers compared to light exhibit a bias in sustained attention only, whereas alcohol-dependent participants seem to exhibit a bias in initial orienting only (Duka & Townshend, 2004; Field et al., 2004a). Smokers demonstrated an attentional bias for smoking-related stimuli at both 200ms and 2000ms, indicating that after smoking cues were perceived, they stayed the center of attention (Bradley et al., 2004). Consequently, signifying that smokers exhibit attentional biases in both sustained attention and initial orienting of attention (Chanon et al., 2010). So, the functions of initial orienting of attention and sustained attention influence the stimulus response time, with quicker times presumed to signify initial orienting of attention and slower times signifying sustained (Türkoğlu et al., 2022). There are conflicting and opposing findings within the research on whether 500ms is symptomatic of initial orienting of attention or a more sustained attentional process (Rehme et al., 2018; Field t al., 2005; Bradley et al., 2003; Field et al., 2004a). For instance, Rehme et al. (2018) and Field et al. (2005) argue that 500ms may capture early attentional engagement, supporting its use as an indicator of initial orienting. In contrast, Bradley et al. (2003) and Field et al. (2004a) contend that this duration is too long to reflect immediate orienting and is more indicative of maintained attention or difficulty disengaging from salient stimuli. Attentional strategies motivate biases and are established when the stimuli display times are 500ms. However, this may be imprecise because a 500ms period is adequate to allow for various changes in attention (Türkoğlu et al., 2022; Fluharty et al., 2016; Posner & Petersen, 1990; Fox et al., 2001). Studies have shown that within this time, individuals can engage in multiple attentional shifts, which may lead to biases in processing stimuli (van Laarhoven et al., 2021). These biases could be influenced by various factors, including individual differences in attentional control, the salience of the stimuli, and contextual factors.

When examining dependence, attentional bias is more evident in individuals with lower levels of dependence compared to moderate-dependent smokers who show higher levels of dependence (Mogg et al., 2005). Heavier social drinkers show higher attentional bias towards alcohol-related stimuli than lighter drinkers (Türkoğlu et al., 2022; Monem et al., 2019; Field et al., 2004b; Duka & Townshend, 2004; Noël et al., 2006). Reaction time data indicated that both groups exhibited a smoking-related attentional bias, with no significant difference between them. However, eye movement data revealed that low dependent smokers, but not moderately dependent smokers, initially fixated more on smoking-related stimuli compared to neutral stimuli. Further analysis of fixation duration throughout each trial showed that both groups spent more time fixating on smoking-related stimuli than neutral ones, with low dependent smokers fixating significantly longer than moderately dependent smokers. Lengthier sustained attention was correlated to higher levels of subjective craving and low dependence. Mogg et al. (2005) indicated that sustained attention is the attentional method impelled by incentive processes, though their findings partially contradicted the IST models of addiction (Franken, 2003; Robinson & Berridge, 1993), which would predict greater attentional bias in more heavily dependent individuals. This discrepancy underscores the complexity of attentional capture and maintenance mechanisms, suggesting that while initial attentional bias might be more prominent in less dependent individuals, the sustained attention, and thereby the maintenance of this bias, is intricately linked to subjective craving and dependence levels.

The visual probe task is not only diagnostic, but also used in attention bias treatment by redirecting attention to non-substance-related stimuli (Ho et al., 2017). The visual probe task has advantages over the Modified Stroop, allowing variations in stimulus presentation times to measure different attentional elements (Mogg et al., 2003). It overcomes some limitations of the Modified Stroop, offering a direct assessment of attention allocation and bias (Türkoğlu et al., 2022; Scarpina & Tagini, 2017; Faunce, 2002). Nonetheless, the visual probe has limitations, including potential measurement errors, and concerns about reliability (Miller & Fillmore, 2010; Field & Cox, 2008). Measurement errors can significantly affect the results of visual probe studies. These errors can arise from various sources, including inconsistent timing of stimulus presentation, individual differences in reaction times, and the precision of the recording equipment (Schmukle, 2005). Additionally, external factors such as participant fatigue, distractions in the testing environment, and variations in the interpretation of instructions can introduce variability in the data (Chapman et al., 2019). Such measurement errors can lead to incorrect conclusions about attentional biases, highlighting the importance of rigorous experimental design and thorough analysis to mitigate their impact. Ensuring high reliability and validity in visual probe studies is crucial for producing accurate and replicable findings in attentional research (Parsons et al., 2019). Response times only provide a glimpse of the allocation of participants' attention, with faster reactions to probes presented in the attended position relative to the unattended position (Koster et al., 2004; Posner et al., 1980). Thus, indicating that while the visual probe task does identify the occurrence of attentional biases, it cannot detect the individual type of bias it established, such as facilitation, disengagement, and avoidance biases (Parsons et al., 2019; Miller & Fillmore, 2010; Field et al., 2013; Schoenmakers et al., 2008; Cisler et al., 2009). Another key limitation of the visual probe task is the questionable reliability of response time as a measure of attentional bias. Ataya et al. (2012) report poor internal reliability, suggesting that the task fails to consistently capture attentional bias within a single session. Likewise, Spiegelhalder et al. (2011) found low test-retest reliability, meaning that results often fluctuate across different testing occasions, thereby raising concerns about the task's stability and overall validity in attentional bias research. Despite its diagnostic use in attentional bias, the visual probe task faces concerns regarding reliability, measurement inaccuracies, and its ability to detect various types of attentional biases. To overcome these challenges, researchers are increasingly utilising eye-tracking studies for a more direct assessment of attentional bias.

Eye-tracking studies. The visual probe task depends on participants' reflexive eye movements to identify patterns of attentional bias (Chapman et al., 2019; Evans & Britton, 2018). Tracking eye movements enhances earlier methods for assessing attentional bias, which depended on indirect indicators of attention. This approach provides directly observable data on attentional distribution (Field et al., 2006). Consequently, by monitoring eye movements, researchers can directly differentiate between the initial orientation of attention and its sustained focus. However, findings utilising the visual probe have been reliable in indicating an attentional bias towards alcohol-related stimuli in social drinkers and smoking-related stimuli in smokers (Türkoğlu et al., 2022). The visual probe task assesses a glimpse of attention.

Eye-tracking technology provides a more direct assessment of attentional bias by recording gaze patterns, indicating sustained attention and initial orienting (Casteau & Smith, 2020; Lochbuehler et al., 2018; Gibaldi et al., 2017; Godijn & Theeuwes, 2003). However, due to a combination of external limitations—such as access to equipment or institutional constraints—and personal factors, it was not possible to incorporate eye-tracking methodology into the present research study. Visual probe task studies have explored attentional bias in various substance use disorders, including tobacco, alcohol, marijuana, caffeine, and prescription drugs (Lochbuehler et al., 2018; Manchery et al., 2017; Garland et al., 2013). An attentional bias score is established for each individual as the mean-variance in fixation time between neutral and substance-related stimuli (Gibaldi et al., 2017; Starzomska, 2017). Attention bias is described as lengthier fixation time concerning substance-related stimuli compared to neutral stimuli (Starzomska, 2017). Research indicates that eye fixation time is susceptible to attentional bias that goes unnoticed by reaction time paradigm (Field et al., 2006; Fernie et al., 2010; Miller & Fillmore, 2010). Eye-tracking technology enhances the precision of attentional bias assessment, measuring fixation time and allowing for direct evaluation of attention allocation (Field et al., 2006; Starzomska, 2017). Fixation time, indicating longer attention on substance-related stimuli, proves to be a more internally reliable measure than reaction time (Field & Christiansen, 2012). Attentional biases can influence the early stages of visual processing, often before conscious awareness, and eye-tracking can capture these initial biases by measuring which stimuli capture the gaze first and hold it longer (Miller & Fillmore, 2010). Furthermore, eye fixation duration can reveal sustained attention towards certain stimuli, such as threat-related images, indicating an attentional bias that might not be evident from reaction times alone (Fernie et al., 2010). Reaction time paradigms often rely on conscious, controlled responses, whereas eye-tracking can uncover automatic attentional shifts (Miller & Fillmore, 2010). In complex visual environments, reaction time measures might not accurately reflect where attention is allocated, whereas eye fixation data provides a detailed map of attentional distribution (Field et al., 2006). Additionally, eye-tracking offers insights into the temporal dynamics of attention, allowing researchers to observe how attention shifts over time, providing a richer understanding of attentional processes compared to the snapshot view offered by reaction times (Fernie et al., 2010). Thus, eye fixation time reveals detailed aspects of attentional allocation that reaction time paradigms might miss due to their reliance on conscious, controlled responses, and inability to measure the temporal dynamics of visual attention in complex scenes.

Studies using eye-tracking reveal sustained attention and initial orienting differences in attentional bias for substance-related stimuli in smokers and social drinkers (Casteau & Smith, 2020; Lochbuehler et al., 2018; Mogg et al., 2003; Mogg et al., 2005; Miller & Fillmore, 2010). While eye-tracking offers a more direct assessment, discrepancies in findings persist, potentially influenced by stimulus complexity and individual variations in attentional processes (Bradley et al., 2000; Mogg et al., 2005; Miller & Fillmore, 2010). Complex stimuli can introduce variability in eye-tracking results due to increased cognitive load (Chen & Epps, 2014). Studies have shown that the more intricate and detailed the stimuli, the greater the variability in eye movement patterns, as different people may focus on different aspects or elements of the stimuli (Biondi et al., 2023; Chen & Epps, 2014). Additionally, individual differences in attentional processes, influenced by factors such as working memory capacity and prior experiences, further contribute to these discrepancies. For example, individuals with better working memory might process complex stimuli more efficiently, leading to different eye movement patterns compared to those with lower working memory capacity (Cornoldi & Giofrè, 2014; Dash et al., 2015; Loh et al., 2023). Emotional states, personal interests and motivations may also play significant roles in directing where and how long an individual looks at particular elements within a visual scene, adding another layer of variability (Calvo & Nummenmaa, 2008; Calvo et al., 2008). Consequently, while eye-tracking offers valuable insights, interpretations of its data must account for these inherent variabilities (Bradley et al., 2000; Mogg et al., 2005; Miller & Fillmore, 2010). Further research is needed to address these inconsistencies and improve the ecological validity of attentional bias assessment in addiction studies.

The visual probe task, despite its potential, faces challenges in accurately assessing attentional bias in real-world settings, necessitating more ecologically valid approaches (Starzomska, 2017; Nees et al., 2012). Overall, the visual probe task and eye-tracking contribute valuable insights into attentional bias but require careful consideration of methodological limitations and ecological validity for a comprehensive understanding of addictive behaviours. According to Nees et al. (2012), in order to enhance ecological validity and create a more naturalistic assessment context, attentional bias should be measured within a single, integrated visual display. This approach may better capture the natural development and reinforcement of attentional biases in addictive behaviours, as opposed to traditional methods that rely on two competing visual stimuli presented simultaneously.

Flicker Induced Change Blindness Paradigm. In studies exploring attentional biases for substance-related cues, researchers have utilised Flicker-Induced Change Blindness (Flicker ICB) paradigms. These paradigms involve rapidly flickering scenes where changes occur, and one example involves using transient changes to explore biases related to social levels of alcohol and drug use (Jones et al., 2002; Rensink et al., 1997). Change blindness refers to the inability to detect large changes following brief disruptions in visual scenes (Ashwin et al., 2017). It occurs due to the inability to retain a full representation of visual details in an environment. Attention is crucial for change detection (Simon et al., 2000). The Flicker ICB task, described as a "spot the difference" task, requires participants to identify changes between two flickering images, divided by a brief blank frame, which makes the change substantially challenging to spot (Gusev et al., 2014; Jones et al., 2003; McConkie & Loschky, 2006). Attentional bias is assessed by the ability to detect changes related to substance use, relative to neutral or non-substance-related stimuli (Jones et al., 2003). In essence, researchers measure how quickly and accurately subjects can detect when a substance-related stimulus changes compared to when a neutral stimulus changes. This process helps assess whether individuals have an attentional bias towards substance-related stimuli. If subjects detect changes related to substance use more quickly or accurately than neutral changes, it suggests they have a bias in their attention towards substance-related cues. Individuals can view that flickering demonstration and press a button when they believe they have identified a change (Jones et al., 2003).

Consequently, the Flicker ICB paradigm grants researchers the ability to utilise complex stimuli that would be compatible with real-life circumstances (Gusev et al., 2014). Researchers are then given the ability to display several stimuli within similar categories to conclusively assess distinct stimuli's ability within a specific field of attentional bias to acquire and sustain attention (Cassimjee & Maree, 2004; Hollingworth et al., 2001; Rensink, 2000). The paradigm has been used to study attentional bias in substance-related stimuli (Jones et al., 2002). Studies using the Flicker ICB task have found that heavy drinkers are more prone to identify alcohol-related alterations than light drinkers (Jones et al., 2002). However, light drinkers demonstrated no variance between the latency to identify neutral and alcohol alterations (Jones et al., 2002). Attentional bias has been shown to correlate with levels of alcohol consumption, with individuals exhibiting hazardous or dependent drinking patterns displaying significantly stronger biases (Jones et al., 2006). These individuals tend to detect alcohol-related stimuli more rapidly than social drinkers, indicating heightened sensitivity to alcohol cues (Jones et al., 2003; 2006). Furthermore, the degree of alcohol-related attentional bias in heavy drinkers is closely associated with their reaction times and perceptual responses, suggesting that increased alcohol use amplifies attentional prioritization of alcohol-relevant information (Jones et al., 2006). However, there is more limited evidence of attentional bias in social drinkers' level of use (Jones et al., 2006).

Attentional biases in substance users vary based on consumption levels and dependence (Field et al., 2009b; Hobson et al., 2012; Cox et al., 2003). Flicker ICB has been used to assess attentional biases in smoking-related stimuli, with smokers exhibiting quicker detection of smoking-related changes compared to non-smokers (Yaxley & Zwaan, 2005). Studies on alcohol-related attentional bias have explored heavy vs. light consumers, dependent vs. non-dependent users, and the relationship between attentional bias and subjective cravings (Field et al., 2004b; Cox et al., 2003; Hobson et al., 2012; Fox et al., 2003). In examining alcohol consumption levels, attentional bias for alcohol-related pictures is significant in heavy social drinkers compared to lighter social drinkers, especially with longer exposure durations (Field et al., 2004a). Heavy alcohol consumers show reduced change blindness, detecting alterations in longer durations (500-2000 ms) compared to lighter consumers (Field et al., 2004a). These results align with similar findings in studies involving tobacco smokers (Bradley et al., 2003; Ehrman et al., 2002; Mogg et al., 2003). Heavy smokers, compared to light smokers, demonstrated similar levels of attentional bias within comparable stimulus durations. Although heavy smokers may engage in smoking behaviour more frequently or in different contexts, no significant differences in attentional bias were observed within the 200ms stimulus duration (Bradley et al., 2003; Ehrman et al., 2002; Mogg et al., 2003).

The Flicker ICB task is considered a more effective tool to assess attentional bias, overcoming limitations of other tasks (Hogarth et al., 2008; Hogarth et al., 2009). The flicker ICB task is believed to overcome several of the visual probe and Stroop tasks' limitations regarding the capability to assess substance-related attentional biases within one visual setting, such as imagery in the individuals' surrounding external environments (Zhang et al., 2018). Concerns about the carryover effect in repeated measures (participants are exposed to the same stimuli or conditions multiple times across different trials) and the focus on immediate foreground objects in change blindness tasks are acknowledged limitations (Moss et al., 2011; Cox et al., 2003; Rensink et al., 1997). The carryover effect, where repeated exposure to stimuli influences memory, raises concerns about the reliability of repeated measures in Flicker ICB studies (Moss et al., 2011; Jones et al., 2003). Set size variations (number of items or elements presented to participants) may impact performance in change blindness tasks, affecting the interpretation of results (Wright et al., 2000).

Flicker ICB task effectiveness is constrained by methodological limitations, such as limited assessment of attentional bias components and dependence on indirect measures like reaction time (Field et al., 2004b; Mogg et al., 2003). Limitations in the Flicker ICB task include scarcity of data on testing reliability, and the need for further exploration of attentional bias subcomponents (Hobson et al., 2012; Jones et al., 2006; Field et al., 2004b). To improve this understanding, several enhancements are necessary. First, refining the experimental design of the flicker ICB task can address shortcomings by altering factors like flicker rate, stimuli nature, or exposure duration to ensure more reliable data (Moss et al., 2011). Increasing the sample size and controlling for potential confounding variables can also improve the statistical power and generalizability of the findings (Field et al., 2007; Moss et al., 2011). Advanced measurement techniques, such as utilising eye-tracking technology for precise measurements and incorporating neuroimaging methods like fMRI or EEG, could provide deeper insights into the neural mechanisms underlying these attentional processes (Field et al., 2007; Liu et al., 2016; Zhu & Lv, 2023). Furthermore, including diverse participant groups and clinical populations with known attentional deficits would help determine the variability and generalizability of the results across different demographics (Moss et al., 2011). Replication of studies across different cohorts and settings can validate the findings and ensure robustness (Field et al., 2007; Moss et al., 2011). Finally, it is important to address uncertainties related to task-specific effects (generalizability, task complexity), underlying neural mechanisms, individual differences (genetic, environmental, and developmental factors), the impact of external factors (environmental influences, technological variability (screen size, resolution)), and the real-world relevance of these findings (Anderson, 2016; Chun et al., 2011; Posner & Rothbart, 2007; Guo et al, 2023). Addressing these points through targeted research efforts will lead to a more comprehensive and reliable understanding of initial orienting and preserved attention. Additionally, studies often use stimuli that may not fully represent real-life circumstances, impacting ecological validity (Stanesby et al., 2019). Real-life situations would more strongly correlate with the surroundings in which the outcomes are being inferred and consequently would have conceivably more ecological validity, particularly as the environment (context) has been demonstrated to affect cue reactivity (Nees et al., 2012). Future research should consider reducing methodological limitations and examining individuals with substance use disorders in various categories to provide a more comprehensive understanding of attentional biases in substance use (Wright et al., 2000).

Questionnaire Use in Assessing Social Media

The widespread presence of social media and the internet in individuals' daily lives has led to increasing concerns about addiction and overuse. While researchers commonly use questionnaires to identify patterns of social media addiction and internet use, yet the challenges associated with self-report data have prompted consideration of alternative methods, including Apple ScreenTime usage tracking. This thesis specifically examines and compares the methodological strengths and weaknesses of questionnaires and objective smartphone usage metrics, with the aim of clarifying how each approach contributes to and limits the accurate assessment of social media addiction and internet use. The following discussion will first review the use and limitations of questionnaires, then address the role of objective smartphone usage metrics, and ultimately consider how combining both approaches may enhance research validity.

Questionnaires are now an integral part of the investigation of social media use addiction. Standard scales utilised to capture social media use include the Bergen Social Media Addiction Scale (BSMAS) and the Social Media Disorder Scale (SMD), which utilise self-report responses to measure individuals' active engagement, behaviour, and attitudes toward social media outlets (Andreassen, 2015; Young, 1998). These questionnaires often include items evaluating preoccupation, tolerance, withdrawal, and conflict, as well as other factors linked to social media addiction. Questionnaires, as a broader category, may also include additional items assessing behavioural tendencies or attitudes beyond those found in standardised scales. Despite their accessibility and cost-effectiveness for collecting data, both questionnaires and embedded scales have limitations. Social desirability bias, which occurs when respondents answer questions in a manner that will be viewed favorably by others, issues of memory recall, and the subjective interpretation of questionnaire items can lead to the distortion and inaccuracy of self-report data (Paulhus, 1991). These limitations are particularly important to consider in the context of accurately assessing social media addiction, as inaccurate self-reports can undermine the validity of research findings and the usefulness of intervention strategies. Some individuals may understate or overstate their social media usage, for example, based on social convention or personal prejudices, which can result in responses not reflecting their true actions and thus may give information of their behaviour to be misleading. Ultimately, such challenges mean that while questionnaires are useful for capturing self-perceived behaviors and attitudes, their methodological constraints directly impact the overall reliability and interpretability of assessments in this field.

Social desirability bias, in which respondents provide answers that reflect their ‘ideal’ personality in a favourable light, is a major issue in addiction self-report measures, as individuals may minimise their social media use to align with societal expectations or to avoid negative judgment, resulting in incomplete and sometimes inaccurate descriptions of their actual behaviour (Paulhus, 1991). Moreover, memory problems can also diminish the validity of self-reported time data, as people may not accurately recall the extent or context of their social media use across different formats. Self-report questions themselves are also open to variability in interpretation as the items in a questionnaire may be understood differently by each participant. For example, terms such as 'excessive use' or 'withdrawal symptoms' are subjective and dependent on personal opinion, making it difficult to ensure a shared and precise language around social media addiction (Kardefelt-Winther et al., 2017).

ScreenTime Metrics. To overcome some of the constraints of self-reports, we are investigating measures of objectively measured technology use, such as Apple ScreenTime to measure user's technology use records in detail. Apple ScreenTime measures the time spent by a general audience within apps with some app categories; this creates clearer, more accurate, and objective descriptions of the users' digital behaviours. One major benefit of Apple ScreenTime is that it mitigates social desirability bias. In contrast to self-report measures, Apple ScreenTime data is collected passively and does not depend on individuals' openness to sharing their behaviour. This helps avoid underreporting or misrepresenting the extent of social media use and allows for a more accurate portrayal of actual internet time. Additionally, Apple ScreenTime addresses memory recall problems by providing real-time and historical information about app usage, reducing the need for individual participants to remember and report on their digital behaviour and thus increasing the accuracy and credibility of the information collected. However, despite these strengths, Apple ScreenTime also has notable limitations. For example, if multiple users use a common device, background activity can distort usage statistics and individuals may manipulate their settings or restrict permissions, resulting in incomplete data. In addition, differences in operating systems and app categorisations can lead to inconsistencies, complicating comparisons between devices and across subjects. Therefore, while Apple ScreenTime enables researchers to analyse fine-grained metrics of digital behaviours, such as the proportion of time spent in particular app categories or screen usage patterns, these methodological challenges must be considered alongside its advantages.

Nevertheless, relying on Apple ScreenTime as an objective metric is not without its own limitations, which can be categorised as practical and psychological. From a practical standpoint, ScreenTime data does not account for multiple users on a single device or background activity that may inflate usage statistics, potentially distorting individual behavioural patterns. For instance, if a family shares an iPhone account and several members use different social media applications throughout the day, the aggregate ScreenTime data would attribute all usage to one account, incorrectly representing a single individual's behaviour. Moreover, some users may intentionally modify their device settings or restrict permissions, leading to incomplete data capture. Additionally, variations in operating systems and app categorisation could create inconsistencies between devices—or between people—that would limit comparison. These methodological problems indicate that, although Apple ScreenTime can help alleviate some bias in respect of self-reporting, it raises clear practical problems that need to be critically discussed. Aside from these practical limitations, Apple ScreenTime has significant psychological limitations. Although ScreenTime provides objective metrics on the quantity and timing of digital engagement, it fails to capture the cognitive, motivational, and emotional drivers of social media use. The tool cannot tell whether individuals use social media out of habit, for social connection, to cope with negative emotions, or for other psychological reasons, nor does it take into account the subjective meanings users assign to their behaviours. For instance, two users may show equal time spent using the application, with one user utilising it mainly for professional obligations and the other using it for compulsive use due to psychological distress. However, in these cases, neither adaptive nor maladaptive behaviour patterns can be clearly identified from measures in isolation. Therefore, Apple ScreenTime provides interesting insights into the 'what' and 'how much' but does not address the psychological causes—the 'why'—of social media use, which are critical to a full understanding of digital addiction.

In summary, this thesis has compared questionnaires and Apple ScreenTime as tools for assessing social media and internet addiction. Questionnaires are a useful measure of individual attitudes, motivations, and experiences, but are affected by social desirability bias, memory recall issues, and subjective interpretation. However, Apple ScreenTime provides objective and specific coverage of digital behaviours, which helps limit some biases associated with self-report measures, but it does not measure psychological and contextual factors driving media use. The analysis demonstrates that although both methods have limitations, their integration may enable a more fine-grained and valid examination of digital behaviours and their motives. This comparative result implies that adopting the combined methodological approach is a better indicator of research reliability and enables a more fruitful interpretation of findings, allowing for the incorporation of behavioural and psychological features of digital addiction. As technology continues to evolve, the use of integrated methodologies will be critical for advancing academic and clinical understanding of the broad and complex impacts of social media on mental health.

What This Thesis Examines

The existing body of literature on substance dependency has consistently demonstrated that heavier drinkers or smokers exhibit a attentional bias towards stimuli associated with their substance use. This bias is evident in their heightened attention and responsiveness to related cues. Drawing parallels to this established research, it is hypothesised that heavy users of social media may similarly show a measurable bias in their attention towards stimuli associated with social media platforms.

Especially, my proposed experiments aim to investigate whether heavy social media users exhibit a noticeable bias in attention similar to substance users. For instance, using a dot probe task, we can measure the attentional bias of individuals by observing their responsiveness to the Twitter logo. Preliminary predictions suggest that heavier users will more consistently notice changes to the Twitter logo compared to lighter users, indicating a significant attentional bias. This phenomenon can be linked to the incentive sensitisation theory (IST), which posits that repeated exposure to a rewarding stimulus enhances its salience and the individual's craving for it.

My research aims to build on the extensive literature that highlights how repeated administration of substances such as alcohol or nicotine leads to chemical changes in the brain. These changes increase the desirability of the substance, making it more "wanted" due to its rewarding effects. Through classical conditioning, objects and environments associated with substance use (e.g., cigarette packets, lighters, ashtrays) become salient cues that capture the user's attention. The brain, having learned to associate these cues with the rewarding effects of the substance, prioritizes them in the individual's perception of their environment.

Individual differences in attentional bias are influenced by various factors, including the type of substance consumed. A smoker, for example, develops a selective bias towards objects related to smoking because the brain has learned to seek the rewarding nicotine hit. This classical conditioning process ensures that objects associated with smoking (e.g., lighters, ashtrays) become prominent in the smoker's environment.

Applying this framework to social media, the "hit" comes from engaging with social media platforms. The peripheral cues associated with social media use, such as logos and devices (e.g., Twitter logo, iPads), become salient to heavy users. These cues, through classical conditioning, are marked in the brain as being associated with the rewarding experience of social media use, leading to an increased attentional bias towards them.

I predict that heavier users of social media will exhibit a stronger attentional bias towards social media-related cues. This prediction is grounded in the classical conditioning model, where the reward (dopamine release) from using social media conditions the brain to recognise and prioritize related stimuli (Robinson & Berridge, 2008).

Previous studies in the substance use domain provide a robust theoretical basis for these predictions (Field & Cox, 2008; Robinson & Berridge, 2008). The same mechanisms observed in substance dependency, where attentional bias is demonstrated through classical conditioning, can be applied to social media use. Behavioural experiments have shown that the predictions made by theories in substance literature also hold true for social media use, suggesting that attentional bias is a behaviour-driven phenomenon, regardless of whether the stimulus is a physical substance or an ephemeral activity like social media (Field & Cox, 2008; Robinson & Berridge, 2008).

Although my research will not conclusively determine whether social media is addictive, it will lend support to the argument that social media can exhibit addictive qualities similar to physical substances (Andreassen et al. 2017). This is based on the observed alignment between theoretical predictions and experimental outcomes in both domains (Brand et al., 2019; Robinson & Berridge, 2008). By investigating whether people's behaviours align with these predictions, my research aims to contribute to the ongoing debate on the addictive nature of social media.

Chapter 2 Experiment 1: An examination of social media-related attentional biases in Instagram Users using the Flicker Induced Change Blindness Paradigm

In Chapter 1, we explored the emergence of social media as a dominant communication platform, balancing its benefits in fostering connection and self-expression with its potential to exhibit characteristics of compulsive behaviour. The modern understanding of addictive behaviour has expanded beyond traditional substance dependencies like alcohol (Enoch & Goldman, 2002), smoking (Brown et al., 2014), and illicit drugs (Sofuoglu & Kosten, 2006). It now includes problematic behaviours such as gambling (Gainsbury, 2015), gaming (Kuss & Griffiths, 2012), and internet use (Kuss & Lopez-Fernandez, 2016). These findings highlight that excessive use share similar underlying biopsychosocial mechanisms—salience, mood modification, tolerance, withdrawal, conflict, and relapse—as substance-related addictions (Griffiths, 2005; 2019). With the rise of social media, excessive use is being argued to meet addiction criteria (Kuss & Griffiths, 2017; Ryan et al., 2014), with a reported prevalence rate of 4.5% among adolescents (Banyai et al., 2017). Despite ongoing debate and its exclusion from formal diagnostic criteria in the DSM-V and ICD-11, excessive use of social media aligns with broader patterns of compulsive behaviours, raising questions about its cognitive and psychological underpinnings.

Importantly, we emphasised how attentional mechanisms, particularly attentional bias, are pivotal in driving and maintaining compulsive tendencies across both substance and non-substance contexts. Chapter 1 also introduced key theoretical framework, such as the incentive sensitisation theory (Robinson & Berridge, 1993), which posits that behaviour-related cues acquire heightened motivational salience, capturing attention and reinforcing repetitive engagement. Addictive behaviours, whether related to chemical substances (i.e. alcohol) or non-chemical activities (i.e. gambling), exhibit similar symptoms and behaviours, notably an "attentional bias" towards addiction-related stimuli (paraphernalia, images, and objects). For example, smokers are more likely to have their attention captured by smoking-related cues such as cigarettes, or lighter. This prioritization of addiction-related stimuli is driven by the 'salience' mechanism (Field & Cox, 2008; Robbins & Ehrman, 2004), where users' goals bias their attention toward reward-based stimuli, linked to increased dopaminergic responses in brain areas mediating goal-directed behaviour (Franken, 2003; Haber, 2016). This mechanism, a key concept in the incentive-sensitisation theory of addiction (Robinson & Berridge, 1993, 2008), suggests that once attention is caught by addiction-related content, users exhibit heightened 'cue reactivity' (Carter & Tiffany, 1999), leading to stronger cravings and increased engagement in addictive behaviours compared to non-users (Brand et al., 2019). The combination of heightened cue reactivity and attentional bias is believed to play a significant role in addiction development, maintenance, and relapse (Drummond, 2000; Papachristou et al., 2014).

Building on the theoretical insights from Chapter 1, this study explores attentional bias in compulsive behaviours, with a specific focus on excessive social media use. By revisiting the foundations of attentional bias outlined in Chapter 1, including its theoretical underpinnings from incentive sensitisation and biased competition theories, we aim to investigate how selective attention processes manifest in problematic social media use. A key emphasis will be on experimental paradigms, such as the flicker-induced change blindness task, which provides a nuanced approach to measuring attentional biases. By bridging theoretical concepts with empirical investigation, this chapter addresses a critical gap: understanding whether the cognitive mechanisms underlying attentional bias in substance-related behaviours extend to excessive social media engagement. This exploration advances our understanding of how compulsive tendencies develop, persist, and may potentially be mitigated.

This study examines the attentional bias component of addiction, which has been documented across various substance-related addictions (Field & Cox, 2008). Research demonstrates that the magnitude of attentional bias can indicate addictive severity. For example, problem drinkers display greater attentional capture by alcohol-related images (e.g. beer bottle) compared to social or non-problem drinkers (Jones et al., 2006; Sharma et al., 2001). This same pattern can be seen in gamblers (Boyer & Dickerson, 2003), smokers (Waters et al., 2003), and gamers (van Holst et al., 2012). Greater attentional bias (i.e. level of related dopaminergic change; Franken, 2003) correlates with higher self-reported engagement in the problematic behaviour.

Notably, several recent studies have explored these effects in non-substance related addictions, including gambling and problematic internet use. Ciccarelli et al. (2016) found an attentional bias to gambling images in problem gamblers using a modified version of the Posner Task. The extent of the bias was positively correlated with scores on a gambling craving scale. Likewise, Jeromin et al. (2016) observed that excessive gamers exhibited an attentional bias toward computer-related words in a modified Stroop task compared to non-gamers. However, a comprehensive analysis of individual differences based on addiction severity was not provided. Lately, Pekal et al. (2018) discovered an attentional bias toward pornographic images in individuals with internet pornography use disorder (IPD) using a visual probe task, noting a significant positive correlation between symptom severity and the extent of the bias.

These findings suggest that attentional biases can be demonstrated in non-substance-related patterns of problematic behaviours (Pekal et al., 2018; Jeromin et al., 2016; Ciccarelli et al., 2016), that variations in the extent of the attentional bias effect seem to reflect the severity of problematic engagement (Ciccarelli et al., 2016; Pekal et al., 2018). This indicates that as these patterns of problematic behaviour progress, the 'incentive salience' of stimuli (Pekal et al., 2018) results in an enhanced dopaminergic response associated with goal-directed behaviour (Franken, 2003), which cognitively manifests as heightened attentional capture by behaviour-related content. However, it remains unclear if such effects extend to excessive social media use.

As far as we know, only a few studies have investigated attentional bias in social media users. Nikolaidou et al. (2019) identified an attentional bias through increased fixation times on social media-related stimuli. However, the artificial nature of the task, which paired oversized social media images (e.g., the Twitter logo) with control images, raises questions about its ecological validity. Real-world user activity, such as navigating a cluttered smartphone screen, may engage attention differently. While the study also reported a strong correlation between the urge to be online and dwell time on social media stimuli, the analysis was underpowered due to its small sample size of 16 participants ($r = 0.703$). In contrast, Thomson et al. (2021) found no evidence of attentional bias toward social media distractor apps on simulated smartphone screens, as users' response times to targets remained unaffected. Even though measures of use, engagement, and "addictive" severity varied significantly among participants, these factors did not predict or correlate with attentional capture by social media stimuli. Zhao et al. (2022) added a different perspective, showing that participants prone to problematic social media use exhibited an attentional bias toward social media-related cues in the dot probe task, though not in the Stroop task. They also observed a positive correlation between attentional bias and the severity of problematic social media use ($r = -0.51$). Cannito et al. (2023) further emphasised this relationship, linking problematic social media use to higher attentional bias toward social media stimuli. Together, these findings suggest that attentional biases toward social media stimuli might depend on specific tasks or individual characteristics. Further research is needed to clarify these relationships and to explore whether such biases are consistently present in social media users.

Aims and Hypotheses

According to IST and classical conditioning models of addictive behaviour, repeated and rewarding engagement with social media increases the motivational salience of social media–related cues. Consequently, individuals who engage more heavily or problematically with social media are expected to exhibit a measurable attentional bias toward social media–related stimuli compared to those who use it less. This bias is reflected in faster detection and preferential orienting to social media cues compared with non-social media control cues and neutral stimuli.

Hypothesis 1 (Condition Effect). It is hypothesised that participants will demonstrate an attentional bias toward social media–related stimuli. Specifically, performance is expected to indicate enhanced attention to social media cues, as reflected in faster response times and/or higher accuracy for trials involving social media stimuli, relative to matched control and neutral stimuli.

Hypothesis 2 (Individual Differences (Use/Severity)). The magnitude of attentional bias toward social media cues is expected to be positively associated with indices of heavier engagement and problematic use. Participants classified as heavier users, based on higher objective or self-reported use, and/or those with greater problematic use severity, as indicated by elevated addiction-related questionnaire scores, are predicted to exhibit a stronger attentional bias toward social media cues than lighter or non-problematic users.

Hypothesis 3 (Motivational State (Craving/Urge)). Attentional bias toward social media cues is expected to be strongest among individuals reporting a greater current desire or urge to be online. Higher levels of craving or urge are predicted to correspond with greater attentional bias, such as faster responding to or preferential orienting toward social media cues. This is consistent with the perspective that cue reactivity fluctuates according to motivational state.

The experiment carried out to study Instagram change blindness focused on addressing the following question concerning methodological aspects of measuring attentional bias:

> Is the attentional bias demonstrated by social media users related to their frequency or intensity of use?

Method

Participants

The The participants were 75 volunteers recruited from the University of Strathclyde Participant Pool using the online SONA Systems Research Management Platform. Of the 75 participants, 61 were females (M = 21.51, SD = 3.16), and 14 were males (M = 22.14, SD = 5.14), aged 18 to 34. Participants were informed that the aim of the study was to investigate how social media network usage influences attention through a series of computer tasks. The eligibility criteria for inclusion in the study were as follows: (a) participants had to be 18 years or older, (b) use a smartphone and consider themselves users of social media, (c) have normal or corrected-to-normal vision, (d) have no colour vision deficiency or colour blindness, (e) complete the survey using a desktop computer or laptop, not a smartphone or Mac computer, (f) individuals with a current or past history of behavioural addictions (e.g., gambling or internet gaming) or impulse control disorders (e.g., kleptomania, pyromania, compulsive sexual disorder, or intermittent explosive disorder) were advised not to participate, and (g) individuals with a history of epilepsy or seizures were also excluded. This study received ethical approval from the Ethics Committee of the University of Strathclyde School of Psychological Sciences and Health.

Apparatus and Materials

Socio-demographics. The dot-probe task included questions on age and gender to obtain a profile of participants' sociodemographic characteristics.

Addiction-Engagement Questionnaire (AEQ). AEQ is a 29-item self-report assessment of the severity of problematic internet use (PIU) and comprises positive and negative items. Respondents rate each item on a 7-point Likert scale (ranging from 1 = *completely agree* to 7 = *completely disagree*). The AEQ consists of two factors: addiction and engagement. The addiction factor consists of 12 items, 7 of which relate to areas termed to be the "core" criteria of addiction (behavioural salience, conflict, relapse and reinstatement, and withdrawal symptoms). Similarly, the engagement factor consists of 12 items, 2 of which relate to what have been termed "peripheral" criteria of addiction (cognitive salience and euphoria). This questionnaire will use the latest version of the scale previously used to assess behavioural patterns in the massively multiplayer online role-playing game Asheron's Call (Charlton & Danforth, 2007), adapted by rewording each item to reference social media. For example, a statement such as "Sometimes neglect important things because of an interest in social media" and "When I see social media, I feel drawn towards it." Participants were assigned to groups based on their responses to the AEQ's peripheral and core criteria. To be considered 'problematic' social media users, participants must have responded positively to at least four of the seven core criteria related to the Addiction factor. 'Non-problematic' social media internet users had to respond negatively to all seven cores and two peripheral criteria. Additionally, high social media engagers must have responded positively to one or two of the "peripheral" criteria for the Engagement factor and to three or fewer of the "core" criteria for the Addiction factor. Negative and positive responses were indicated through the core and peripheral criteria of addiction, which were dichotomised (cut-off point 4), such that higher scores (5, 6, 7) were identified with positive responses and lower (3, 2, 1) with negative ones. The Cronbach's α coefficient for this questionnaire was .80.

Questionnaire on Internet Use Urges (QIUU). QIUU is a 10-item self-report questionnaire that assesses the severity of online urges. Respondents rate each item on a 7-point scale (ranging from 1 = *completely disagree* to 7 = *completely agree*). The QIUU is an adapted form of the Questionnaire on Smoking Urges-Brief (Cox et al., 2001; Tiffany & Drobes, 1991). To assess levels of the urge to be online, each item has been reworded to reflect online activity. For example, a statement such as "I have the desire for a cigarette right now" was reworded to "I have the desire to be online right now." The Cronbach's α coefficient for this questionnaire was .89.

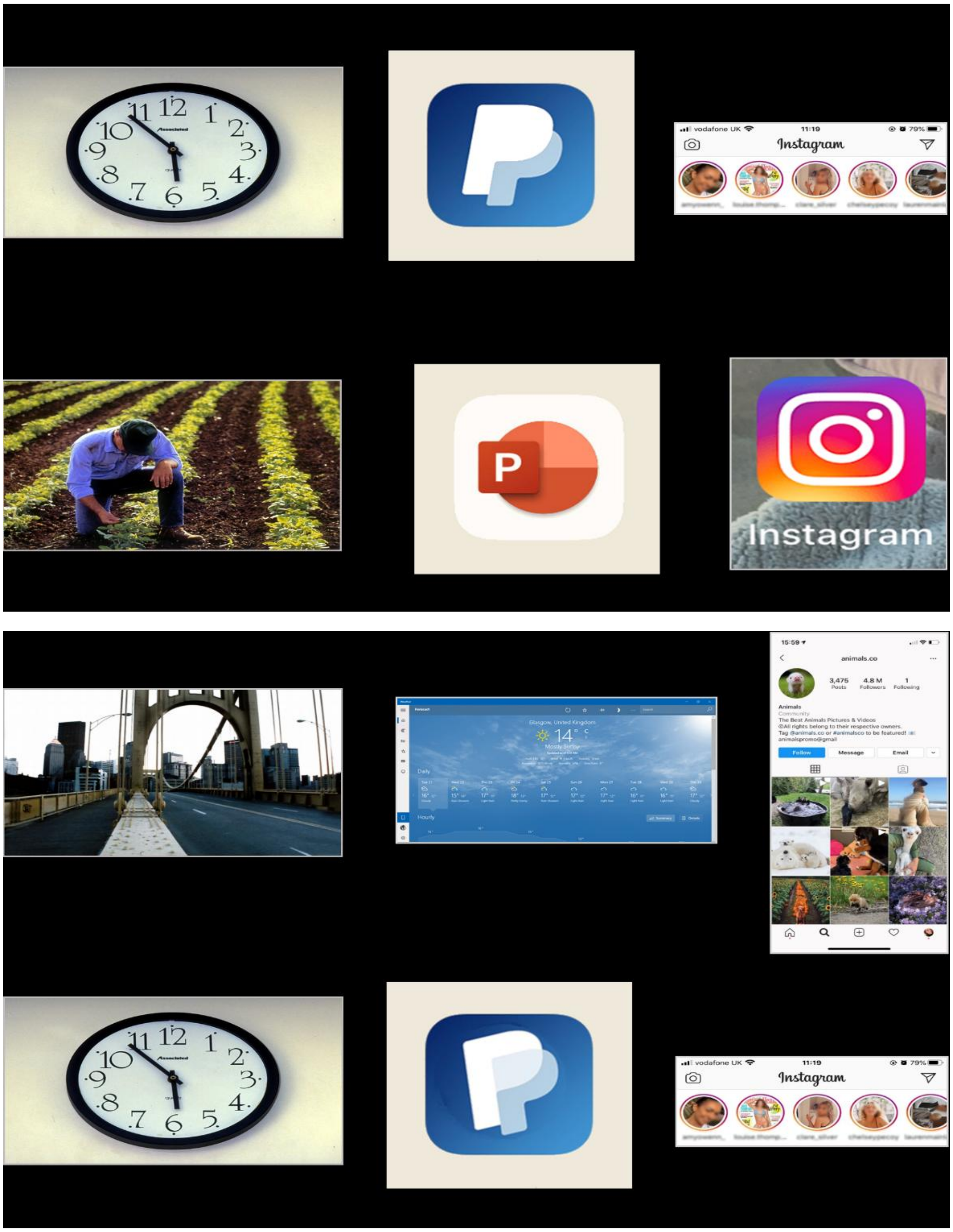
Bergen Social Media Addiction Scale (BSMAS). BSMAS is a modified version of the previously validated Bergen Facebook Addiction Scale (BFAS; Andreassen et al., 2012). The modification involves using the words 'social media' instead of the word 'Facebook,' with social media being defined as "Facebook, Twitter, Instagram and the like" within the instructions. The scale comprises six items, each representing a dimension of addictive behaviour, yielding diverse data. The items include mood modifications, salience, tolerance, conflict, relapse, withdrawal, and symptoms (Duradoni et al., 2020). A higher BSMAS score suggests a higher risk of developing an addiction to social media, with a cut-off score (19 out of 30) proposed recently to indicate problematic use of social media (Bányai et al., 2017). The Cronbach's α coefficient for this questionnaire was .93.

ScreenTime (Apple iPhone). ScreenTime was assessed by asking participants to report the number of hours and minutes they spent on social media per typical day over the past seven days. This was measured using an 8-part questionnaire that examined the following: "Daily Average" screen time, "Weekly" average social media time, "Daily" average social media time, daily average notifications, daily average device pickups, the top three most-used social media apps for the day, the top three most-used social media apps for the week, and the weekly average time spent on Instagram.

Change-Blindness Stimuli. A preliminary rating task was conducted to select the stimuli for the present experiment (see Appendix A). Three different types of stimuli were employed in the study: social media-related stimuli (Appendix D, Figure D1), control stimuli (Appendix D, Figure D2), and neutral stimuli (Appendix D, Figure D3). The 12 Instagram images, 12 control images, and 12 neutral images were repeated, yielding a total of 72 trials. Instagram images included various icons and screenshots related to the application, such as the application icon, the like symbol, the follow-back symbol, and the heart symbol. Using different stimuli allowed the images to capture a broader range of attention-grabbing elements and associations with Instagram. Control images included different icons and desktop screenshots from familiar applications. These icons resembled smartphone or tablet application icons, although the screenshots were taken from a desktop computer. Neutral images included neutral events (e.g., neutral faces, household objects, places) from the International Affective Picture System (IAPS). They were matched to the Instagram images in terms of size and brightness. The 36 different images were placed with six stimuli per trial, arranged in a rectangle (3x2) with a resolution of 1600x1200 (*Figure 1*). Each stimulus consisted of two images presented in alternating positions. These image pairs were drawn from three sets: Set A (social media-related images), Set B (control images), and Set C (neutral images), previously on a Bitmap (Appendix D1).

Figure 1

Change Blindness Task



Note. This is an example of a trial structure. Three image pairs (e.g., X1/X2, Y1/Y2, Z1/Z2) are placed in six positions. In the first trial, all six images are shown. In the next trial, they are shifted one spot clockwise. This continues so that each image appears twice in every position. There are 72 trials in total, with 24 trials in each condition where a change occurs. Each image changes position twice, as seen in the second and third images.

Procedure

In the task, participants sit at a computer or laptop screen. Firstly, participants are provided informed consent through Qualtrics (Qualtrics, 2021). After giving consent, the Qualtrics platform directed participants to the Change Blindness Task in E-Prime (Psychology Software Tools, 2020). During this task, participants completed practice trials to understand what would happen in the actual trials. After completing six practice trials, they clicked Y (yes) or N (no) to proceed to the exact task; these trials did not contribute to the analyses. There would be six images, with only the original and the manipulated images continually interchanging on a chosen black background, in a procedure aimed at producing a unique flickering effect (Gusev et al., 2014; Rensink et al., 1997). This flicker task is repeated for 60s or until the participant detects the change. Each set of six images is present against a black background for 250 ms, followed by an 80 ms black interstimulus interval. Participants then indicate when they saw the change by pressing the space bar and then indicate where they noticed the change in the image (top right, bottom right, top middle, bottom middle, top left, or bottom left). The 36 images, each with two different changes per trial, for a total of 72 trials per individual experiment. After completing the flicker Change Blindness task, participants moved to Qualtrics to complete the AEQ, QIUU, BSMAS, and ScreenTime questionnaires. Participants were then fully debriefed as to the true aims of the study.

Results

Data Analysis

i. ***Data cleaning.*** The Cleaned the initial results to remove unnecessary information before analysis. Firstly, remove duplicate entries to prevent cases from appearing more than once. Next, checked for missing values. Then, standardised the dataset by correcting formatting issues, including inconsistent capitalisation and spelling errors. Finally, removed outliers, non-responses, and practice trials.

ii. ***Defining metrics.*** We discard reaction time data from practice trials and from trials during which subjects made errors. To address outliers, RTs shorter than 250 ms and those exceeding three standard deviations above the participant's mean were removed, following established procedures (Monem et al., 2019). Calculated each participant's attentional bias score by averaging reaction times across trials in which they correctly detected the change (Field et al., 2013).

iii. ***Questionnaire data.*** Allocated QIUU groups based on participants' total scores, with lower scores indicating stronger cravings (urge to be online) and higher scores indicating lower cravings (median split at 50). ScreenTime data was allocated based on Instagram "Week" average (median split 140 minutes).

iv. ***We will address.*** We will examine whether the amount of time spent on Instagram relates to measures of attentional bias in the change blindness task for Instagram stimuli. We will therefore use ScreenTime metrics to allocate people to a low or high group membership. Then, we used this categorical allocation to examine its relationship with change blindness performance. This results in a two-way ANOVA design, with group (three levels) as one factor and RT bias scores as the dependent variable. Finally, the analysis will examine the relationship between attentional bias and scores on the three additional questionnaires (e.g., BSMAS and AEQ). Specifically, conduct three separate Pearson correlation analyses to assess the association between each questionnaire score and the RT-based measure of attentional bias.

Flicker Change Blindness Task

A two-way ANOVA was conducted to examine the effects of AEQ_Group (non-problematic vs. problematic) and Condition (Computer_control, Instagram, Neutral) on reaction time. The means and standard deviations for reaction time are presented in Table 2.1. Descriptive statistics indicated that mean reaction times varied across conditions, with the highest reaction times in the Neutral condition relative to the other conditions (Computer_control: M = 9879.59, SD = 2871.81; Instagram: M = 10196.32, SD = 3119.66; Neutral: M = 16473.75, SD = 5362.31). The interaction between AEQ_Group and Condition was not significant, $F(2, 240) = 0.27$, $p = .77$, $\eta^2p = .002$. The results indicated a significant main effect of Condition, $F(2, 240) = 71.18$, $p < .001$, $\eta^2_p = .372$. Tukey HSD post hoc comparisons indicated that reaction times were significantly higher in the Neutral condition than in Computer_control (mean difference = 6594.16, 95% CI [5138.53, 8049.79], $p < .001$) and Instagram (mean difference = 6277.43, 95% CI [4821.79, 7733.06], $p < .001$). Reaction times did not differ significantly between Instagram and Computer_control (mean difference = 316.73, 95% CI [−1138.90, 1772.36], $p = .865$). The main effect of AEQ_Group was not significant, $F(1, 240) = 1.82$, $p = .18$, $\eta^2_p = .008$. Overall, these findings suggest that Condition influenced reaction time regardless of AEQ group, with participants responding substantially more slowly in the Neutral condition, while performance in the Instagram and Computer_control conditions was comparable.

Table 2.1

Mean Reaction Times and Standard Deviations by AEQ Group and Condition

AEQ Group	*Condition*	*Mean (ms)*	*SD (ms)*
Non-problematic	Computer Control	9519.30	2661.81
	Instagram	10062.78	2791.05
	Neutral	15843.49	5465.73
Problematic	Computer Control	10175.83	3030.95
	Instagram	10306.13	3393.42
	Neutral	16991.96	5280.43

Note. This table displays the mean reaction times (in milliseconds) and standard deviations for each condition (Computer Control, Instagram, Neutral) across AEQ groups (Non-problematic vs.

Problematic). The reaction time bias score reflects participants' responses during change detection trials.

A two-way ANOVA was conducted to evaluate the effects of ScreenTime_Group (high vs. low) and Condition (Computer_Control, Instagram, Neutral) on reaction time. The means and standard deviations for reaction time are presented in Table 2.2. Descriptive statistics revealed notable differences in reaction times across conditions and ScreenTime groups, with the Neutral condition consistently associated with longer reaction times compared to the Computer_Control and Instagram conditions. The ScreenTime_Group × Condition interaction was not significant, $F(2, 219) = 0.46$, $p = .634$ $\eta^2_p = .004$. There was a significant main effect of Condition, $F(2, 219) = 64.19$, $p < .001$, $\eta^2_p = .370$. Tukey HSD post hoc comparisons indicated that reaction times in the Neutral condition (*M* = 16226.69, *SD* = 5451.21) were significantly longer than in both Computer_Control *(M* = 9818.82, *SD* = 2779.94), mean difference = 6407.87, 95% CI [4902.74, 7913.00], $p < .001$, and Instagram (*M* = 10142.72, *SD* = 3083.32), mean difference = 6083.97, 95% CI [4578.84, 7589.10], $p < .001$. Reaction times did not differ between Computer_Control and Instagram, mean difference = 323.90, 95% CI [−1181.23, 1829.03], $p = .868$. The main effect of ScreenTime_Group was significant, $F(1, 219) = 7.82$, $p = .006$, $\eta^2_p = .034$, such that the low ScreenTime group showed longer overall reaction times (*M* = 12800.82, *SD* = 4937.30) than the high ScreenTime group (*M* = 11344.09, *SD* = 4822.55). Overall, these findings suggest that reaction time was primarily driven by condition (with Neutral stimuli eliciting substantially slower responding), and this pattern was consistent across ScreenTime groups (i.e., no evidence that the condition effect depended on ScreenTime_Group).

Table 2.2

Mean Reaction Times and Standard Deviations by Screen Time Group and Condition

Screen Time Group	*Condition*	*Mean (ms)*	*SD (ms)*
High	Computer Control	9271.97	2903.46
	Instagram	9599.26	2930.94
	Neutral	15161.03	5613.24
Low	Computer Control	10380.45	2565.42
	Instagram	10700.87	3175.04
	Neutral	17321.15	5125.31

Note. This table shows the mean reaction times and standard deviations (in milliseconds) across conditions for participants categorised as either High or Low screen time users. Each group's total row reflects the average performance across all three conditions.

The two-way ANOVA was conducted to examine the effects of QIUU_Group (No Urge vs. Urge) and Condition (Computer_Control, Instagram, Neutral) on reaction time. The means and standard deviations for reaction time are presented in *Table 2.3* below. Descriptive statistics revealed notable differences in reaction times across conditions and QIUU groups, with the Neutral condition consistently associated with longer reaction times. The interaction between QIUU_Group and

Condition was not significant, $F(2, 219) = 1.67$, $p = .191$, $\eta^2_p = .015$. The results indicated a significant main effect of Condition, $F(2, 219) = 46.20$, $p < .001$, $\eta^2_p = .297$. Tukey HSD post hoc comparisons indicated that reaction times were significantly longer in the Neutral condition (estimated $M = 15{,}596.77$, $SE = 492.76$) than in the Computer_Control condition (estimated $M = 9{,}618.40$, $SE = 492.76$), mean difference (MD) = 6,407.87, 95% CI [4,910.46, 7,905.28], $p < .001$, and the Instagram condition (estimated $M = 9{,}990.81$, $SE = 492.76$), MD = 6,083.97, 95% CI [4,586.56, 7,581.38], $p < .001$. Reaction times did not significantly differ between the Computer_Control and Instagram conditions, MD = −323.90, 95% CI [−1,821.31, 1,173.51], $p = .866$. The main effect of QIUU_Group was significant, $F(1, 219) = 7.75$, $p = .006$, $\eta^2_p = .034$, indicating that participants in the Urge group responded more slowly overall (estimated $M = 12{,}527.47$, $SE = 308.17$) than those in the No Urge group (estimated $M = 10{,}943.18$, $SE = 478.32$; MD = 1,584.28). Overall, these findings suggest that reaction times were reliably slower in the Neutral condition than in both Computer_Control and Instagram, and that reporting an urge to use (QIUU) was associated with generally longer reaction times across conditions.

Table 2.3

Mean Reaction Times and Standard Deviations by QIUU Group and Condition

QIUU Group	*Condition*	*Mean (ms)*	*SD (ms)*
No Urge	Computer Control	9133.49	2472.87
	Instagram	9623.28	2653.62
	Neutral	14072.77	5435.31
Urge	Computer Control	10103.30	2871.74
	Instagram	10358.34	3244.02
	Neutral	17120.77	5251.62

Note. Mean reaction times and standard deviations (in milliseconds) are reported for participants grouped by urge strength to be online, as measured by the QIUU (No Urge vs. Urge). The total reflects the mean performance across all conditions.

An independent-samples t-test was conducted to examine whether the strength of the urge to be online, based on QIUU-derived “Low” and “High” groups, was associated with change blindness performance, as measured by reaction-time bias scores. The results indicate a significant difference in scores between the Low and High conditions, $t(73) = -2.26$, p = .027 (< .05), Cohen’s $d = −0.52$, 95% CI [−0.98, −0.06]. The magnitude of the effect was medium, suggesting a meaningful difference in attentional bias between individuals with lower versus higher urges to be online. A post hoc power analysis was conducted using G*Power 3.1 (Faul et al., 2009) to determine the achieved statistical power of the independent-samples t-test. Using the observed effect size ($|d| = 0.52$), an alpha level of .05, and a total sample size of 75, the analysis indicated that the study achieved a statistical power of .73. This suggests reasonable sensitivity to detect medium effects, though smaller effects may not have been reliably detectable. These results suggest that the urge to be online is associated with attentional bias toward Instagram-related stimuli. Additionally, we examined the correlation between QIUU scores and measures of attentional bias (implying that a lower score is a higher urge to be online) (*Table 2.4)*. A Pearson correlation coefficient was computed, indicating a statistically significant negative association between the two variables (r = 0.34).279, N =75, p =.016 (<.05). Overall, d was a negative correlation between QIUU scores and the measure of bias (*Figure 2*).

Table 2.4

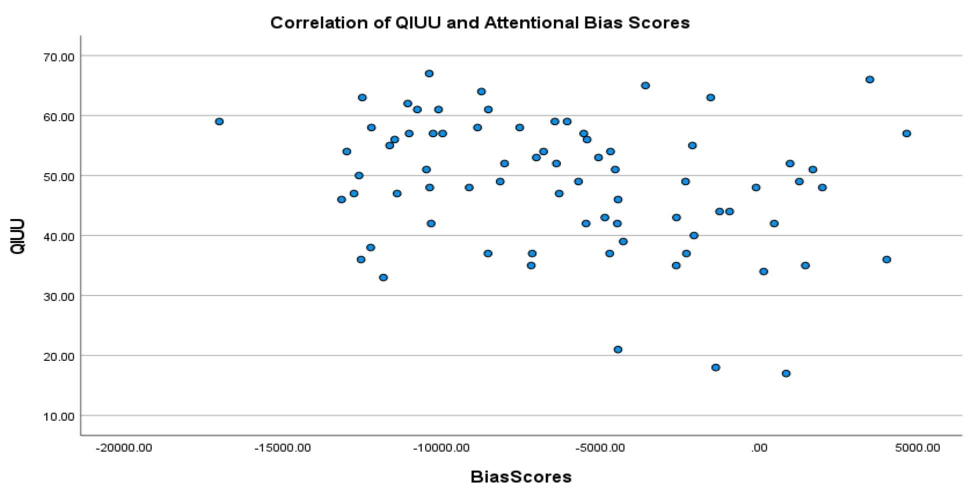
Attentional Bias Scores by Strength of Urge to Be Online (QIUU)

QIUU	*M*	*SD*
Low	-7321.13	40779.99
High	-4813.37	4810.17

Note. This table presents the mean RT bias scores and standard deviations for participants classified into Low- and High-urge groups based on their QIUU scores. Negative values indicate faster responses to Instagram-related stimuli, suggesting greater attentional bias toward social media cues.

Figure 2

Relationship Between Urge to Be Online (QIUU) and Attentional Bias Scores



Note. QIUU scores were negatively correlated with attentional bias measures, indicating that higher craving levels were associated with faster reaction times to social media-related stimuli. This suggests more substantial attentional bias in individuals with more problematic use, consistent with theories linking craving to enhanced automatic attention toward relevant cues (Nikolaidou et al., 2019; Field et al., 2009a; Robinson & Berridge, 1993).

An independent-samples t-test was conducted to examine whether attentional bias, as measured by change blindness performance, differs between participants categorised as non-problematic or problematic users based on their AEQ scores. The results indicate no significant difference in scores between non-problematic and problematic users: $t(73) = .523$, $p = .602$ (>.05), Cohen's $d = 0.12$, 95% CI [−0.33, 0.57]. The observed effect size was small, and the confidence interval crossed zero, indicating substantial uncertainty regarding the presence and direction of any true effect. Post hoc power analysis indicated very low achieved power ($1 - \beta = .11$) for detecting the observed effect size ($d = 0.12$) with an alpha level of .05 and $N = 75$. This suggests the study was underpowered to detect small effects, and null results should be interpreted cautiously. Accordingly, the present findings cannot provide strong evidence for the absence of an effect, but rather suggest that any true association between addictive severity and attentional bias is likely to be small. These results suggest that the level of addictive severity does not affect attentional bias for Instagram-related stimuli (*Table 2.5*). A Pearson correlation coefficient was used to assess the relationship between AEQ scores and measures of attentional bias. The assessment showed that the two were not statistically related, r =-.085, N =75, p =.469 >.05.

Table 2.5

Attentional Bias Scores by Online Use Group Based on AEQ Classification

AEQ	*M*	*SD*
Non-problematic	-5780.72	4765.85
Problematic	-6379.24	5125.06

Note. This table presents the mean RT bias scores and standard deviations for participants grouped by AEQ scores (non-problematic vs. problematic). Negative values indicate faster responses to Instagram stimuli, reflecting stronger attentional bias toward social media-related cues.

An independent-samples t-test was conducted to examine whether attentional bias, as measured by change blindness performance, differs between participants with low and high weekly Instagram use, based on ScreenTime-derived groupings. The results indicate no significant difference in the scores for Low and High conditions; $t(73) = -.929$, $p = .356$ >.05, Cohen's $d = -0.21$, 95% CI [−0.67, 0.24]. The observed effect size was small, and the confidence interval included zero, indicating uncertainty regarding the presence and direction of any true effect. Post hoc power analysis indicated low achieved power ($1 - \beta = .17$) for detecting the observed effect size ($d = 0.21$) with an alpha level of .05 and $N = 75$. This suggests that the study was underpowered to reliably detect small effects, and therefore the non-significant result should be interpreted with caution. These findings indicate that while weekly Instagram use does not appear to influence attentional bias in this sample, small effects cannot be ruled out, and larger samples would be necessary to detect subtle associations. Study indicates that the amount of time spent on Instagram a "Week" does not have an effect on attentional bias for Instagram-related stimuli (*Table 2.6*). A Pearson correlation coefficient assessed the relationship between ScreenTime scores and measures of attentional bias. The assessment showed that the two were not statistically related r =.074, N =75, p =.529 >.05. Overall, no correlation between ScreenTime scores and measure of bias.

Table 2.6

Attentional Bias Scores by Screen Time Allocation

ScreenTime	*M*	*SD*
Low	-6620.28	5125.24
High	-5561.77	4735.12

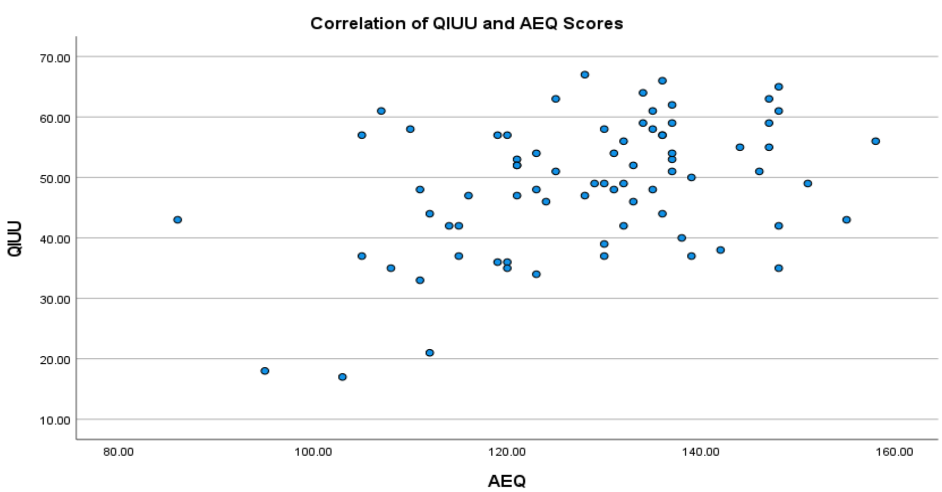
Note. This table presents the mean RT bias scores and standard deviations for participants categorised into Low and High screen time groups based on weekly Instagram usage. Negative values indicate greater attentional bias, as participants responded more quickly to Instagram-related stimuli.

The relationship between the amount of time a Week spent on Instagram and ‘addictive’ severity is then examined. A Pearson correlation coefficient was conducted which showed that the two were not significantly related r =.164, N =75, p =.159 >.05. Overall, there was no correlation between BSMAS scores (‘addictive’ severity) and amount of time a week spent on Instagram (ScreenTime scores).

A Pearson correlation coefficient was conducted to assess the relationship between urge to be online and ‘addictive’ severity (AEQ scores). The assessment showed that the two were significantly related, r =.413, N =75, p = <.05. Overall, there was a positive correlation between the urge to be online and ‘addictive’ severity (*Figure 3*).

Figure 3

Relationship Between Urge to Be Online (QIUU) and Online Expectancies (AEQ) Scores

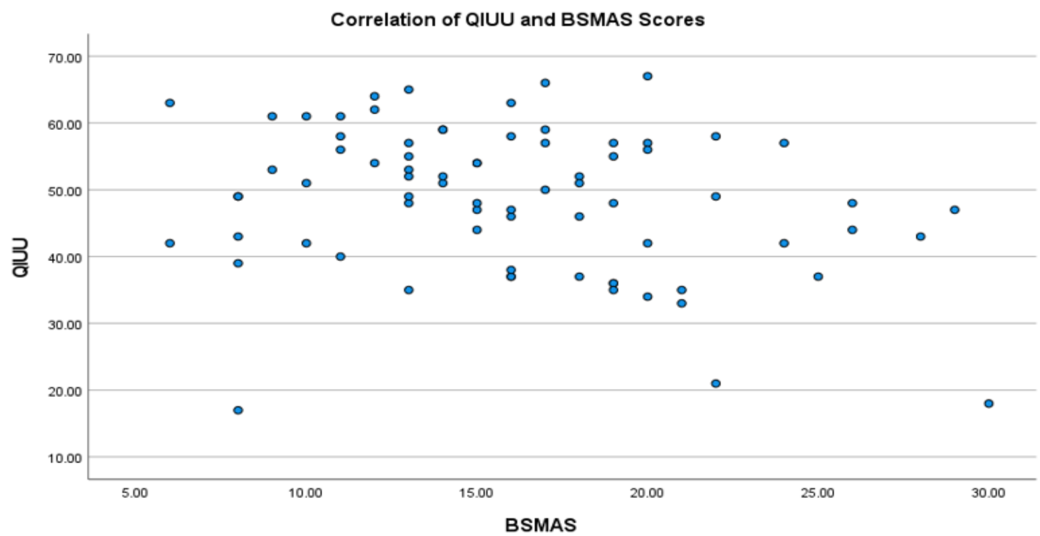


Note. Higher AEQ scores were associated with stronger urges to be online, indicating that as craving for online engagement increases, so does the severity of problematic use. This urge reflects a form of craving linked to compulsive or addictive behaviours, such as excessive time spent online, impaired control, and negative consequences. The findings support the notion that craving plays a central role in driving compulsive engagement with online activities, thereby reinforcing patterns of problematic use (Nikolaidou et al., 2019; Field et al., 2009a; Robinson & Berridge, 1993).

The relationship between the urge to be online and 'addictive' severity is then examined. A Pearson correlation coefficient was conducted which showed that the two were significantly related r =-.266, N =75, p =.021 <.05. Overall, there was a negative correlation between BSMAS scores ('addictive' severity) and urge to be online (QIUU scores) (*Figure 4*).

Figure 4

Relationship Between Urge to Be Online (QIUU) and Social Media Addiction (BSMAS) Scores



Note. As the 'addictive' severity increases the urge to be online decreases. Higher BSMAS scores (greater problematic use or addiction severity) are associated with a lower urge to be online (QIUU). Lower BSMAS scores (less problematic use or addiction severity) are associated with a higher urge to be online.

Discussion

In this study, we explored whether social media users exhibit an attentional bias towards social media-related stimuli. The present study aimed to explore the relationship between attentional bias and social media usage, particularly focusing on the influence of addiction levels according to the questionnaires, time spent online, and the urge to be online. The sample was well-powered, showcasing significant variation in social media use, engagement, and 'addictive' severity, as measured through self-reported platform use, objective smartphone data, and established social media scales (BSMAS, AEQ, QIUU). We also aimed to examine methodological factors influencing the measurement of attentional bias, such as the type of stimuli used. The analysis revealed several important findings.

Our results indicate that social media stimuli did not affect users' target response times, providing no support for an attentional bias towards these stimuli. When evaluating attentional bias related to social media through indirect measures of visual attention over multiple trials, it was observed that nonproblematic users responded slightly faster than problematic users. This finding contradicts the predictions made by IST models of addiction (Franken, 2003; Robinson & Berridge, 1993). According to IST, craving enhances the motivational salience of addiction-related cues, leading to stronger attentional biases. While this was partially supported by the significant link between craving and attentional capture, the lack of sustained attention suggests that the cognitive processes underlying craving in social media contexts differ from those in substance addictions. These findings are consistent with Field et al. (2016), who argued that attentional bias effects in addiction are more dynamic and context-dependent than previously assumed. Across the various analyses, there was no evidence of a strong or consistent attentional bias toward social media stimuli. For instance, there was no significant difference in reaction times to Instagram-related stimuli between non-problematic and problematic users. Additionally, time spent on Instagram, as measured by ScreenTime, was not found to be correlated with attentional bias. These findings contrast sharply with studies on substance-related addictions, where attentional biases are robustly linked to addiction severity (e.g., Field & Cox, 2008; Jones et al., 2003). For example, problem drinkers consistently show faster reaction times to alcohol-related images, reflecting heightened attentional capture (Franken, 2003).

The study demonstrated a significant negative association between QIUU scores and attentional bias, indicating that stronger urges to be online were linked to greater attentional bias. Participants with higher craving levels (lower QIUU scores) exhibited quicker reaction times to social media-related stimuli, suggesting that craving increases the salience of these cues. This aligns with previous research (e.g., Nikolaidou et al., 2019; Robinson & Berridge, 1993), which asserts that craving amplifies the attentional pull of addiction-related stimuli. This finding challenges the predictions of IST, which suggests that craving not only enhances initial attentional capture but also sustains attention on addiction-related cues (Robinson & Berridge, 1993, 2008). The transient nature of attentional capture observed here may reflect a less intense dopaminergic response to social media stimuli compared to substance-related cues.

This contrasts with studies showing attentional biases to addiction-related stimuli in both substance-related (see Field & Cox, 2008) and non-substance-related addictions. For instance, previous research reported attentional biases to gambling images, computer-related words, and pornographic images in associated users (Ciccarelli et al., 2016; Jeromin et al., 2016; Pekal et al., 2018). However, our findings do not support the extension of these biases to social media stimuli among social media users. If excessive social media use were to fit within an addiction framework, we would expect to see evidence of an attentional bias. Instead, in contrast, within the context of social media use, our findings show no evidence of the typical changes in attentional processes seen in other addictive behaviours. These changes are believed to be caused by neurochemical alterations in brain regions that regulate goal-directed behaviour (Franken, 2003; Robinson & Berridge, 1993, 2008).

Although the two-way ANOVA analyses revealed no significant interactions between group factors (AEQ_Group, ScreenTime_Group, QIUU_Group) and condition, several significant correlations emerged that warrant interpretation. Specifically, the positive correlation between urge to be online and AEQ scores indicates that stronger cravings to be online are associated with greater expectancy of positive reinforcement from online engagement. This supports theoretical predictions from the Incentive Sensitisation Theory (IST), which posits that addiction-related cues gain motivational salience through repeated exposure and conditioning (Robinson & Berridge, 1993; 2016).

However, the lack of significant interaction effects in the ANOVA suggests that although certain individuals report higher cravings and expectancies, these subjective differences do not translate into significantly different attentional performance across stimulus types (Instagram vs. control vs. neutral) in the flicker change blindness task. This divergence may reflect the complexity of attentional bias phenomena, particularly when assessed using indirect measures such as reaction time, and aligns with recent literature suggesting that craving may modulate initial attentional capture more than sustained attention over time (Field et al., 2016; Mogg et al., 2005).

Furthermore, although Nikolaidou et al. (2019) reported a link between the urge to be online and attentional dwell time on social media-related stimuli, this finding was based on a relatively small sample size (N = 16). In contrast, the present study provides converging evidence from a larger sample using a change blindness paradigm: the urge to be online was associated with attentional bias toward Instagram-related cues as observed across QIUU groups. Specifically, individuals reporting stronger urges to be online exhibited greater attentional capture by Instagram stimuli, reflected in faster responses to social media-related changes (i.e., more pronounced bias scores). This pattern is consistent with incentive-sensitisation accounts, suggesting that motivational states such as craving increase the salience of addiction-relevant cues and bias early attentional processing toward them. At the same time, the broader pattern of findings—particularly the absence of robust effects across other severity and use measures—suggests that urge-related attentional biases in social media contexts may be more context-dependent and transient than those typically observed in substance-related addictions.

Taken together, the significant correlations suggest that motivational factors such as craving and expectancies are meaningfully related. However, their effects may be obscured or moderated by task design, measurement sensitivity, or individual variability in attentional strategies. The absence of interaction effects in the ANOVA does not preclude underlying psychological associations; instead, it calls for a more nuanced interpretation and possibly alternative methodologies—such as eye-tracking or event-related potentials—to capture attentional dynamics in response to social media stimuli more precisely.

Our research did not allow us to examine the relationships between the sub-components of attentional bias, as proposed by IST models of addictive behaviours (Franken, 2003; Robinson & Berridge, 1993), and both levels of subjective craving and time spent online by analysing the initial orienting of attention to social media-related stimuli and the sustained attention on these stimuli. Notably, this study measured these biases across multiple visual scenes, using stimuli that are arguably more representative of the environments that may actually elicit attentional biases (Nees et al., 2012), thereby overcoming many methodological and measurement limitations of previous research, as discussed in chapter 1. The study highlights the transient nature of craving and its influence on attentional processes. Craving may peak during specific moments, such as after posting content and anticipating feedback. During these periods, the incentive salience of social media cues is likely maximal, thereby driving attentional capture. However, outside these contexts, the salience of social media stimuli may diminish, resulting in weaker or absent attentional biases. This interpretation aligns with Field et al. (2016), who argued that attentional biases are not stable traits but rather fluctuate with subjective craving and situational factors. Applying this to social media use, the findings suggest that craving-related attentional biases may be most detectable in contexts where users are actively seeking rewards. Notably, social media-related attentional biases were unrelated to time spent online in non-problematic users, challenging predictions from IST models and research using indirect measures of attention (Jones et al., 2002; Jones et al., 2003).

The findings raise questions about the applicability of IST to social media use. While IST provides a robust framework for understanding attentional biases in substance and behavioural addictions, its predictions may not fully extend to the digital environment. For example, social media use often involves diverse cognitive and emotional drivers, making it less directly comparable to substance use disorders. The salience of social media cues may be influenced by user context and goals, such as seeking validation or escaping boredom. These findings suggest that the mechanisms underlying compulsive social media use may differ from those in other addictions. For instance, while craving plays a role in driving attentional capture, the absence of sustained biases and weak associations with use severity indicates that other factors, such as habit formation and social norms, may also be critical.

Consistent with the absence of an attentional bias effect, our analysis of individual differences found no associations between social media use, engagement, or 'addictive' severity. Neither the time spent on social media, the number of daily checks, nor the number of notifications received predicted the extent of attentional capture by social media distractions. Additionally, there were no correlations between the level of attentional capture and scores on established social media engagement and 'addictive' severity scales (AEQ, BSMAS, QIUU). This contrasts with previous studies on non-substance-related addictions, which reported positive associations between attention bias levels and use/severity measures (Ciccarelli et al., 2016; Jeromin et al., 2016; Pekal et al., 2018). Furthermore, although Nikolaidou et al. (2019) reported a link between the urge to be online and attentional dwell time on social media-related stimuli, this finding was based on a small sample size (N = 16). Our findings demonstrated that the urge to be online was not significantly associated with attentional bias, indicating that this urge does not affect attentional bias toward social media-related stimuli.

Unlike the broader pattern where no effect was found, urge-related motivation (QIUU) had a clear impact on attentional bias. Participants who felt a stronger urge to be online (shown by lower QIUU scores) were quicker to notice Instagram-related changes, which means their attention was more easily captured by these cues. This finding fits with incentive-sensitisation theories, which suggest that craving makes addiction-related cues stand out more and affects early attention. It also supports earlier research that connects urge-related factors to how people pay attention to social media cues (e.g., Nikolaidou et al., 2019). This study adds to that work by using a change-blindness task with a larger group of participants.

Questionnaires that measure attentional bias toward social media have some challenges. Self-report scales depend on people accurately judging their own behavior, but these can be affected by social desirability and memory errors, especially when trying to measure automatic processes that people may not notice. The results here show that how well questionnaires work depends on what they are measuring. General measures of engagement or problematic use (like AEQ/BSMAS) and objective data (like ScreenTime) did not predict attentional capture in the change blindness task. This suggests that these broad measures do not reflect the moment-to-moment motivations that affect visual attention. However, QIUU, which measures craving or urge, was clearly linked to RT bias scores. This means that people with higher urges were more likely to have their attention captured by Instagram cues. So, motivational state may have a more direct effect on attentional bias in digital settings than overall use or severity.

Retrospective questionnaires may miss how attentional bias changes in different situations. People's attention to social media cues can shift depending on factors like boredom, stress, goals, or immediate cravings, such as after posting and waiting for feedback. Future studies should use a mix of methods, combining experiments with tools that better measure motivation in the moment. These could include craving assessments tied to specific times, experience-sampling, or real-time measures like eye-tracking. This would help show when questionnaires can accurately predict attention, such as with urges or cravings, and when they only give a general picture that does not match real-time attention.

Our study utilised various social media use, engagement, and 'addictive' severity questionnaires, but a new measure should be developed to assess 'craving' for social media access and validation (Savci & Griffiths, 2019). This would align social media use measures with other addiction-related questionnaires. Similarly, although our sample included a wide range of individual differences in social media use, engagement, and 'addictive' severity, future research should aim to establish standard criteria for categorising excessive social media use, akin to those used for substance-related and other non-substance-related addictive behaviours. This would improve future studies' ability to conduct individual-differences analyses, not only to examine potential attentional bias effects but also to further evaluate the positive and negative impacts of social media use, as discussed in the introduction (see also Wegmann et al., 2020).

An intriguing reason we might not have found an attentional bias or a related relationship with use, engagement, and severity measures is discussed in a recent review of this literature by Field et al. (2016). Field et al. (2016) argue that research on substance users does not consistently show strong evidence of an attentional bias effect. Instead of viewing this bias as a fundamental aspect of addictive behaviour, they suggest it is better characterised as temporary changes in the evaluation of addiction-related stimuli during periods of subjective craving, described as an 'appetitive motivational process.' Applying this to social media use, the period of subjective craving is most likely to occur after a user has posted content. During this time, the incentive salience of social media stimuli is likely at its peak as users seek behavioural rewards, such as likes and comments. Therefore, if a social media attentional bias exists, it is likely a transient effect that is most detectable after the user has posted content and is awaiting peer feedback.

The study used the flicker-induced change blindness (ICB) paradigm, which has limitations in capturing the full complexity of attentional processes. While this method effectively simulates real-world visual environments, it may not differentiate between the initial orienting of attention and sustained attention. Additionally, the use of generic social media stimuli (e.g., Instagram icons) may have reduced the emotional or reward-related salience of the cues. Other paradigms, such as dot-probe tasks, may provide a more nuanced understanding of attentional processes. For instance, Zhao et al. (2022) found evidence of attentional bias using the dot-probe task but not the Stroop task, highlighting the importance of task design in detecting biases. Future research could incorporate these methods to capture the dynamics of attentional bias better.

In summary, social media use has become pervasive in society. Research has predominantly concentrated on the negative consequences of excessive use, sparking an ongoing debate about whether it should be classified as a clinically relevant addictive behaviour. An attentional bias towards addiction-related stimuli is a key indicator of the neurochemical and attentional changes that result from addictive behaviours. Although such biases have been observed in both substance and non-substance addictions, we did not find this effect among a diverse group of social media users when it came to social media stimuli. In conclusion of experiment 1, by directly measuring the attention of social media users as they completed the flicker ICB task using real-world scene stimuli and single objects, the results revealed that social media-related attentional bias, specifically the ability of social media-related cues to capture attention, is associated with subjective craving (urge to be online), in accordance with IST models of addictive behaviours. Contrary to the IST models of addictive behaviours, this study did not find an association between maintained attention and subjective craving, nor did it find any link between levels of social media consumption and measures of attentional bias among social media users. Additionally, this study identified potential methodological limitations in the use of the flicker ICB, particularly regarding stimulus type and trial number. The findings suggest conceptual challenges for IST models and raise questions about the flicker ICB's effectiveness in measuring attentional bias.

Chapter 3 Experiment 2: An experimentation of social media-related attentional bias in Instagram users using the Dot Probe Paradigm

While the internet has brought numerous positive changes to society, it has also led to issues with problematic internet usage and addiction. Extensive research shows that this dysfunctional condition can significantly impact real-life quality by diminishing social interaction time (Enez Darcin et al., 2016), hindering the ability to meet professional and academic responsibilities (Young, 1996; Annunzi et al., 2022), and disrupting engagement in personal interests (Hellström et al., 2012; Rehbein & Baier, 2013). Among the various forms of internet addiction, gambling, gaming, and social network addictions are the most thoroughly studied phenomena (Gainsbury, 2015; Calluso et al., 2020; Cannito et al., 2023). However, due to the more recent proliferation of social networks, there is significantly more evidence on gaming addiction. Recent studies, however, suggest that social network addiction is more prevalent and is equally, if not more, strongly associated with psychosocial challenges (Burén et al., 2021). The widespread use of mobile devices, such as smartphones and tablets, has led to a significant increase in social network addiction, as these devices enable constant connectivity (Kuss & Griffiths, 2017). Since this phenomenon first appeared, there have been conflicting views in the literature on whether it constitutes a pathological addiction or simply an extreme form of normal behaviour that can become problematic (Varona et al., 2022).

As discussed in Chapter 1, although excessive social media use is not formally recognised as a distinct disorder within DSM-5 or ICD-11, accumulating evidence suggests meaningful overlap with established behavioural and substance-related addictions. Problematic Internet use (PIU) has been shown to exhibit similarities to substance-related and other addictive disorders both in behaviour (Bielefeld et al., 2017; Grant et al., 2010) and in neurobiology (Dong et al., 2011). Davis (2001) proposes that PIU can be divided into two distinct types: specific and general. The general form encompasses a broad range of behaviours, whereas the specific form pertains to the use of particular Internet applications, such as social networking sites (SNSs). General PIU is a contentious topic, with researchers debating whether the Internet itself is the cause of problematic behaviour or whether specific Internet applications are responsible for these issues (Griffiths, 2010; Shaffer et al., 2000; Yellowlees & Marks, 2007). This debate has prompted the recommendation that the use of specific applications, such as SNSs, should be evaluated rather than general PIU (Griffiths et al., 2014). Therefore, in line with these suggestions, this study concentrates on the use of specific SNSs. This provides the theoretical basis for examining attentional bias within social networking contexts in Experiment 2.

SNSs encompass online applications like Instagram, Facebook, Twitter, etc., designed to facilitate social interactions among their users. Considerable research has focused on identifying usage patterns and personality traits of both problematic and non-problematic SNS users (Casale & Fioravanti, 2018; Casale et al., 2016; Frost & Rickwood, 2017). However, there is limited understanding of the behavioural characteristics of individuals who lose control over their SNS use and develop problematic patterns. This is evident in the widely varying prevalence rates, with studies reporting addiction to Facebook ranging from 4.5% to 47% (Bányai et al., 2017; Jafarkarimi et al., 2016). Moreover, recent evidence indicates that more intensive use of SNSs is linked to addictive symptoms and other addictive behaviours, such as shopping and food addiction (Müller et al., 2015; Tang et al., 2017). Research exploring whether problematic SNS users exhibit addiction-like tendencies, such as biases toward their preferred specific applications, will enhance our understanding of the potential mechanisms underlying this contentious emerging disorder.

A notable feature of substance-related and addictive disorders is the ability of substance-related stimuli to provoke and encourage substance-seeking behaviour (Field & Cox, 2008) by enhancing attentional focus on those cues. Additionally, attention, the most studied cognitive domain affected by substance use disorders, is also crucial in internet and social media addiction. There is clear evidence of attentional deficits and attentional bias in these cases (Jeromin et al., 2016; Wang et al., 2016; Nikolaidou et al., 2019). Research on the cognitive aspects of addiction has long revealed a well-established mechanism called attentional bias (AB). AB occurs as a distortion of normal selective attention processes, resulting in a strong tendency to focus on addictive stimuli (engagement phase) and/or difficulty diverting attention away from these stimuli (disengagement phase). As outlined earlier, incentive sensitisation theory (Robinson & Berridge, 1993, 2001), stimuli associated with substances of abuse acquire incentive motivation through classical conditioning, eliciting conditioned responses. The rise in incentive salience implies that substance-related stimuli are seen as highly significant and attract attention (Robinson & Berridge, 1993). Although this theory was initially developed to explain the effects of psychostimulant drugs (like amphetamine and cocaine), evidence now suggests that the same processes can account for behavioural addictions, such as pathological gambling (Brevers et al., 2011; Honsi et al., 2013), shopping addiction (Jiang et al., 2017), and online pornography addiction (Pekal et al., 2018). Consequently, these processes could also apply to problematic SNS use.

AB is typically assessed using a dot-probe task, in which an addiction-related image is shown alongside a neutral image (Lorenz et al., 2013). One of the two images is then replaced by a target (x), and participants are asked to identify its location. In this scenario, people respond more quickly to the target if it appears in a spatial area; they most frequently attend to one of the images (Posner et al., 1980). Since individuals with addiction respond more quickly to targets that replace addiction-related images, it is suggested that they exhibit heightened attention to these stimuli (Field and Cox, 2008). This bias is thought to be crucial in the development and maintenance of dysfunctional addictive behaviours across several types of addiction. In the context of internet- and social media-based addiction, this bias is described as a tendency to focus more on internet-related cues, such as images of computer screens or social media notifications, rather than on neutral stimuli (Nikolaidou et al., 2019; Zhao et al., 2022).

Additionally, research in the field of addiction has discovered that craving levels and evaluative bias (perceiving substance-related stimuli as highly pleasant) are connected to attentional bias and, consequently, to substance-seeking behaviour (Field & Cox, 2008; Field et al., 2004b). While the role of craving and evaluative bias in drug-seeking behaviour is well established, there is a shortage of studies examining their influence in the context of problematic SNS use (Kim & Hodgins, 2018). Franken (2003) proposed that the relationship between attentional bias and craving is reciprocal. Attentional bias can cause increased cravings and drug-seeking behaviour, while increased cravings can also lead to attentional bias and drug-seeking behaviour. Similarly, Pekal et al. (2018) found a relationship between attentional bias and the severity of Internet pornographic disorder, mediated by cue-reactivity and craving indicators. Thus, this study assessed and compared levels of online urge among SNS users. Urges to be online were conceptualised as reflecting craving levels, indicating an increased urge to engage in the activity.

Aim and Hypotheses

Hypothesis 1 (Attentional bias toward Instagram cues). We hypothesise that participants will show an attentional bias toward Instagram-related stimuli on the dot-probe task. Participants will respond faster on congruent than on incongruent trials, producing a positive attentional-bias score ($RT\_incongruent - RT\_congruent > 0$).

Hypothesis 2 (Group differences by usage and urge). We expect that participants identified as high Instagram users (high ScreenTime) or as having a high desire to be online (high craving, defined as lower QIUU scores or high-urge group membership) will show larger positive attentional bias scores than low-use or low-urge participants.

Hypothesis 3 (Dose–response prediction across individual differences). We hypothesise that attentional-bias scores will increase with higher levels of Instagram engagement and problematic use. Specifically, higher BSMAS, SMAQ, and SMES scores, along with a greater urge to be online (as indicated by lower QIUU scores or membership in the high-urge group), will be associated with a more pronounced attentional bias toward Instagram cues.

The experiment carried out to study the Instagram dot probe focused on addressing the following question concerning methodological aspects of measuring attentional bias:

To what extent do social media users exhibit attentional bias toward social media-related content?

Method

Participants

There were 360 initial participants in the study, but three failed to provide all required questionnaire data and had missing task data. After excluding the three participants who did not meet all the inclusion criteria, 357 respondents met the inclusion criteria. The participants were 357 volunteers recruited from undergraduate and postgraduate students via the University of Strathclyde Participant Pool on the online SONA Systems Research Management Platform (N = 9) and via Prolific, an online participant recruitment platform for surveys and marketing (*N* = 348) (Prolific, 2021). The School of Psychology utilises the SONA Systems Research Management System to oversee experiments and track participants involved in the Psychology Research Participant Scheme (PRPS). Of the 357 participants, 199 were females (*M* = 22.97, *SD* = 2.95), 152 were males (*M* = 22.94, *SD* = 2.94), and 6 were other (*M* = 23.00, *SD* = 3.95), aged 18 to 30. The eligibility criteria for inclusion in the study were as follows: (a) participants had to be 18 years or older, (b) use a smartphone and consider themselves users of social media, (c) have normal or corrected-to-normal vision, (d) have no colour vision deficiency or colour blindness, (e) complete the survey using a desktop computer or laptop, not a smartphone or Mac computer, (f) individuals with a current or past history of behavioural addictions (e.g., gambling or internet gaming) or impulse control disorders (e.g., kleptomania, pyromania, compulsive sexual disorder, or intermittent explosive disorder) were advised not to participate, and (g) individuals with a history of epilepsy or seizures were also excluded. This study received ethical approval from the Ethics Committee of the University of Strathclyde School of Psychological Sciences and Health.

Dot-Probe Stimuli. A preliminary rating task was conducted to select the stimuli for the present experiment (see Appendix B). Three different types of stimuli were employed in the study: Instagram-related stimuli (Appendix E, Figure E1), control stimuli (Appendix E, Figure E2), and filler stimuli (Appendix E, Figure E3) [1]. The 20 Instagram images, 20 control images, and 40 filler images were carefully positioned and controlled, resulting in a total of 160 trials (Appendix E1). Instagram images included the application icon, the Instagram Messenger icon, and others. The 20 control images included words and modern digital branding elements, such as icons/logos and recognisable branding (e.g., Polaroid, Community Fund, an Instagram-like colour gradient). Filler

[1] The numbers of IAPS (Kappenman et al., 2015; Kappenman et al., 2014) pictures used were as follows. Neutral: 2038, 2102, 2190, 2393, 2397, 2840, 2880, 2890, 5510, 5534, 6150, 7000, 7002, 7004, 7006, 7009, 7010, 7020, 7034, 7035, 7036, 7038, 7041, 7050, 7055, 7056, 7059, 7090, 7160, 7161, 7170, 7175, 7179, 7185, 7187, 7217, 7233, 7235, 7491, and 7950

images included 40 neutral stimuli (e.g., neutral faces, household objects, places) from the International Affective Picture System (IAPS).

Apparatus and measures

Socio-demographics. The study included questions on age and gender to obtain a profile of participants' sociodemographic characteristics.

Social Media Addiction Questionnaire (SMAQ). SMAQ is an 8-item self-report assessment (Hawi & Samaha, 2017) derived from the Facebook Intrusion Questionnaire (FIQ), in which social media is replaced with Instagram, and it assesses social media use and severity. Doing so ensures a shift in focus from social media in general to a particular site. Respondents rate each item on a 7-point Likert scale (ranging from 1 = *strongly agree* to 7 = *strongly disagree*). For example, a statement such as "I interrupt whatever else I am doing when I feel the need to access Instagram" and "I feel connected to others when I use Instagram". It is short, has good psychometric properties, is reliable, and covers the symptoms of behavioural addiction—Cronbach's coefficient for this questionnaire is .87.

Questionnaire on Internet Use Urges (QIUU). QIUU is a 10-item self-report questionnaire that assesses the severity of online urges. Respondents rate each item on a 7-point scale (ranging from 1 = *completely disagree* to 7 = *completely agree*). The QIUU is an adapted form of the Questionnaire on Smoking Urges-Brief (Cox et al., 2001; Tiffany & Drobes, 1991). To assess levels of the urge to be online, each item has been reworded to reflect online activity. For example, a statement such as "I have the desire for a cigarette right now" was reworded to "I have the desire to be on Instagram right now." Cronbach's coefficient for this questionnaire is .94.

Bergen Social Media Addiction Scale (BSMAS). BSMAS is a modified version of the previously validated Bergen Facebook Addiction Scale (BFAS; Andreassen et al., 2012). The modification involves using the word 'Instagram' instead of the word 'Facebook'. The scale comprises six items, each representing a dimension of addictive behaviour, yielding a range of data. The items include mood modifications, salience, tolerance, conflict, relapse, withdrawal, and symptoms (Duradoni et al., 2020). The scale is reported to have good psychometric properties, whereby addiction is determined by utilising polythetic (scoring three or above on at least four of the six items) and monothetic (scoring three or above on all six items) scoring schemes. The scale is non-specific and provides reliable results on general severity on social media. A higher BSMAS score suggests a higher risk of developing an addiction to social media, with a cut-off score (19 out of 30) proposed recently to indicate problematic use of social media (Bányai et al., 2017). Participants rate each item on a 5-point scale (ranging from 1 = *very rarely* to 5 = *very often*). For example, a statement such as "How often during the last year have you tried to cut down on the use of Instagram without success?" The internal consistency of the BSMAS was satisfactory, with a Cronbach's α coefficient of .85.

Social Media Engagement Scale (SMES). SMES is a 5-item self-report questionnaire (Przybylski et al., 2013) which assesses the extent to which people engage with Instagram in their daily lives. Participants were instructed to: "Please reflect on how you used Instagram in the past week (i.e., the previous seven days) and report the number of times you used it......" under the circumstances listed below. Participants were asked to rate all items on an 8-point Likert scale (ranging from 1=*Not one day last week* to 8 = *Every day last week*) to rate five statements: "within 15min of waking up" (*M* = 4.30, *SD* = 2.65), "when eating breakfast" (*M* = 3.46, *SD* = 2.43), "when eating lunch" (*M* = 3.52, *SD* = 2.32), "when eating dinner" (*M* = 3.14, *SD* = 2.30), and "within 15min of going to sleep" (*M* = 5.28, *SD* = 2.53). The internal consistency was satisfactory, with a Cronbach's α coefficient of .86.

Screen Time (Apple iPhone). Screen Time was assessed by asking participants to report the number of hours and minutes they spent on social media per typical day over the past seven days. This was measured using an 8-part questionnaire that examined the following: "Daily Average" screen time, "Weekly" average social media time, "Daily" average social media time, daily average notifications, daily average device pickups, the top three most-used social media apps for the day, the top three most-used social media apps for the week, and the weekly average time spent on Instagram.

Procedure

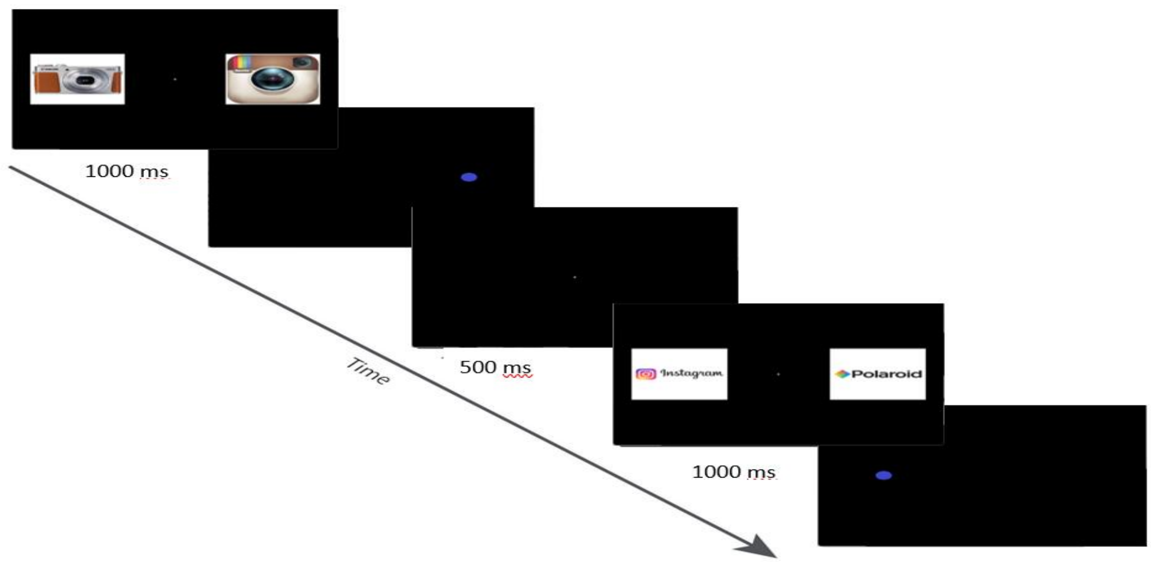
In such a task, participants are seated at a computer or laptop and informed that the online experiment will take approximately 20 minutes to complete. Firstly, participants on Prolific (Prolific, 2021) clicked a link that directed them to Qualtrics (Qualtrics, 2021), where they provided informed consent and received study information before consent. After giving consent, the Qualtrics platform directed participants to the Dot Probe E-Prime Task, which we ran on E-Prime Go (Psychology Software Tools, 2020), a psychology software tool displayed on a monitor (Carlson & Fang, 2020). During the task, we asked participants to complete a practice trial to understand what the subsequent trials would require. After participants completed a brief practice trial, they could click Y (yes) or N (no) to proceed to the main task; we excluded these practice trials from the analysis. During the task, we asked participants to focus on a fixation cross ("+") at the centre of the screen for 500 ms, and then we displayed a pair of stimuli simultaneously near the fixation cross (one to the left and one to the right) for 1,000 ms (*Figures 5* and *6*). Stimuli will be either Instagram-related images, control images, or filler images with similar visual complexity. These Instagram and filler images were familiar to all users. During the offset of the exposure duration for stimuli, a neutral item, known as a probe (e.g., a dot or small circle), is presented on either the right- or left-hand side of the computer screen, replacing one of the images. We then asked participants to respond as quickly and accurately as possible by pressing one of the designated keys corresponding to the probe's location (e.g., left or right, as indicated in the task instructions). The dot remained on the screen until the participant made a response, indicated by pressing one of the response buttons on the keyboard ("←" when the dot appeared on the left side of the computer screen and "→" when it appeared on the right side). Once a participant responded, the trial terminated, and the next one began 1,000 ms later.

There were six practice trials and 160 experimental trials (80 Instagram-control and 80 filler). In the 80 Instagram-control trials (in which the pair of images consisted of an Instagram image and a matched control), each of the 20 Instagram-related images was presented 4 times, appearing twice on the right and twice on the left sides of the screen. Moreover, they were matched and counterbalanced with control images. We took steps to ensure that the Instagram-control and filler trials were visually and contextually matched, thereby reducing the likelihood that participants could predict or distinguish between image types based on low-level features. Control images were carefully selected and counterbalanced to match Instagram images in terms of visual complexity, colour composition, and thematic content, thereby minimising confounding variables and ensuring ambiguity across conditions. We presented the Instagram control and filler trials to each participant in a random order. After completing the Dot Probe E-Prime task, participants returned to Qualtrics to complete the SMAQ, SMES, QIUU, BSMAS, and ScreenTime questionnaires. Participants were then fully debriefed as to the true aims of the study.

.

Figure 5

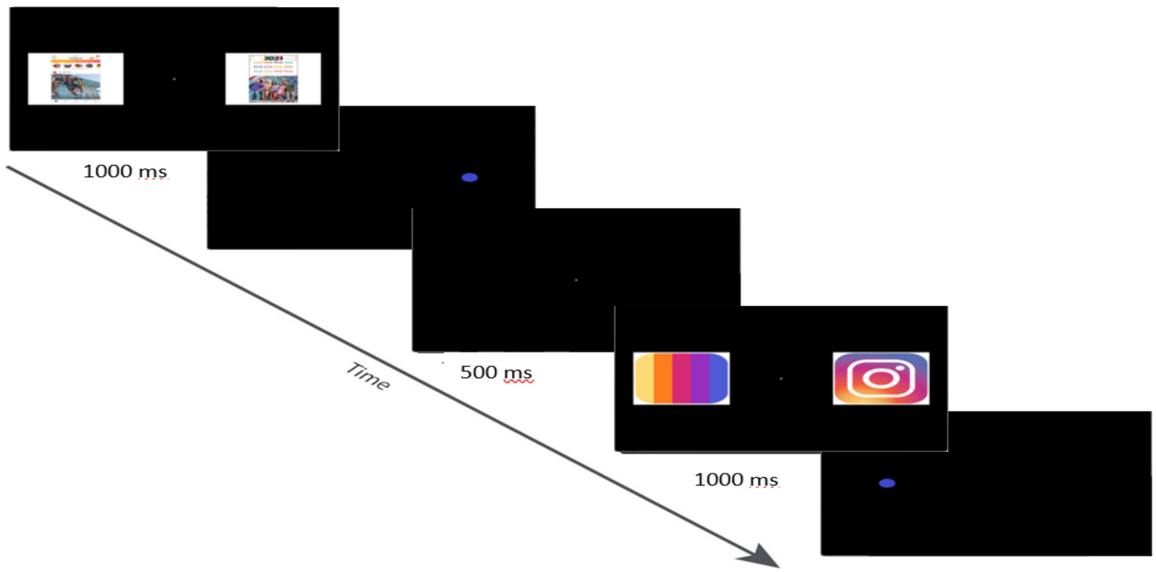
Dot Probe Congruent Trials Stimuli



Note. This illustrates two consecutive congruent trials, where the probe appears in the same location as the Instagram-related image. Each trial includes a fixation cross, a pair of images (Instagram-related and control), and a probe replacing one of the images. The sequence is then repeated with new stimuli and probe positioning, allowing analysis of reaction times to Instagram-related cues.

Figure 6

Dot Probe Incongruent Trials Stimuli



Note. This illustrates two consecutive incongruent trials, where the probe appears in a different location from the Instagram-related image. Each trial includes a fixation cross, a pair of images (Instagram-related and control), and a probe replacing one of the images. The sequence is then repeated with new stimuli and probe positioning, allowing analysis of reaction times to Instagram-related cues.

Results

Data Analysis

i. ***Data cleaning.*** We cleaned the initial results to remove unnecessary information before analysis. First, we removed duplicate entries from the dataset to avoid multiple occurrences. There were checks on missing values. There were corrections to the data format to standardise it, including corrections to capitalisation and spelling mistakes. We computed the bias score using the appropriate method to account for deviations from the baseline.

i. ***Defining metrics.*** We excluded reaction time data from filler trials and trials with errors. To address outliers, we removed RTs below 100 ms or above 1,000 ms (Turkoglu et al., 2022; Monem et al., 2019). For each participant, we calculated mean RTs separately for correct congruent and incongruent trials. We then computed an attentional bias score by subtracting the mean RT for congruent trials from that for incongruent trials (Field & Cox, 2008). A positive score indicates a bias toward Instagram stimuli, while a negative score suggests greater attention to neutral cues.

ii. ***Questionnaire data.*** Group allocation for QIUU was determined by overall scores, with lower scores indicating greater online cravings and higher scores indicating reduced online cravings (median split at 57). ScreenTime data were categorised according to the “Week” Instagram average, using a median split of 155 minutes.

iii. ***We will address.*** We will examine whether time spent on Instagram is associated with attentional bias in the dot-probe task for Instagram stimuli. ScreenTime metrics will be used to assign participants to low- or high-usage groups. We will use these groupings to assess differences in dot-probe performance, analysing RT bias scores as the dependent variable with independent-samples t-tests for two-group comparisons and one-way ANOVAs for three-group comparisons. Additionally, we will conduct Pearson correlation analyses to examine relationships between attentional bias scores and questionnaire scores from the BSMAS, SMAQ, and SMES, running separate correlations for each measure.

Dot Probe E-Prime Task

An independent-samples t-test was conducted to determine whether the time spent on Instagram is associated with measures of attentional bias in the dot-probe task for Instagram stimuli. The means and standard deviations for reaction time are presented in *Table 3.1* below. Descriptive statistics indicated that mean reaction times differed across groups, with a notable increase in the Low condition relative to the other conditions. Therefore, use ScreenTime metrics to assign participants to a "Low" or "High" group. Using this categorical allocation to examine how it relates to dot probe performance (reaction time bias scores). The results indicate no significant difference in the scores for Low and High conditions; $t(256.157) = -.863$, $p = .389$ (>.05), Hedges' $g = -0.09$, 95% CI [−13.39, 5.23], suggesting that time spent on Instagram does not affect attentional bias to Instagram-related stimuli. Post hoc power analysis indicated very low achieved power ($1 - \beta \approx .08$) for detecting the observed effect size ($g = 0.09$) with alpha = .05 and $N = 258$, suggesting the null result reflects the negligible effect rather than sample limitations.

Table 3.1

Attentional Bias Scores (ms) by Screen Time Allocation

ScreenTime	*M*	*SD*
Low	-9.79	57.02
High	-5.71	27.36

Note. This table presents mean attentional bias scores and standard deviations for participants grouped by Instagram screen time (Low vs. High). Negative scores indicate a greater attentional bias toward Instagram-related stimuli. The results suggest minimal differences in attentional bias based on reported screen time.

An independent-samples t-test was conducted to assess whether the strength of the urge to be online is associated with measures of attentional bias. The means and standard deviations for reaction time are presented in *Table 3.2* below. Descriptive statistics indicated that mean reaction times differed across groups, with little difference between the low and high conditions. Therefore, use the QIUU metrics to assign participants to a "Low" or "High" group. Using this categorical allocation to examine how it relates to dot probe performance (reaction time bias scores). The results indicate no significant difference in scores between the Low and High conditions; $t(355) = -0.060$, $p = .952$ (> .05), Hedges' $g = -0.01$, 95% CI [−9.60, 9.02], suggesting that the urge to be on Instagram does not affect attentional bias toward Instagram-related stimuli. Post hoc power analysis indicated extremely low achieved power ($1 - \beta \approx .05$) for detecting the observed effect size (g = 0.01) with alpha = .05 and N = 357, suggesting that the null result primarily reflects the absence of a detectable effect.

Table 3.2

Attentional Bias Scores by Urge to Be Online (QIUU) Allocation

QIUU	*M*	*SD*
Low	-7.90	40.92
High	-7.61	48.22

Note. This table presents the mean attentional bias scores and standard deviations for participants classified as Low- or High-urge groups. Negative values indicate a bias toward Instagram-related stimuli. The minimal difference in scores between groups suggests only slight variation in attentional bias associated with self-reported urge strength.

The relationship between BSMAS scores (indicating a higher risk of developing an addiction to Instagram) and measures of attentional bias was assessed (*Table 3.1*). A Pearson correlation coefficient was conducted, which showed that the two were not significantly related, r = -.015, N = 357, p = .773 >.05. Overall, there was no correlation between BSMAS scores ('addictive' severity) and the measure of bias.

A Pearson correlation coefficient was used to assess the relationship between SMAQ scores (Instagram use/addiction) and measures of attentional bias (reaction times). The assessment showed that the two were not significantly related, r = -.036, N = 357, p = .495 >.05. Overall, there was no correlation between SMAQ scores (Instagram usage) and measures of bias.

The relationship between SMES scores (social media engagement) and measure of attentional bias was assessed. A Pearson correlation coefficient was conducted, which showed that the two were not statistically related, r = -.093, N = 357, p = .081 > .05. There was no correlation between SMES scores (Instagram engagement) and the measure of bias.

Discussion

This study aims to examine attentional biases among Instagram users using the dot-probe paradigm, alongside self-reported measures of Instagram use, engagement, and addiction. Contrary to expectations derived from IST (Robinson & Berridge, 1993, 2001), the results indicated no significant relationships between attentional bias and (1) the amount of time spent on Instagram, (2) urges to be online, or (3) self-reported addiction and engagement scores. These findings raise important questions about the applicability of addiction models to social media use and the mechanisms driving problematic behaviours.

One key hypothesis was that problematic Instagram use would be associated with heightened attentional biases toward Instagram-related stimuli, as indicated by faster response times in congruent trials and slower response times in incongruent trials. However, no significant differences in attentional bias were found between participants with high versus low ScreenTime or high versus low cravings. These results suggest that neither heavy Instagram use, nor elevated online urges significantly modulate attentional processes.

Similarly, the absence of significant correlations between attentional bias and self-reported measures of Instagram addiction, usage, and engagement further challenges the assumption that problematic Instagram use is strongly linked to cognitive biases. These findings indicate that Instagram-related attentional bias might not align with patterns observed in other addictive behaviours, such as substance use disorders, where attentional bias is a hallmark feature (Field & Cox, 2008).

The absence of significant attentional bias challenges the universality of incentive sensitisation mechanisms in behavioural addictions. One possible explanation is that the "wanting" and "liking" dynamics in social media addiction differ fundamentally from those observed in substance use disorders. Social media use often involves multitasking and diverse goals, such as social connection, entertainment, or self-presentation, which may dilute the consistent attribution of salience to specific cues (e.g., Instagram icons). Furthermore, the constantly evolving and personalised nature of social media platforms may prevent the establishment of strong associative learning mechanisms that underlie incentive sensitisation (Wegmann et al., 2020).

Craving is a key construct in incentive sensitisation theory, closely linked to the "wanting" of addiction-related cues (Franken, 2003). Our findings revealed no significant relationship between craving (as measured by QIUU scores) and attentional bias, suggesting a more complex interaction between craving and attentional processes in social media use. Unlike substance-related cravings, which are often triggered by specific cues (e.g., the sight or smell of alcohol), social media cravings may arise from abstract, context-dependent factors such as boredom, stress, or social isolation (Wegmann et al., 2020; Zhao et al., 2022). This variability could weaken the connection between craving and attentional allocation to static, generic Instagram-related stimuli.

The t-tests revealed no statistically significant differences in attentional bias scores between individuals with high versus low Instagram usage or craving levels. Participants classified as having low ScreenTime exhibited a mean attentional bias score of approximately minus ten, whereas those with high ScreenTime showed a mean score of approximately minus six. This slight difference does not suggest a consistent attentional bias toward Instagram-related stimuli. Likewise, individuals with high Instagram craving scores had a mean attentional bias score of approximately -8, which was nearly identical to that of individuals with low craving scores. These patterns indicate that attentional bias, as measured in this task, may not be strongly influenced by self-reported Instagram use or craving intensity. It is possible that other cognitive or emotional mechanisms underlie the relationship between Instagram engagement and attention, or that the dot-probe task used here may not have been sensitive enough to detect such effects.

The lack of significant correlations between attentional bias and self-reported measures (BSMAS, SMAQ, SMES) also potentially questions about the validity of the dot-probe paradigm for studying social media-related attentional biases. The paradigm relies on static stimuli, such as icons or screenshots, which may not fully capture the dynamic and personalised nature of social media interactions (Nikolaidou et al., 2019; Zhao et al., 2022). Real-world social media use involves a constant stream of user-generated content, notifications, and interactive features, which likely engage attention in more complex and context-dependent ways.

A notable contrast with Experiment 1 concerns the relationship between the urge to be online (QIUU) and attentional bias. While Experiment 1 identified a significant negative correlation—suggesting that stronger cravings were linked to greater attentional bias—no such association emerged in the current study. This discrepancy may reflect task-related differences in sensitivity, with the flicker change blindness paradigm potentially capturing early attentional capture more effectively than the dot-probe task. These findings underscore the importance of methodological considerations when investigating cognitive mechanisms underlying problematic social media use.

Additionally, the non-clinical sample used in this study may have limited the ability to detect attentional biases. Participants exhibited relatively low levels of potentially problematic Instagram use, as indicated by their BSMAS and SMAQ scores, which may not be sufficient to elicit strong attentional biases. Future studies could recruit individuals with higher levels of social media use or problematic engagement than those observed in the current sample, in order to better assess the relevance of incentive sensitisation theory.

In traditional addiction research, attentional bias has been viewed as both a consequence and a driver of addictive behaviours, reinforcing craving and substance-seeking cycles (Field & Cox, 2008). However, the current findings suggest that attentional bias may not serve as a reliable marker of social media addiction, at least in its early or moderate stages. This raises important questions about the cognitive mechanisms underlying social media addiction and whether they align with those observed in substance-related and other behavioural addictions.

One possibility is that attentional processes in social media addiction are more transient and context-dependent than in other forms of addiction. For example, users may exhibit attentional biases only in specific contexts, such as when experiencing stress or anticipating social validation. This context-specific nature of attentional bias might explain the null findings in a controlled experimental setting.

Future research should incorporate dynamic, personalised stimuli that better reflect real-world social media interactions. For example, using participants' own Instagram feeds or notifications as stimuli could provide more ecologically valid insights into attentional biases (Zhao et al., 2022). Integrating neuroimaging techniques, such as fMRI or EEG, could help identify neural correlates of attentional processes and their relationship with craving and salience in social media addiction (Wegmann et al., 2020). Longitudinal studies are needed to examine how attentional and evaluative biases develop over time and whether they predict the escalation of problematic social media use. Recruiting participants with higher levels of use than that in the current study could help clarify whether attentional biases emerge only at more severe stages of the disorder (Bányai et al., 2017). Investigating the role of contextual factors, such as stress or social isolation, in moderating attentional biases could enhance our understanding of the situational triggers for problematic social media use.

While the results did not support the presence of significant attentional or evaluative biases toward Instagram-related stimuli, they highlight the complexities of applying traditional addiction frameworks, such as incentive sensitisation theory (IST), to social media use. The dynamic and context-dependent nature of social media interactions may require new theoretical and methodological approaches to understand the cognitive and motivational mechanisms underlying problematic use.

Chapter 4 Experiment 3: An experimentation of Instagram-related attentional bias in Instagram users using Dot Probe Paradigm

The integration of social media into contemporary society has profoundly affected communication, with over 3.8 billion active users worldwide engaging on platforms such as Facebook, Instagram, TikTok, and YouTube (Statista, 2020). Indeed, social media has many benefits, among them online communities and self-expression. However, increased use has become associated with negative mental health effects, such as anxiety, depression, or sleep problems (Kırcaburun & Griffiths, 2018; Woods & Scott, 2016). The contrast between positive social engagement and problematic use demonstrates increased interest in addictive behaviour caused by social media use.

The DSM-V and ICD-11 do not formally classify social media addiction as a specific disorder like gaming addiction (WHO, 2018), although social media is widely used in contemporary environments. Research has gone to the mat, and researchers debate the status of problematic use, defined by excessive social media engagement, as an addiction. This debate is informed by the finding that behavioural and substance addictions have some striking parallels, with shared constructs including impulsivity, emotional dysregulation and compulsivity (Grant et al., 2010). The classification of social media use as a behavioural addiction requires attention to the cognitive origins of this behaviour. In contrast, some colleagues have cautioned against overpathologising behaviour, pointing to differences in behaviour patterns and lack of any single diagnostic structure (Chamberlain et al., 2016). However, the similarities in behavioural and substance addictions, particularly in the shared mechanisms underpinning impulsivity, compulsivity and emotional dysregulation, lend credence to the argument that the use of excessive social media should be understood as a behavioural addiction (Grant et al., 2010).

There is a need to understand the cognitive mechanisms underlying these behaviours, with attentional processing as a primary focus. Selective attention is one of the fundamental cognitive processes affecting decision-making and behaviour, defined as 'the ability to prioritise relevant stimuli while ignoring distractions' (Klinger, 1996; Chun & Wolfe, 2001). In research on addiction, attentional bias (AB) refers to the tendency for addiction cues to recruit undue attention, even when other stimuli would tend to receive less attention (Field & Cox, 2008). Such cognitive bias enhances craving and perpetuates the cycle of addictive behaviour, rendering it an important subject for knowledge as well as intervention.

Various theoretical perspectives, like Incentive Sensitisation Theory (IST), provide a strong basis for analysing attentional bias in the context of addiction. According to IST, repeated exposure to addictive substances sensitises neuronal reward systems and increases the motivational salience of substance-related cues (Robinson & Berridge, 1993). This process converts neutral stimuli into potent stimuli that elicit craving and substance-seeking behaviour. Given that these mechanisms were detailed in Chapter 1, the present section focuses specifically on how attentional bias is operationalised experimentally within social media contexts.

Experimental work has supported these predictions of IST using paradigms such as the dot-probe task. In this approach, attentional bias is assessed by providing pairs of stimuli (addiction-related and neutral) along with a probe that substitutes one of the stimuli. Faster reaction times to probes replacing addiction-related stimuli suggest a bias in attentional allocation. Manipulating stimulus presentation durations has enabled researchers to distinguish two types of attentional processing: shorter durations (e.g., 200 ms) indicate initial orienting, whereas longer durations (e.g., 500 ms or more) indicate sustained attention (Field et al., 2004a). This evidence can also be found among alcohol and tobacco users, where evidence shows that these attentional processes can differ by degree of dependency, showing a complex representation of attentional bias in addiction (Mogg et al., 2005; Duka & Townshend, 2004). Heavy users might have prolonged attention on cues associated with their addiction, whereas light users might show biases when first orienting to an event.

There was no difference in attentional bias scores between Instagram use and self-reported craving when stimuli were presented for a fixed 1000 ms (experiment 2). These null results imply that the dot-probe paradigm does not detect phases of attentional processing. Specifically, it remains unclear whether attentional biases associated with social media cues are more likely to emerge during early orienting or through sustained attentional engagement. To compensate for this limitation, we systematically manipulate stimulus presentation times: short durations (100 ms and 200 ms) to investigate initial orienting, and a longer duration (2000 ms) to measure sustained attention. This methodological refinement is based on previous studies in addiction research, which suggest that attentional biases in terms of social cues can play out differently across temporal stages depending on users' level of response to addiction-related cues (Field et al., 2004a; Mogg et al., 2005). The current study, therefore, seeks to develop a richer understanding of attentional bias, thereby mitigating the limitations of the fixed-duration approach as it has been utilised in previous research.

Although there is extensive evidence that IST has a relation to substance addiction, its applicability to behavioural addictions, such as problematic social media use, remains underexplored. Examples of mechanisms that could help explain IST include the ability of social media cues to stimulate and/or maintain our attention in this context. Analysing attentional bias among social media users may uncover similarities with substance addiction and inform recommendations for preventing substance misuse interventions.

The methodological advantages and previous research also led to the use of a smaller set of stimuli in the current experiment. Traditional dot-probe designs often utilise a wide variety of stimuli to achieve an optimal degree of contrast because such exposure offers variable variation; however, new research has demonstrated a comparative advantage in employing a smaller number of narrow stimuli, especially in relation to some attentional biases.

Caudek et al. (2017) examined the reliability and validity of attentional bias metrics from the dot-probe task (DPT), highlighting that stimulus and task design can contribute to outcome measurement. The classic DPT, which is generally based on cumulative RT difference scores, is low reliability (Caudek et al., 2017). This limitation results from the inherent variability in RT data and the increased likelihood that RT data will be affected by noise from heterogeneous or overly complex stimuli (Caudek et al., 2017). Instead of using GLI alone, the researchers conducted a trial analysis to assess variation bias, showing that trial-to-trial biases affect measurement reliability by a statistically significant amount.

Dynamic stimuli, for example, the tendency for facial expressions to change based on time, were found to be more effective than static stimuli in eliciting robust, reliable measurements of the attentional bias. Dynamic stimuli enhance task salience and ensure that attention remains focused on the target (Caudek et al., 2017; Robinson et al., 2022). This bolsters the notion that attention is more readily elicited by stimuli that mirror real-world dynamism and strengthens the ecological validity of the task. In this study, Instagram-relevant images that participants are acquainted with will cause stronger and more reliable attentional biases (Robinson et al., 2022; Caudek et al., 2017). Moreover, Schmukle (2005) and Staugaard (2009) found the measures more accurate with more control stimuli, thereby reducing the impact of extrinsic visual and contextual stimuli. As a result, smaller samples offer greater clarity by directing participants' attention to specific features of interest, thereby increasing the validity of the findings.

The relevance of stimuli to participants' everyday experiences is essential for accurately measuring attentional biases. In individuals who use problematic social networking sites, attentional bias is closely associated with the salience of relevant social media stimuli (Nikolaidou et al., 2019; Wilcockson et al., 2021). By using a focused series of Instagram-relevant images, the current study increases the ecological generalizability of the stimuli by providing an ecological context that closely approximates environmental conditions. Such alignment is important, particularly when examining attentional processes influenced by habitual exposure to specific cues, as highlighted by social media users. Smaller stimulus sets also respond to a long-standing methodological criticism of dot-probe paradigms. Response-time difference scores used to examine attentional biases exhibit lower reliability when heterogeneous or overly extensive stimulus sets are used (Waechter et al., 2014; Wilcockson et al., 2021). Greater variability in stimuli is associated with larger differences in response scores and greater uncertainty in the results. A consistent baseline in these trials helps alleviate this problem. The aim of this study is therefore to minimise stimuli to improve reliability and comparability across conditions.

Lane et al. (2017), whose findings are closely related to the scope of the present study, emphasise the appropriateness of the stimuli in the design of the current experiment, in accordance with the research question. Their study demonstrates that:

- Stimulus type and presentation can affect the outcomes of attentional bias measures.
- Priming effects, such as exposure to high-focus cues, such as thin-ideal images or Instagram-based cues, can heighten attentional responses.
- Methodological changes, including the addition of ecologically relevant stimuli, are crucial for studying relevant attentional biases.

To analyse attentional biases in the context of social media behaviour, the current study targets contextually relevant stimuli, i.e., Instagram-related imagery. Such targeting enables a more direct analysis of whether and how Instagram-specific cues attract attention, thereby attenuating the dilution effects of less relevant stimuli.

Studies of substance-related attentional biases have shown that smaller, focused stimulus sets are more effective. For instance, Robinson et al. (2023) showed that attentional bias modification tasks with smoking-related stimuli reduced attentional bias relative to that of participants in the study population. This emphasises the need to select stimuli that are relevant to participants' actual experiences and dependencies (Wilcockson et al., 2021). Research has shown that dot-probe tasks are more reliable when stimulus variability is reduced, thereby improving the detection of true attentional biases (Wiers et al., 2017; Wilcockson et al., 2021). By considering these concepts, the current study maintains methodological soundness and ecological significance. Finally, a small stimulus sample provides greater control to mitigate potential confounders, such as visual complexity and emotional valence (e.g., image variety and standardisation). The reduction in stimuli helps in the comparison of the images visually: The more diverse the stimuli, the less visually similar the images, by contrast, contrast and composition, and less likely it is that attentional responses will be influenced more by surface (i.e., superficial) as opposed to significant (or profound) differences in feature information. Affective valence can also be more effectively controlled because each image can be pretested to elicit a similar emotional response, thereby reducing variability in its impact on affective states. This small stimulus heterogeneity improves the internal validity of the study by reducing variation in stimulus selection and confirming that the attentional bias is more appropriate, i.e., it is likely a true response to substance-based cues rather than uncontrolled visual/emotional stimuli. This methodological optimisation ensures that biases arising from the experimental manipulation and non-correlated effects are attributed to experimental artefacts rather than to random effects in the control (Wilcockson et al., 2021; Lane et al., 2017). The targeted application of Instagram-related stimuli both enhances the reliability of these findings and provides key insights into the attentional mechanisms that drive problematic social media use.

Aim and Hypotheses

Hypothesis 1 (Attentional-bias effect). Individuals with higher Instagram use, as measured by Screen Time, or stronger online cravings, as indicated by higher urge scores on the QIUU, are expected to exhibit greater attentional bias toward Instagram-related cues on the dot-probe task compared to those with lower use or urge. This bias will be reflected by faster responses on congruent trials relative to incongruent trials, resulting in a positive attentional-bias score (RT_incongruent − RT_congruent > 0).

Hypothesis 2 (Temporal specificity). Attentional bias in addiction is generally most apparent during rapid, automatic orienting. Consequently, group differences based on Screen Time or urge are expected to be most pronounced at short stimulus exposure durations (e.g., 100–200 ms), reflecting initial orienting toward Instagram cues. At longer durations (e.g., 2000 ms), when controlled processing and disengagement occur, these group differences are expected to diminish.

Hypothesis 3 (Individual-difference associations). Greater self-reported Instagram involvement, problematic use (such as engagement or addiction-risk indices), and stronger momentary urge to be online are expected to correlate with larger positive attentional-bias scores. This expectation is consistent with the IST, which posits that motivational salience increases with repeated reward learning.

The experiment investigating the Instagram dot-probe addresses explicitly the following methodological questions regarding the measurement of attentional bias:

To what extent is attentional bias toward social media-related content exhibited?

Method

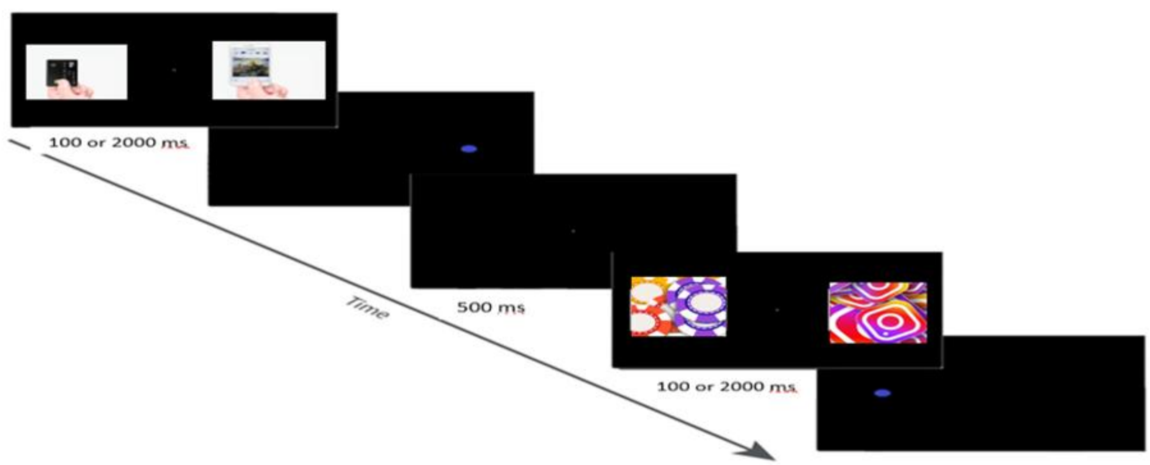
Participants

The participants were 306 undergraduate and postgraduate students recruited via Prolific, an online participant recruitment platform for surveys and marketing (Prolific, 2021). Of the 306 participants, 167 were females (*M* = 24.56, *SD* = 3.95), 134 were males (*M* = 25.36, *SD* = 2.94), 4 were gender variant/non-conforming (*M* = 21.75, *SD* = 1.71), and one preferred not to say (*M* = 25.00, *SD* = 0), aged 18 to 40. Participants were informed that the study aimed to investigate how social media network use influences attention through a series of computer tasks. The eligibility criteria for inclusion in the study were a) participants should be 18 and older, b) either use a smartphone and consider themselves to be a user of social media, c) have normal or corrected to normal vision, d) have no colour vision deficiency/colour blindness, and e) not use a smartphone or Mac computer to do the survey, only a desktop computer or laptop. This study was conducted with ethical approval from the Ethics Committee of the University of Strathclyde School of Psychological Sciences and Health.

Dot-Probe Stimuli. A preliminary rating task was conducted to select the stimuli for the present experiment (see Appendix C). Three different types of stimuli were employed in the study: Instagram-related stimuli (Appendix F, Figure F1), control stimuli (Appendix F, Figure F2), and filler stimuli (Appendix F, Figure F3) [2]. The 10 Instagram images, 10 control images, and 20 filler images were paired, and the number of times each image appeared was controlled to yield 80 trials (Appendix F1). Instagram images included the application icon, the Instagram messenger icon, and others. Using different stimuli allowed the images to include a broader range of colours rather than relying solely on the standard blue Instagram symbol. The 10 control images consisted of ordinary images, including words, generic images, and desktop screenshots from non-social media applications. These icons resembled smartphone or tablet application icons, although the screenshots were taken from a desktop computer. Filler images included 20 neutral images (e.g., neutral faces, household objects, places) taken from the International Affective Picture System (IAPS) (Figures *7 & 8*).

Figure 7

Dot Probe Congruent Trial Stimuli

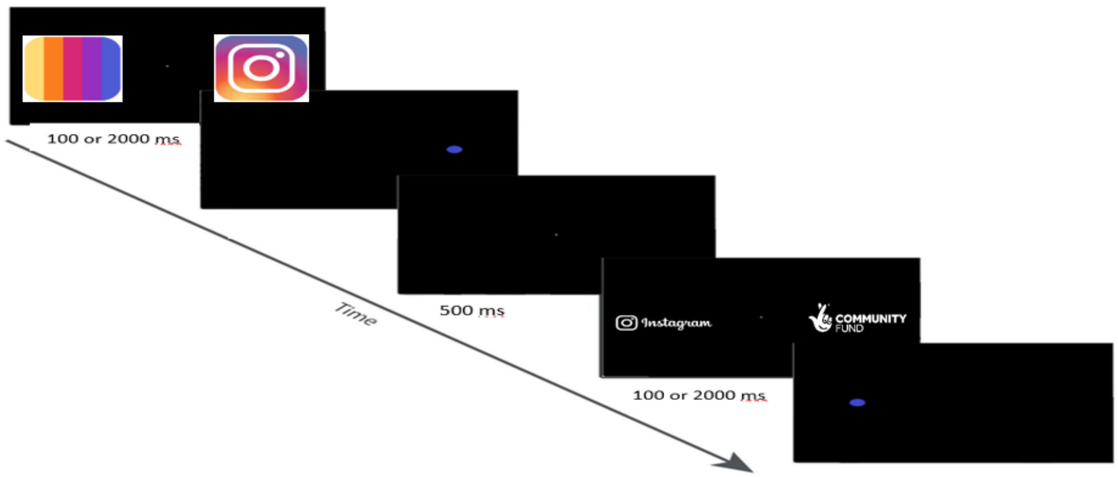


Note. This illustrates two consecutive congruent trials in which the probe appears at the same location as the Instagram-related image. Each trial includes a fixation cross, a pair of images (Instagram-related and control), and a probe replacing one of the images. The sequence is then repeated with new stimuli and probe positioning, allowing analysis of reaction times to Instagram-related cues.

Figure 8

[2] The numbers of IAPS (Kappenman et al., 2015; Kappenman et al., 2014) pictures used were as follows. Neutral: 2190, 2397, 2840, 7000, 7004, 7006, 7010, 7020, 7035, 7041, 7050, 7059, 7090, 7175, 7185, 7187, 7217, 7233, 7491, and 7950

Dot Probe Incongruent Trial Stimuli



Note. This illustrates two consecutive incongruent trials in which the probe appears in a different location from the Instagram-related image. Each trial includes a fixation cross, a pair of images (Instagram-related and control), and a probe replacing one of the images. The sequence is then repeated with new stimuli and probe positioning, allowing analysis of reaction times to Instagram-related cues.

Apparatus and measures

Socio-demographics. The dot-probe task included questions on age and gender to obtain participants' sociodemographic profiles.

Social Media Addiction Questionnaire (SMAQ). SMAQ is an 8-item self-report assessment (Hawi & Samaha, 2017) derived from the Facebook Intrusion Questionnaire (FIQ), in which social media is replaced with Instagram, and it assesses social media use and addiction. Doing so ensures a shift in focus from social media in general to a particular site. Respondents rate each item on a 7-point Likert scale (ranging from 1 = *strongly agree* to 7 = *strongly disagree*). For example, a statement such as "I interrupt whatever else I am doing when I feel the need to access Instagram" and "I feel connected to others when I use Instagram." It is short, has good psychometric properties, is reliable, and covers the symptoms of behavioural addiction. The Cronbach's α coefficient for this questionnaire was .65. The internal consistency of the SMAQ was modest (α = .65), which is slightly below the conventional threshold of .70. This result is not uncommon for brief scales or those assessing heterogeneous constructs. The adaptation of the SMAQ to Instagram and the use of an online student sample may have restricted the variance in problematic-use symptoms, both of which could attenuate the alpha coefficient.

Questionnaire on Internet Use Urges (QIUU). QIUU is a 10-item self-report questionnaire that assesses the severity of online urges. Respondents rate each item on a 7-point scale (ranging from 1 = *completely disagree* to 7 = *completely agree*). The QIUU is an adapted form of the Questionnaire on Smoking Urges-Brief (Cox et al., 2001; Tiffany & Drobes, 1991). To assess levels of the urge to be online, each item has been reworded to reflect online activity. For example, a statement such as "I have the desire for a cigarette right now" was reworded to "I have the desire to be on Instagram right now." The Cronbach's α coefficient for this questionnaire was .94.

Bergen Social Media Addiction Scale (BSMAS). BSMAS is a modified version of the previously validated Bergen Facebook Addiction Scale (BFAS; Andreassen et al., 2012). The modification involves using the word 'Instagram' instead of the word 'Facebook'. The scale comprises six items, each representing a dimension of addictive behaviour, yielding a range of data. The items include mood modifications, salience, tolerance, conflict, relapse, withdrawal, and symptoms (Duradoni et al., 2020). The scale is reported to have good psychometric properties, whereby addiction is determined by utilising polythetic (scoring three or above on at least four of the six items) and monothetic (scoring three or above on all six items) scoring schemes. The scale is non-specific and provides reliable results on general addiction to social media. A higher BSMAS score suggests a higher risk of developing an addiction to social media, with a cut-off score (19 out of 30) proposed recently to indicate problematic use of social media (Bányai et al., 2017). Participants rate each item on a 5-point scale (ranging from 1 = *very rarely* to 5 = *very often*). For example, a statement such as "How often during the last year have you tried to cut down on the use of Instagram without success?" The internal consistency of the BSMAS was satisfactory, with a Cronbach's α coefficient of .81.

Social Media Engagement Scale (SMES). SMES is a 5-item self-report questionnaire (Przybylski et al., 2013) which assesses the extent to which people engage with Instagram in their daily lives. Participants were instructed to: "Please reflect on how you used Instagram in the past week (i.e., the previous seven days) and report the number of times you used it......" under the circumstances listed below. Participants were asked to rate all items on an 8-point Likert scale (ranging from 1=*Not one day last week* to 8 = *Every day last week*) to rate five statements: "within 15min of waking up" (M = 3.98, SD = 2.47), "when eating breakfast" (M = 3.29, SD = 2.30), "when eating lunch" (M = 3.41, SD = 2.16), "when eating dinner" (M = 3.04, SD = 2.23), and "within 15min of going to sleep" (M = 5.04, SD = 2.51). The internal consistency was satisfactory, with a Cronbach's α coefficient of .80.

Screen Time (Apple iPhone). Screen Time was assessed by asking participant to report the number of hours and minutes spent on social media per typical day in the past seven days with a 8-part questions: looking at 'Daily Average' screen time, 'Week' average social media time, 'Day' average social media time, daily average notifications, daily average pickups, top 3 most used social media apps for the day, top 3 most used social media apps for the week, and the weekly average time spent on Instagram. Participants would automatically then record the periods at the end of the study.

Procedure

In such tasks, participants are asked to sit at a computer or laptop and informed that the online experiment will take approximately 30 minutes. Firstly, participants on Prolific clicked a link that brought them to Qualtrics, where they provided informed consent and received study information before giving consent. After providing consent, the Qualtrics platform (Qualtrics, 2021) directed participants to the Dot Probe E-Prime Task, which we ran on E-Prime Go (Psychology Software Tools, 2020), a psychology software tool displayed on a monitor (Carlson & Fang, 2020). During the task, we asked participants to complete a practice trial to understand the requirements for subsequent trials. In each practice trial, we displayed a central fixation cross, then presented a pair of images (one Instagram-related and one neutral) side by side. After a brief stimulus presentation, a dot-probe (e.g., a small asterisk) appeared in the location of one of the images. We instructed participants to respond as quickly and accurately as possible by pressing the corresponding key to indicate the probe's location (e.g., "←" for left, "→" for right).

We provided feedback after each trial to help participants understand the task demands. We designed the practice trials to mirror the main-trial format, but we excluded them from the final analysis. After participants completed the practice trials, we asked them to press "Y" (yes) or "N" (no) to proceed to the main task. Each trial began with a fixation cross ("+") displayed at the centre of the screen for 500 ms, followed by a pair of stimuli presented simultaneously—one on the left and one on the right of the fixation—for 100 ms. The stimuli consisted of Instagram-related, control, or filler images matched for visual complexity. These image sets were identical across participants. Immediately after the stimulus offset, a neutral probe (e.g., a dot or small circle) appeared in the location of one of the images (left or right). We instructed participants to respond as quickly and accurately as possible by pressing the designated key corresponding to the probe's position (e.g., the left or right arrow key, as specified in the instructions). The probe remained on screen until the participant responded, and the response triggered the subsequent trial after a 100 ms inter-trial interval.

The task included six practice trials and 80 experimental trials, comprising 40 Instagram-control trials and 40 filler trials. A counterbalanced version of the task used the same images but presented them for 2000 ms to control for exposure duration. In the 40 Instagram-control trials, we showed each of the 10 Instagram-related images four times—twice on the left and twice on the right. The trial breakdown included 20 trials with Instagram images on the left and control images on the right; 20 trials with the identical image pairs reversed; 20 filler image pairs with the filler on the left; and 20 filler image pairs with the filler on the right. We presented all the Instagram-control and filler trials to each participant in a random order. Upon completing the Dot Probe task, participants were redirected to Qualtrics to complete the SMAQ, SMES, QIUU, BSMAS, and ScreenTime questionnaires. Finally, we thoroughly debriefed participants on the study's true aims.

Results

Data Analysis

i. ***Data cleaning and defining metrics.*** We excluded practice trials from the analysis. We also discarded reaction time data from filler trials and trials with errors. To remove outliers, reaction times below 100 ms or above 1000 ms were excluded (Turkoglu et al., 2022; Monem et al., 2019). The final dataset includes mean reaction times per participant for congruent and incongruent trials. For each participant, we calculated the attentional bias score by subtracting the mean response time in congruent trials from that in incongruent trials (Field & Cox, 2008). A positive score indicates a preference for the Instagram stimulus, while a negative score suggests a tendency to focus on the neutral cue.

ii. ***Questionnaire data.*** Group allocation for the QIUU was determined by total score, with lower scores reflecting a greater urge to be online and higher scores reflecting a reduced urge to be online (median split at 54). We categorised ScreenTime data using the Instagram weekly average, splitting at the median of 116 mins.

iii. ***We will address.*** To examine how Instagram use affects attentional bias, participants will be grouped by their ScreenTime metrics. We will first classify them as 'low' or 'high' users, then use a three-level classification: 'low,' 'moderate,' and 'high.' These groups will be compared on attentional bias scores, calculated from dot-probe task response times, using an independent-samples t-test for two groups or a one-way ANOVA for three groups. Participants will also be grouped by QIUU scores to assess the effect of urge strength on attentional bias, following the same analysis. Pearson correlation analyses will then be conducted to evaluate the relationship between attentional bias scores and responses on the BSMAS, SMAQ, and SMES questionnaires, with separate correlations for each measure.

Dot Probe E-Prime Task.

T-test (Difference 1=100ms). An independent-samples t-test was conducted to determine whether the time spent on Instagram is associated with measures of attentional bias in the dot-probe task for Instagram stimuli. Therefore, use ScreenTime metrics to assign participants to a “Low” or “High” group (*Table 4.1*). Using this categorical allocation to examine how it relates to dot probe performance (reaction time bias scores). The results indicate a significant difference in scores between the Low and High conditions; $t(304) = 2.03$, $p = .043$ ($< .05$), Cohen’s $d = 0.23$, 95% CI [0.01, 0.46]. The mean difference was 5.85 ms, 95% CI [0.18, 11.52], suggesting that higher time spent on Instagram is associated with greater attentional bias toward Instagram-related stimuli.
Post hoc power analysis indicated achieved power of approximately .82 for detecting the observed effect size ($d = 0.23$) with an alpha level of .05 and $N = 306$. This suggests that the present study had adequate sensitivity to detect small-to-medium effects, supporting confidence in the observed significant difference.

Table 4.1

Attentional Bias Scores (ms) by Screen Time Allocation

ScreenTime	*M*	*SD*
Low	-0.65	22.55
High	-6.50	27.59

Note. This table presents the mean attentional bias scores and standard deviations for participants grouped by Instagram screen time (Low vs. High). The data suggest that participants with higher Instagram use showed a slightly greater attentional bias than those with lower use, although the magnitude of the difference appears modest.

An independent-samples t-test was conducted to determine whether the strength of urge to be online relates to measures of attentional bias. Therefore, employed the QIUU metrics to allocate participants into a “Low” or “High” group (*Table 4.2*). Using this categorical allocation to examine how it relates to dot probe performance (reaction time bias scores). The results indicate significant difference in the scores of Low and High conditions; $t(304) = -2.21$, $p = .028$ (<.05), Cohen’s $d = -0.25$, 95% CI [−0.48, −0.03]. The mean difference was −6.35 ms, 95% CI [−12.00, −0.70], suggesting that the urge to be on Instagram does have an affect on attentional bias for Instagram related stimuli. Post hoc power analysis indicated achieved power of approximately .81 for detecting the observed effect size (d = -0.25) with an alpha level of .05 and N = 306. This suggests that the present study had adequate sensitivity to detect small-to-medium effects, supporting confidence in the observed significant difference.

Table 4.2

Attentional Bias Scores (ms) by QIUU Allocation

QIUU	*M*	*SD*
Low	-6.67	25.57
High	-0.32	24.67

Note. This table presents the mean attentional bias scores and standard deviations for participants classified into Low and High urge groups. The results suggest that individuals with lower self-reported urge to be online exhibited slightly greater attentional bias toward Instagram stimuli, although the difference between groups is relatively small.

T-test (Difference 2=2000ms). An independent-samples t-test was conducted to determine whether the amount of time spent on Instagram relates to measures of attentional bias in the dot probe for Instagram stimuli. Therefore, employ the ScreenTime metrics to allocate participants into a “Low” or “High” group (*Table 4.3*). Using this categorical allocation to examine how it relates to dot probe performance (reaction time bias scores). The results indicate no significant difference in the scores of Low and High conditions; $t(304) = 1.26$, $p = .207$ (>.05), Cohen’s d = 0.14, 95% CI [−0.08, 0.37]. The small effect size and confidence interval crossing zero suggest that any true effect is minimal. Post hoc power analysis indicated low achieved power ($1 - \beta \approx .20$) for detecting the observed effect size (d = 0.14) with an alpha level of .05 and N = 306. Therefore, the study was underpowered to detect small effects, and null results should be interpreted cautiously. These results suggest that the amount of time spent on Instagram does not have an affect on attentional bias for Instagram related stimuli.

Table 4.3

Attentional Bias Scores (ms) by Screen Time Allocation

ScreenTime	*M*	*SD*
Low	-2.64	56.74
High	-10.70	54.64

Note. This table displays the mean attentional bias scores and standard deviations for participants grouped (Low vs. High). The results suggest that participants in the High ScreenTime group did not exhibited a stronger attentional bias toward Instagram-related content than those in the Low ScreenTime group.

An independent-samples t-test was conducted to determine whether the strength of urge to be online relates to measures of attentional bias. Therefore, employ the QIUU metrics to allocate participants into a "Low" or "High" group (*Table 4.4*). Using this categorical allocation to examine how it relates to dot probe performance (reaction time bias scores). The results indicate no significant difference in the scores of Low and High conditions, $t(304) = -.971$, $p = .332$ (>.05), Cohen's $d = -0.11$, 95% CI [−0.34, 0.11]. The small effect size and confidence interval including zero suggest that any true effect of urge on attentional bias is likely minimal. Post hoc power analysis indicated low achieved power ($1 - \beta \approx .15$) for detecting the observed effect size (d = -0.11) with an alpha level of .05 and $N = 306$. Therefore, the study was underpowered to reliably detect small effects, and therefore the null result should be interpreted with caution. These results suggest that the urge to be on Instagram does not have an affect on attentional bias for Instagram related stimuli.

Table 4.4

Attentional Bias Scores (ms) by QIUU Allocation

QIUU	*M*	*SD*
Low	-9.67	73.98
High	-3.48	26.19

Note. This table presents mean attentional bias scores and standard deviations for participants categorised into Low and High urge groups. The results suggest that both groups demonstrated a bias toward Instagram-related content, with the Low urge group showing a slightly greater bias; however, the larger variability in this group may reflect greater individual differences.

Correlation coefficients for Difference 1(100ms). The relationship between BSMAS scores (suggesting that a higher score is a higher risk of developing an addiction to Instagram) and measure of attentional bias was assessed. A Pearson correlation coefficient was conducted which showed that the two were not significantly related $r = .000$, $N = 306$, $p = 1.00$ >.05. Overall, there was no correlation between BSMAS scores ('addictive' severity) and measure of bias.

A Pearson correlation is a parametric statistical test used to measure the strength and direction of association between two ranked variables. A Pearson correlation coefficient was conducted to assess the relationship between SMAQ scores (Instagram use/addiction) and measures of attentional bias (reaction times). The assessment showed that the two were not significantly related $r = -.034$, $N = 306$, $p = .553$ >.05. Overall, there was no correlation between SMAQ scores (Instagram usage) and measures of bias.

The relationship between SMES scores (social media engagement) and measure of attentional bias was assessed. A Pearson correlation coefficient was conducted which showed that the two were not statistically related $r = -.013$, $N = 306$, $p = .824 > .05$. There was no correlation between SMES scores (Instagram engagement) and measure of bias.

Correlation coefficients for Difference 2(2000ms). The relationship between BSMAS scores (suggesting that a higher score is a higher risk of developing an addiction to Instagram) and measure of attentional bias was assessed. A Pearson correlation coefficient was conducted which showed that the two were not significantly related $r = -.028$, $N = 306$, $p = .631 > .05$. Overall, there was no correlation between BSMAS scores ('addictive' severity) and measure of bias.

A Pearson correlation coefficient was conducted to assess the relationship between SMAQ scores (Instagram use/addiction) and measures of attentional bias (reaction times). The assessment showed that the two were not significantly related $r = -.012$, $N = 306$, $p = .835 > .05$. Overall, there was no correlation between SMAQ scores (Instagram usage) and measures of bias.

The relationship between SMES scores (social media engagement) and measure of attentional bias was assessed. A Pearson correlation coefficient was conducted which showed that the two were not statistically related $r = -.044$, $N = 306$, $p = .440 > .05$. There was no correlation between SMES scores (Instagram engagement) and measure of bias.

Discussion

The findings of this experiment highlight significant insights into the attentional biases associated with Instagram usage, though some results underscore limitations and areas for further research. The independent t-tests reveal a significant difference in attentional bias scores at the 100 ms stimulus duration for both screen time and online urge variables. Participants in the "high Instagram screen time" group demonstrated significantly greater attentional bias toward Instagram-related stimuli compared to those in the "low screen time" group. Similarly, participants with a stronger urge to be online showed significantly greater attentional bias than those with weaker urges. These results indicate that individuals who spend more time on Instagram or experience a stronger craving to go online tend to prioritize Instagram-related cues during early stages of attention. This supports the hypothesis that habitual Instagram use influences attentional processes, aligning with previous research on attentional biases in substance and behavioural addictions (Field & Cox, 2008; Robinson & Berridge, 2008). Additionally, this supports the predictions of IST, which argues that addiction-related cues acquire heightened motivational salience (Robinson & Berridge, 1993; 2016). In this case, Instagram-related stimuli are rapidly and automatically prioritized, reflecting an attentional bias consistent with IST's framework for behavioural and substance addictions. These results align with findings that addiction-related cues disproportionately capture attention during early stimulus exposure (Field et al., 2004a; Mogg et al., 2004). The findings also suggest a link between craving and attentional bias, as cravings are theorized to amplify the salience of addiction-related stimuli.

However, at the 2000 ms stimulus duration, no significant differences were observed between high and low groups for both screen time and online urge variables. No significant difference in attentional bias was observed between the "high" and "low" ScreenTime groups. Similarly, there was no significant difference in attentional bias between the "high" and "low" craving groups. The absence of significant differences at the 2000 ms duration suggests that attentional biases associated with Instagram use are transient and primarily manifest during initial orienting rather than sustained attention. This discrepancy suggests that Instagram-related attentional bias may primarily manifest during initial orienting phases rather than during sustained attention. This result suggests that the influence of craving on attentional allocation is most pronounced during early, automatic processing but diminishes as sustained attention mechanisms take over. Similar temporal patterns have been observed in research on alcohol and tobacco use, where craving-related biases are evident in initial orienting but not in prolonged engagement with cues (Mogg et al., 2005; Duka & Townshend, 2004). This reinforces the idea that craving primarily modulates rapid, automatic attentional processes rather than longer-term cognitive control. This finding aligns with studies on substance use, where attentional biases are often more pronounced during the early stages of attention allocation but may diminish as cognitive control mechanisms engage (Mogg et al., 2005; Bollen et al., 2021; Huang et al., 2023). It also suggests that craving-related attentional biases may be more automatic and less persistent over longer exposure durations, highlighting the role of rapid, unconscious processing in problematic Instagram use. These findings resonate with earlier studies that reported similar temporal dynamics in attentional biases within the context of substance use (Duka & Townshend, 2004).

Pearson correlation analyses yielded no significant relationships between attentional bias scores and measures of social media addiction (BSMAS), Instagram usage (SMAQ), or engagement (SMES). These results suggest that attentional biases observed in the dot-probe task are not strongly tied to participants' self-reported behaviours, including addiction severity, frequency of use, or engagement. This divergence may reflect the limitations of self-report measures, which rely on subjective perceptions and may not align with implicit cognitive processes. Alternatively, it may indicate that attentional bias, as measured in this study, is more influenced by automatic, context-specific factors (e.g., momentary craving or situational salience of Instagram-related stimuli) rather than chronic usage patterns. Previous research has similarly highlighted potential limitations in the ecological validity of self-reported metrics for assessing attentional biases (Schmukle, 2005; Staugaard, 2009).

The results partially support IST, which suggests that addiction-related cues capture attention through heightened motivational salience (Robinson & Berridge, 1993). The presence of significant biases at shorter stimulus durations aligns with IST's predictions for initial attentional capture. This supports the idea that social media cues capture attention rapidly, reflecting their motivational salience in users who engage heavily with these platforms. The significant biases observed at 100 ms align with IST, which predicts that addiction-related cues (e.g., Instagram stimuli) gain exaggerated motivational salience through repeated exposure (Robinson & Berridge, 2008). The absence of sustained attentional biases at longer durations, however, suggests that the heightened salience may not persist when more cognitive resources are engaged, indicating a divergence from findings in substance addiction research. The significant relationship between craving (QIUU) and attentional bias at 100 ms suggests that craving amplifies the salience of Instagram-related cues during rapid attentional processes. This reinforces the role of craving as a key driver of attentional biases, consistent with IST's emphasis on the motivational pull of addiction-related stimuli. However, the absence of sustained attention effects and significant correlations with self-reported measures suggests a complex interaction between behavioural patterns and cognitive mechanisms. This aligns with debates on the applicability of addiction models to social media use, where variability in use patterns complicates diagnostic consistency (Chamberlain et al., 2016).

According to IST, craving amplifies the motivational salience of addiction-related cues, making them more likely to capture attention (Robinson & Berridge, 1993; Robinson & Berridge, 2008). In this study, Instagram-related stimuli served as such cues, particularly for individuals with strong online urges. The heightened attentional bias observed at 100 ms aligns with IST's prediction that craving triggers rapid, automatic attentional shifts toward stimuli associated with the object of desire (Franken, 2003). This relationship between craving and attentional bias suggests that craving functions as both a cognitive and emotional driver. It not only reflects the user's desire for Instagram but also facilitates attentional prioritization of related cues. This process creates a feedback loop where craving reinforces attentional biases, which in turn sustain the cycle of problematic Instagram use. Similar findings have been documented in substance use research, where craving strengthens attentional biases toward drug-related cues, perpetuating addictive behaviours (Field et al., 2004a; Mogg et al., 2005).

The experiment's focus on Instagram-specific stimuli enhances ecological validity, as participants likely encountered familiar cues. However, the lack of significant findings at longer durations and in correlation analyses may indicate limitations in the sensitivity of the dot-probe paradigm or the chosen stimuli. Previous studies emphasise that dynamic and ecologically relevant stimuli yield more robust attentional bias measurements (Caudek et al., 2017; Wilcockson et al., 2021). Future studies should consider these refinements to better capture attentional processes.

This study presents several limitations that should be addressed in future research. First, the reliance on self-report questionnaires may not fully capture the complexity of Instagram use behaviours, potentially leading to discrepancies between reported addiction levels and observed attentional biases (Hawi & Samaha, 2017; Przybylski et al., 2013). The absence of significant correlations with self-reported metrics (BSMAS, SMAQ, SMES) suggests that explicit measures may not adequately reflect the implicit cognitive processes involved in attentional biases. This underscores the importance of using multimodal approaches, such as integrating behavioural tasks with neurophysiological measures like eye-tracking or EEG. Second, the sample—comprising undergraduate and postgraduate students—may limit the generalizability of the findings to broader populations with more diverse Instagram usage patterns. Third, the range and complexity of the stimuli used in the dot-probe task could be expanded in future studies to include more dynamic and ecologically valid content, which may offer a more comprehensive understanding of attentional processes in social media contexts (Robinson et al., 2022). Finally, the results revealed that attentional bias was present at the 100 ms stimulus duration but not at 2000 ms, suggesting that such biases may be transient and confined to early stages of attentional allocation. Future research should explore these temporal dynamics further, as this temporal specificity could help distinguish behavioural addictions like problematic Instagram use from substance addictions, where attentional biases are often more sustained (Wiers et al., 2017).

This study provides preliminary evidence that habitual Instagram use influences attentional allocation during initial orienting phases. This study demonstrates that Instagram-related cues capture attention rapidly in heavy users and individuals with high cravings, supporting IST's predictions about the heightened salience of addiction-related stimuli. However, the transient nature of these biases and the lack of correlation with self-reported measures highlight the complexity of attentional processes in behavioural addictions. While the results offer valuable insights, the complex relationship between attentional biases, self-reported behaviours, and temporal dynamics warrants further exploration. Addressing the identified limitations and incorporating more nuanced methodological approaches will enhance our understanding of attentional processes in the context of problematic social media use. These findings provide a foundation for future research into the cognitive underpinnings of problematic social media use and suggest that interventions targeting early attentional biases may be effective in mitigating excessive use.

Chapter 5 Conclusion

This series of experiments aimed to examine the presence of Instagram-related attentional bias among social media users and to determine whether this bias is influenced by factors such as the urge to be online, screen time, and problematic social media use. Grounded in cognitive and addiction-based theories—most notably the Incentive Sensitisation Theory (Robinson & Berridge, 1993, 2001, 2016)—the research employed a combination of paradigms: flicker-induced change blindness in Experiment 1 and dot-probe tasks in Experiments 2 and 3, to investigate selective attention processes in relation to Instagram engagement. Collectively, the findings suggest that attentional biases toward social media-related cues are present and can vary as a function of usage patterns, task parameters, and individual differences among participants.

Evidence of Attentional Bias Across Paradigms

The findings from the three experiments presented in this thesis provide converging, albeit nuanced, evidence for the presence of attentional bias toward social media-related stimuli, particularly Instagram images. The demonstration of such biases across distinct experimental paradigms—Flicker-Induced Change Blindness (Experiment 1) and the Dot Probe Task (Experiments 2 and 3)—supports the notion that social media cues, especially those from frequently used platforms, acquire enhanced attentional salience. This is in line with the Incentive Sensitisation Theory (IST), which posits that repeated engagement with rewarding stimuli, such as social media, sensitises the brain's dopaminergic systems and renders associated cues increasingly attention-capturing (Robinson & Berridge, 1993, 2001, 2016; Franken, 2003).

In Experiment 1, participants displayed significantly longer reaction times in the neutral condition relative to both Instagram and control images, indicating that the Instagram-related cues more readily captured attention within the flicker paradigm. This effect was particularly salient among participants with high screen time and greater urge to be online, as indexed by the QIUU. The significant negative correlation between QIUU scores and average detection time further implies that subjective craving plays a facilitative role in attentional prioritization of Instagram content. These results support the facilitation component of attentional bias (Field & Cox, 2008), whereby addiction-related stimuli are detected more rapidly than neutral stimuli due to increased motivational salience. Although AEQ scores (a measure of problematic social media use) did not significantly moderate detection latency, the attentional capture associated with Instagram cues appeared to be functionally linked to usage intensity and craving, consistent with the predictions of IST and the Elaborated Intrusion Theory (Kavanagh et al., 2005).

Experiment 2 used the classic dot probe task with a fixed stimulus presentation duration (1000 ms) to examine attentional bias across a broader range of social media use and craving levels. Contrary to expectations, attentional bias scores did not significantly differ as a function of Instagram use intensity or craving. This absence of group-level bias may reflect limitations in the temporal sensitivity of the fixed-duration dot probe task in capturing specific components of attentional bias (Field et al., 2009a). Indeed, a 1000 ms duration may fall into an ambiguous temporal range—too long to index initial orienting, yet insufficient to reliably assess sustained attention (Mogg et al., 2005; Bradley et al., 2004). Moreover, individual variability in attentional strategies and temporal dynamics of bias may have contributed to null findings at the group level.

To address these methodological limitations, Experiment 3 introduced a refined dot probe task with three distinct timing conditions: 100 ms and 200 ms to capture initial orienting, and 2000 ms to assess sustained attention. This design yielded more differentiated results. Attentional bias was observed primarily at the 200 ms and 2000 ms durations, suggesting that Instagram-related cues elicit both early and sustained attentional engagement, but only among participants with elevated screen time or craving scores. Specifically, participants with high urge to be online responded more quickly to probes replacing Instagram images than to those replacing neutral ones, particularly in the 200 ms and 2000 ms conditions. This supports previous findings in substance use research indicating that different attentional bias components are temporally dissociable and dependent on levels of dependency or craving (Bradley et al., 2004; Field et al., 2004a).

Taken together, the results across these three experiments reinforce the validity of attentional bias to Instagram-related stimuli in heavy or craving-prone users. However, they also underscore the variability of this effect depending on both task design and individual differences. The consistency of attentional prioritization in Experiment 1 and the timing-sensitive findings in Experiment 3 suggest that attentional biases are most reliably observed when using paradigms that closely align with users' cognitive processing of social media cues. The flicker-induced change blindness task may be particularly effective because it embeds stimuli within dynamic and context-rich visual scenes, simulating real-world conditions in which attention is selectively directed toward meaningful changes (Nees et al., 2012). In contrast, the dot probe task, particularly when constrained to a single exposure duration, may inadequately capture the temporal nuance of attentional engagement unless multiple time points are employed.

These findings have important implications for the broader addiction literature. First, they extend the principles of attentional bias research from traditional domains such as alcohol or tobacco (Field & Cox, 2008; Bradley et al., 2004) into the domain of behavioural addictions, such as problematic social media use. Second, they provide empirical support for IST's core prediction that stimuli associated with compulsive engagement become disproportionately salient and attention-grabbing due to sensitised neural pathways. Third, the results highlight craving—not merely usage frequency—as a key moderator of attentional bias, echoing the conceptual linkage between subjective motivational states and attentional prioritization mechanisms (Franken, 2003; Klinger & Cox, 2008). Finally, the heterogeneity in bias across task types and temporal windows suggests that attentional bias is not a unitary construct but a dynamic phenomenon that unfolds over time and is contextually dependent.

In summary, the evidence collected across three experimental paradigms points to a meaningful and context-dependent attentional bias toward Instagram-related stimuli in users who exhibit higher craving or usage intensity. The use of multiple paradigms, particularly those sensitive to temporal dynamics (Experiment 3) or embedded in complex visual environments (Experiment 1), is crucial to uncovering such biases. These results contribute novel insights to the growing body of literature on the cognitive mechanisms underlying behavioural addiction, emphasising the importance of selective attention as a mediating factor in the compulsive use of social media.

Methodological Considerations

The methodological design of this thesis integrated multiple experimental paradigms to investigate attentional bias toward Instagram-related stimuli. This multimodal approach—comprising the Flicker-Induced Change Blindness (ICB) paradigm in Experiment 1 and variations of the Dot Probe Task in Experiments 2 and 3—enabled a more comprehensive assessment of attentional bias mechanisms. While each paradigm provided unique insights, the findings also underscored the methodological challenges inherent in measuring attentional bias, especially within the context of behavioural (as opposed to substance-related) addiction.

Paradigm Validity and Ecological Relevance

Experiment 1 employed the Flicker ICB paradigm, a task rarely used in social media-related attentional research but increasingly recognised for its ecological validity (Nees et al., 2012). By embedding Instagram and neutral images within naturalistic visual scenes, the task arguably approximated real-world attentional dynamics more closely than traditional paradigms. Participants were required to detect changes in alternating image sequences, and results showed significantly faster detection for Instagram-related stimuli, particularly among high-usage and high-craving individuals. These findings demonstrate that the Flicker ICB task may be sensitive to attentional prioritization mechanisms when stimuli are complex, immersive, and meaningful to the participant.

However, the paradigm is not without limitations. Unlike direct measures of spatial attention (e.g., gaze tracking or probe-based tasks), the Flicker ICB task indirectly infers attentional bias through detection speed and error rate. This indirectness raises concerns about interpretability—slower detection could reflect divided attention, lower stimulus salience, or general perceptual inefficiency (Rensink et al., 1997). Moreover, the paradigm cannot disentangle specific components of attentional bias, such as facilitation (faster engagement), delayed disengagement, or attentional avoidance (Cisler & Koster, 2010). These distinctions are crucial in the study of addiction-related attentional mechanisms and are better captured in tasks designed for temporal and spatial sensitivity.

Temporal Specificity in Dot Probe Designs

Experiments 2 and 3 utilised the Dot Probe paradigm, a widely adopted method for assessing attentional bias via reaction time differentials to probes replacing salient vs. neutral stimuli (MacLeod et al., 1986). While Experiment 2 employed a fixed stimulus presentation time of 1000 ms, Experiment 3 introduced three durations (100 ms, 200 ms, and 2000 ms) to differentiate between initial orienting and sustained attention.

The lack of significant attentional bias in Experiment 2 at 1000 ms suggests a methodological limitation common in fixed-duration dot probe studies. This intermediate duration may be suboptimal for capturing either reflexive attention (initial orienting) or deliberate processing (sustained attention). Past research has indicated that attentional bias is highly sensitive to exposure time, with early biases (100–200 ms) reflecting automatic, unconscious attentional capture and longer durations (>500 ms) reflecting prolonged engagement or difficulty disengaging (Bradley et al., 2004; Mogg et al., 2005). The ambiguous findings in Experiment 2 illustrate the importance of stimulus timing in determining task sensitivity.

By incorporating multiple durations, Experiment 3 addressed this limitation and provided evidence for temporally dissociable attentional processes. Biases emerged at 200 ms (initial orienting), but not at 2000 ms (sustained attention), particularly among participants with elevated craving or usage. These results validate the importance of temporal manipulation in attentional bias research and underscore the need to align task design with theoretical models such as IST, which posit distinct attentional phases depending on cue salience and user motivation (Field & Cox, 2008). However, it is worth noting that the choice of 2000 ms as a marker of sustained attention remains contested, as some studies suggest that true disengagement difficulties may require even longer exposure durations or the use of dynamic stimuli (Rehme et al., 2018; Field et al., 2004a).

Measurement Precision and Task Reliability

A broader concern across Experiments 2 and 3 involves the reliability of reaction time (RT)-based indices. While the dot probe is widely used, it has been criticised for poor internal consistency and test–retest reliability (Ataya et al., 2012; Spiegelhalder et al., 2011). RT data can be affected by a range of confounding factors, including motor response variability, environmental distractions, and individual differences in processing speed. These limitations can obscure genuine attentional biases, especially when the expected effects are subtle, as is often the case in non-clinical samples of social media users.

Further, the dot probe task provides only a composite attentional bias score, failing to distinguish between distinct bias subtypes (facilitation, disengagement, and avoidance). This restriction may explain the absence of findings at longer durations in Experiment 3, as different bias components can cancel each other out in RT averages (Koster et al., 2004). Recent methodological advances, such as eye-tracking, offer more granular insights into these components by capturing gaze location and fixation duration, but such equipment was not available for this study. Future research incorporating eye-tracking or event-related potentials (ERP) could address these shortcomings by directly indexing attentional allocation in real-time (Lochbuehler et al., 2018; Starzomska, 2017).

Stimulus Selection and Personal Relevance

An important methodological strength across all three experiments was the careful control of stimuli. Instagram-related images were standardised for content and format and were matched to neutral images in terms of visual complexity, colour, and framing. This helped minimise perceptual confounds and ensured that differences in response times could be more confidently attributed to the content's motivational relevance. However, one limitation was the use of generic Instagram images rather than participant-specific or personally salient cues. According to IST, attentional salience is enhanced through repeated associative learning (Robinson & Berridge, 2008), and personalised stimuli (e.g., screenshots from a participant's own feed) may elicit stronger bias effects. Studies in substance use (Field et al., 2009b) and gaming (Nikolaidou et al., 2019) have shown that personally meaningful stimuli produce greater attentional bias than standardised content, suggesting a potentially fruitful direction for future research.

Participant Characteristics and Sampling

The participant samples across all three experiments consisted of non-clinical Instagram users, predominantly university students. While this demographic is appropriate given the research aim of exploring normative (but potentially problematic) patterns of social media use, it also limits generalizability. Notably, the absence of sustained attention effects in Experiment 3 may reflect a lack of participants with high levels of dependence or craving. Clinical studies of behavioural addiction typically find stronger and more consistent attentional biases, particularly in sustained attention (Field & Cox, 2008). The moderate variability in craving and usage levels observed here may have diluted effect sizes, especially when examined using between-group designs. Future research should consider recruiting individuals with clinically significant social media addiction symptoms (e.g., using validated cut-offs on the BSMAS or SMAQ) to more robustly test IST predictions.

Theoretical Implications

The findings of this thesis offer a valuable, if complex, contribution to the literature on behavioural addictions and attentional bias, particularly in the context of social media use. Across the three experiments, evidence was found to partially support the predictions of the Incentive Sensitisation Theory (IST; Robinson & Berridge, 1993, 2001, 2016), particularly in relation to the attentional salience of social media stimuli and their relationship to usage intensity and craving. However, the picture is far from unequivocal, and the results also raise important questions about the boundary conditions and task sensitivity of the theory when applied to behavioural—as opposed to substance—addictions.

At its core, IST posits that repeated exposure to rewarding stimuli (e.g., Instagram use) sensitises mesocorticolimbic dopamine systems, thereby attributing heightened incentive salience to related cues. As a result, these cues should preferentially capture attention and drive compulsive behaviour through "wanting," even in the absence of "liking" (Berridge & Robinson, 2016). The present research supports this prediction in several key respects. First, Experiment 1 showed that Instagram-related cues were detected more quickly than neutral stimuli in a change blindness paradigm, particularly among participants with higher craving (QIUU) and screen time. This is consistent with the notion that sensitised reward cues trigger more efficient attentional processing. Second, Experiment 3 provided further support through temporally dissociated dot-probe results: participants with elevated craving showed greater attentional bias at early (200 ms) stages of processing, which aligns with the IST prediction that sensitised cues are prioritized automatically and unconsciously during initial orienting.

However, findings across the experiments also demonstrate boundaries to IST's explanatory power. Notably, Experiment 2 failed to find evidence of attentional bias using a 1000 ms dot-probe task, regardless of craving or Instagram usage level. This result calls into question whether bias is universally detectable or whether the attentional capture by social media cues is context- and task-dependent. IST assumes a relatively stable attribution of salience once sensitisation has occurred, yet the findings here suggest that attentional bias is highly sensitive to task design, stimulus duration, and possibly situational motivational states such as immediate craving (Field & Cox, 2008; Robinson & Berridge, 2008). The absence of bias at 1000 ms in Experiment 2 may reflect a transitional stage of attentional processing where neither initial orienting nor sustained attention mechanisms dominate, resulting in a flattened attentional profile (Field et al., 2009a).

One of the most theoretically intriguing aspects of the findings comes from Experiment 3, where significant attentional bias was observed at 200 ms (initial orienting) but not at 2000 ms (sustained attention)—a reversal of what has often been observed in substance-related paradigms, where sustained attention biases (especially at 2000 ms) tend to dominate among high-dependence users (Bradley et al., 2004; Mogg et al., 2005). This discrepancy raises important questions about the nature of attentional engagement with social media stimuli. One possibility is that social media cues elicit an automatic, rapid orienting response—especially among high users—but fail to maintain attention over longer durations due to the inherently dynamic and fast-paced nature of social media use itself. That is, Instagram content may be especially potent in triggering initial salience but less effective in holding attention when presented in static, artificial formats typical of laboratory tasks (Lochbuehler et al., 2018). This temporal dissociation may reflect a fundamental difference between behavioural and substance-based rewards: whereas drug cues are tied to powerful physiological cravings, social media cues may rely more on habitual, short-burst engagement patterns driven by novelty-seeking (Montag et al., 2019).

Alternatively, the failure to observe sustained attention effects may be due to the lack of sufficiently high dependence levels in the participant sample. As Mogg et al. (2005) suggest, sustained attention effects tend to emerge more reliably in participants with higher levels of addiction or dependence, where internal craving states are chronically elevated. In contrast, the participants in this study were likely drawn from a non-clinical population of Instagram users, many of whom may use the platform intensively but do not meet formal criteria for addiction. This would be consistent with IST's view that salience attribution exists along a continuum and that stronger neural sensitisation may be necessary for sustained attentional engagement (Robinson & Berridge, 2008). Future studies might benefit from comparing clinically diagnosed individuals with problematic social media use to non-addicted high users to test this proposition more directly.

The findings also contribute to ongoing debates about the specificity of attentional bias as a cognitive marker of behavioural addiction. While the results support attentional prioritization of social media cues under certain conditions, the variability across tasks and timing durations suggests that attentional bias is not a stable trait but rather a state-like phenomenon influenced by both internal and external factors (Field et al., 2016). For example, craving may be transient and context-sensitive—e.g., peaking during moments of social anticipation or notification delivery (Moretta et al., 2023)—which could modulate the strength of attentional capture. This aligns with the elaborated intrusion theory (Kavanagh et al., 2005), which emphasises the dynamic interplay between cognitive elaboration and attentional control.

In this light, the findings advocate for a hybrid theoretical perspective that incorporates the neurobiological grounding of IST with the cognitive-affective models of desire and motivation, such as the Theory of Current Concerns (Cox & Klinger, 2004) or the Elaborated Intrusion Theory. The presence of orienting bias without sustained attention suggests that social media stimuli may activate pre-conscious attention systems (System 1 in dual-process models; Wiers et al., 2007), while failing to engage the reflective system (System 2) over extended intervals unless the stimuli are emotionally or contextually enriched.

Taken together, the findings present partial support for IST in the context of social media use: Instagram cues can capture attention, particularly during the early stages of processing and under conditions of heightened craving or frequent use. However, the variability in bias expression—across tasks, durations, and individual differences—suggests that IST's predictions may need to be refined when applied to behavioural addictions. Future theoretical models may benefit from acknowledging the conditional and temporally dynamic nature of attentional bias, especially when examining non-substance-based behaviours that may lack the same physiological reinforcement mechanisms.

Limitations

While this thesis contributes novel insights into the cognitive underpinnings of problematic social media use, several limitations should be acknowledged to contextualize the findings and guide future research. These limitations pertain to the experimental paradigms employed, measurement sensitivity, participant sampling, stimulus relevance, and broader theoretical generalizability. Recognising these constraints is essential for interpreting the results with appropriate caution and for delineating the scope of their applicability within addiction and attentional bias research.

Task-Specific Constraints and Paradigm Sensitivity

A major limitation across the thesis lies in the differential sensitivity of the attentional bias paradigms employed. Although each paradigm was chosen to capture distinct aspects of attentional processing, their capacity to isolate attentional subcomponents—such as initial orienting, attentional capture, sustained attention, or disengagement—was limited. For instance, the Flicker-Induced Change Blindness task used in Experiment 1 effectively highlighted stimulus salience through change detection latency, but it did not offer precise temporal resolution or direct indices of spatial attention. As such, the interpretation that faster detection times reflected attentional capture remains inferential, rather than directly observable.

In contrast, the dot probe paradigm in Experiments 2 and 3 offered more explicit indices of attentional allocation but is widely criticised for low internal reliability and susceptibility to motor response noise (Ataya et al., 2012; Field & Cox, 2008). Moreover, reaction time-based attentional bias scores cannot reliably distinguish between facilitation and disengagement biases, potentially obscuring important cognitive dynamics (Koster et al., 2004). Although Experiment 3 attempted to address this limitation by including multiple stimulus durations, the underlying attentional mechanisms remain speculative without the use of more direct measures such as eye-tracking or electrophysiological techniques (e.g., ERP components such as the N2pc; Lochbuehler et al., 2018).

Stimulus Limitations and Ecological Validity

Another important limitation pertains to the design and selection of stimuli. While stimuli were matched for visual complexity and standardisation, they were not personalised. The Instagram images used were generic and unrelated to participants' own feeds or social context. This may have attenuated the salience of the stimuli, as prior research indicates that attentional bias is significantly enhanced when addiction-related stimuli are personally relevant (Field et al., 2009b; Nikolaidou et al., 2019). Given the role of incentive salience in attentional prioritization (Robinson & Berridge, 1993, 2001), the absence of personally meaningful cues likely underestimates the true magnitude of attentional biases in real-world settings.

In addition, the static nature of the stimuli limits ecological validity. Social media use is characterised by dynamic, interactive content—scrolling, likes, notifications, and videos—that engage users through multiple sensory and emotional channels. The use of still images fails to fully capture the reward-based interactivity that fuels engagement and craving on platforms like Instagram (Montag et al., 2019). Consequently, the experimental tasks may only provide a partial approximation of the attentional dynamics operative in everyday digital environments.

Sample Characteristics and Generalizability

The participant samples used across Experiments 1–3 consisted primarily of university students, most of whom did not exhibit clinical levels of social media addiction. While this sampling strategy was adequate for detecting individual differences in craving and screen time, it limits the generalizability of the findings to the broader population of users, especially those with diagnosed or high-severity problematic use. Previous literature suggests that attentional biases are more robust among individuals with clinical levels of dependency, particularly in studies on alcohol, nicotine, and gambling (Field & Cox, 2008; Mogg et al., 2005).

Furthermore, the use of self-report questionnaires to index craving and problematic use (e.g., QIUU, AEQ, SMAQ) introduces potential biases related to introspective inaccuracy, social desirability, or limited self-awareness. Although such measures are commonly used and provide psychometrically validated indices, they may not fully capture the dynamic, fluctuating nature of craving or the more unconscious aspects of compulsive engagement. Complementing these measures with passive smartphone-based tracking (e.g., Screen Time logs) or physiological indices could improve the ecological accuracy of user profiling.

Measurement Reliability and Internal Consistency

As noted in the methodological considerations, the reaction time measures used in the dot probe tasks suffer from questionable internal reliability (Ataya et al., 2012; Spiegelhalder et al., 2011). While attentional bias scores were derived using standard subtraction methods, the variability inherent in response time data may introduce noise, particularly in non-clinical samples where effects are likely to be smaller. This limitation is particularly salient for Experiment 2, where no significant biases were detected despite theoretical expectations based on participants' craving levels and Instagram usage.

Furthermore, the constructs of craving, addiction, and usage were each assessed using multiple instruments (e.g., SMAQ, BSMAS, AEQ), which introduces complexity in interpretation. While this multi-instrument approach increases construct validity, it also poses a risk of multicollinearity or conceptual overlap. For example, the distinction between craving and problematic use may be blurred in self-report formats, complicating analyses that aim to isolate their independent contributions to attentional processes.

Theoretical Interpretations and Boundary Conditions of IST

Although the Incentive Sensitisation Theory provided a strong theoretical framework for the thesis, the inconsistent findings across paradigms raise questions about its full applicability to behavioural (non-substance) addictions. For example, while early attentional bias (e.g., at 200 ms in Experiment 3) aligns with IST's prediction that sensitised cues capture automatic attention, the absence of sustained attention effects (e.g., at 2000 ms) complicates this interpretation. It is unclear whether this reflects a limitation of the theory itself, a methodological artifact, or a feature specific to social media stimuli, which may not elicit the same neurobiological sensitisation processes as drugs of abuse (Berridge & Robinson, 2016).

Moreover, IST assumes that attentional biases should correlate consistently with subjective craving, yet findings in this thesis—and elsewhere (Field et al., 2009a)—suggest this relationship may be weak or task-dependent. Such variability raises the possibility that attentional bias is not a unitary phenomenon but one that is shaped by multiple, interacting cognitive, affective, and contextual factors. This complexity limits the extent to which findings can be neatly mapped onto linear theoretical models, highlighting the need for integrative frameworks that account for both automatic and deliberative processing, such as the I-PACE model (Brand et al., 2019).

Future Directions

The findings of this thesis offer preliminary but important evidence that attentional bias plays a role in social media engagement, particularly among individuals reporting higher craving and screen time. However, the inconsistencies across paradigms and individual differences underscore the need for further research that builds on and extends this work in more robust, diverse, and ecologically valid ways. This section outlines several key directions for future inquiry, emphasising improvements in methodology, theoretical integration, population sampling, and translational relevance.

Integration of Direct Measures of Attention

Future research should incorporate eye-tracking technologies to provide a more direct and granular assessment of attentional processes. Unlike reaction time-based paradigms, which rely on indirect inferences, eye-tracking allows researchers to precisely quantify initial fixations, dwell times, and attentional shifts between competing stimuli (Gibaldi et al., 2017; Field et al., 2006). This would facilitate a clearer distinction between different attentional bias components—facilitation, delayed disengagement, and avoidance—all of which may play distinct roles in behavioural addictions (Cisler & Koster, 2010). For example, social media users may quickly orient to Instagram cues but disengage just as rapidly, a dynamic that could not be captured in the current study but is highly relevant to understanding compulsive checking behaviour.

In addition, event-related potentials (ERPs) such as the N2pc component could be used to track the time course of attention with millisecond precision, offering insight into the neurocognitive processes that underlie orienting versus sustained engagement (Luck & Kappenman, 2012). These techniques would allow for testing more precise predictions derived from dual-process theories and the Incentive Sensitisation Theory, especially regarding the speed and automaticity of attentional capture.

Use of Personalised and Dynamic Stimuli

A significant methodological enhancement would be the use of personally salient stimuli, such as images or notifications from a participant's own social media feed. Studies in other behavioural domains (e.g., gambling, gaming) have shown that personalised cues elicit stronger attentional and affective responses than standardised images (Nikolaidou et al., 2019; Field et al., 2009b). This approach would better reflect the reward associations formed through real-world usage, in line with the core assumptions of Incentive Sensitisation Theory—that cues gain motivational salience through repeated, individualized reinforcement (Robinson & Berridge, 2008).

Similarly, future studies should explore dynamic and interactive social media simulations rather than static image pairs. Simulated scrolling environments, timed push notifications, or controlled engagement with app-like interfaces could better mimic real-world usage patterns and provide a more ecologically valid platform for measuring attentional biases. Virtual reality (VR) platforms may even offer an avenue for real-time monitoring of attentional and affective engagement in immersive digital environments.

Broadening Population Samples

To strengthen generalizability and test theoretical predictions across the full spectrum of social media use, future research should include more diverse and clinically relevant populations. The current thesis drew primarily on non-clinical university students, many of whom exhibited moderate use but fell below clinical thresholds for social media addiction. While appropriate for detecting baseline attentional differences, such samples may underrepresent the intensity of craving and compulsivity found in clinically significant cases.

Future studies should recruit participants with high scores on validated addiction scales (e.g., BSMAS, SMAQ) or those who meet emerging criteria for problematic social media use. This would allow for testing dose–response relationships between craving/dependence and attentional bias, as well as potential thresholds beyond which attentional salience becomes pathological. Longitudinal designs could also be used to examine whether changes in attentional bias precede or follow increases in problematic use, offering insights into causal mechanisms.

Examining the Role of Context and Motivation

Emerging evidence suggests that attentional biases are state-dependent, fluctuating in response to internal motivational states and external contextual cues (Field et al., 2016). Future research should examine how variables such as acute craving, stress, boredom, or anticipation of feedback modulate attentional processing of social media stimuli. Experience sampling or ecological momentary assessment (EMA) techniques may be especially useful for capturing these real-time fluctuations in naturalistic settings.

In addition, researchers could explore the influence of specific motivational constructs—e.g., social comparison orientation, fear of missing out (FoMO), or validation-seeking behaviour—on attentional bias. These constructs may represent distinct motivational pathways that sensitise users to particular types of cues (e.g., likes, comments, peer content) and thus shape the attentional landscape differently than generic craving or usage metrics.

Theoretical Refinement and Model Integration

The findings of this thesis suggest that attentional bias in behavioural addiction may not always conform neatly to predictions made by the Incentive Sensitisation Theory, particularly in cases where sustained attention is not observed. Future work should continue to evaluate the boundary conditions of IST and consider integrating alternative frameworks that better account for the complexities of digital engagement.

One promising direction is the I-PACE model (Brand et al., 2019), which emphasises the dynamic interplay of person-related predispositions, affective and cognitive responses, and executive functioning over time. This model allows for more nuanced hypotheses about when and why attentional biases emerge and how they interact with craving, cognitive control, and situational cues. Integrating IST's focus on incentive salience with I-PACE's person-context interactions may yield a more comprehensive understanding of the mechanisms underlying compulsive social media use.

Translational Implications: Bias Modification and Intervention

Finally, future research should explore whether attentional bias modification (ABM) techniques can reduce compulsive social media use. In substance use disorders, ABM has shown some success in retraining attentional patterns away from addiction-related cues (Lopes et al., 2015). Applying similar techniques to digital addiction contexts—e.g., redirecting attention from social media stimuli to neutral or goal-directed alternatives—could provide a low-cost, scalable intervention strategy. The effectiveness of such interventions could be enhanced by incorporating personalised stimuli and delivered through mobile apps or browser extensions.

Moreover, attentional bias measures could be used diagnostically or prognostically to identify individuals at risk of developing problematic use patterns. For example, sustained attentional bias toward social media stimuli might predict escalation in usage or failure to respond to abstinence attempts, thus serving as a cognitive marker for early intervention. Finally, future studies should broaden the scope to include cross-platform comparisons and explore age and gender differences in attentional processing of social media stimuli.

Reference

Ahmed, S. H., & Koob, G. F. (1998). Transition from Moderate to Excessive Drug Intake: Change in Hedonic Set Point. *Science*, *282*(5387), 298-300. https://doi.org/10.1126/science.282.5387.298

Aksoy, M. E. (2018). A Qualitative Study on the Reasons for Social Media Addiction. *European Journal of Educational Research*, *7*(4), 861-865. https://doi.org/10.12973/eu-jer.7.4.861

Alavi, S. S., Ferdosi, M., Jannatifard, F., Eslami, M., Alaghemandan, H., & Setare, M. (2012). Behavioural Addiction versus Substance Addiction: Correspondence of Psychiatric and Psychological Views. *International journal of preventive medicine*, *3*(4), 290-294.

Allahverdi, F. Z. (2022). Relationship between perceived social media addiction and social media applications frequency usage among university students [https://doi.org/10.1002/pits.22662]. *Psychology in the Schools*, *59*(6), 1075-1087. https://doi.org/https://doi.org/10.1002/pits.22662

Anderson, B. A. (2013). A value-driven mechanism of attentional selection. *J VISION*, *13*(3), 7-7. https://doi.org/10.1167/13.3.7

Anderson, B. A. (2016). The attention habit: how reward learning shapes attentional selection: The attention habit. *Annals of the New York Academy of Sciences*, *1369*(1), 24-39. https://doi.org/10.1111/nyas.12957

Andreassen, C. S. (2015). Online Social Network Site Addiction: A Comprehensive Review. *Current Addiction Reports*, *2*(2), 175-184. https://doi.org/10.1007/s40429-015-0056-9

Andreassen, C. S., Pallesen, S., & Griffiths, M. D. (2017). The relationship between addictive use of social media, narcissism, and self-esteem: Findings from a large national survey. *Addictive Behaviours*, *64*, 287-293. https://doi.org/10.1016/j.addbeh.2016.03.006

Andreassen, C. S., Torsheim, T., Brunborg, G. S., & Pallesen, S. (2012). Development of a Facebook Addiction Scale. *Psychological Reports*, *110*(2), 501-517. https://doi.org/10.2466/02.09.18.PR0.110.2.501-517

Annunzi, E., Cannito, L., Piccinini, A., Di Domenico, A., Dell'Osso, B., Palumbo, R., & D'Addario, C. (2022). Genetic and epigenetic of internet addiction in young adult university students – suggesting a role for oxytocin receptor gene DNA methylation. *Neuroscience Applied*, *1*, 100715. https://doi.org/10.1016/j.nsa.2022.100715

Anselme, P., & Robinson, M. J. F. (2020). From sign-tracking to attentional bias: Implications for gambling and substance use disorders. *Progress in Neuro-Psychopharmacology and*

Biological Psychiatry, *99*, 109861. https://doi.org/https://doi.org/10.1016/j.pnpbp.2020.109861

Arulkadacham, L. J., Richardson, B., Staiger, P. K., Kambouropoulos, N., O'Donnell, R. L., & Ling, M. (2017). Dissociation between wanting and liking for alcohol and caffeine: A test of the Incentive Sensitisation Theory. *J PSYCHOPHARMACOL*, *31*(7), 927-933. https://doi.org/10.1177/0269881117711711

Ashwin, C., Wheelwright, S., & Baron-Cohen, S. (2017). Differences in change blindness to real-life scenes in adults with autism spectrum conditions. *PLOS ONE*, *12*(10), e0185120-e0185120. https://doi.org/10.1371/journal.pone.0185120

Austin, A. J., & Duka, T. (2012). Mechanisms of attention to conditioned stimuli predictive of a cigarette outcome. *BEHAV BRAIN RES*, *232*(1), 183-189. https://doi.org/10.1016/j.bbr.2012.04.009

Baker, T. B., Piper, M. E., McCarthy, D. E., Majeskie, M. R., & Fiore, M. C. (2004). Addiction Motivation Reformulated: An Affective Processing Model of Negative Reinforcement. *PSYCHOL REV*, *111*(1), 33-51. https://doi.org/10.1037/0033-295X.111.1.33

Bányai, F., Zsila, Á., Király, O., Maraz, A., Elekes, Z., Griffiths, M. D.,…Jiménez-Murcia, S. (2017). Problematic social media use: Results from a large-scale nationally representative adolescent sample. *PLOS ONE*, *12*(1), e0169839-e0169839. https://doi.org/10.1371/journal.pone.0169839

Basu, S. (2023). Examining the reliability and validity of computerized stroop test in children aged 5-13 years: a preliminary study. *Qual Quant*, *57*(1), 645-653. https://doi.org/10.1007/s11135-022-01376-y

Bechara, A. (2005). Decision making, impulse control and loss of willpower to resist drugs: a neurocognitive perspective. *Nat Neurosci*, *8*(11), 1458-1463. https://doi.org/10.1038/nn1584

Begh, R., Smith, M., Ferguson, S. G., Shiffman, S., Munafò, M. R., & Aveyard, P. (2016). Association Between Smoking-Related Attentional Bias and Craving Measured in the Clinic and in the Natural Environment. *PSYCHOL ADDICT BEHAV*, *30*(8), 868-875. https://doi.org/10.1037/adb0000231

Ben-Haim, M. S., Williams, P., Howard, Z., Mama, Y., Eidels, A., & Algom, D. (2016). The Emotional Stroop Task: Assessing Cognitive Performance under Exposure to Emotional Content. *J Vis Exp*(112). https://doi.org/10.3791/53720

Berger, M. N., Taba, M., Marino, J. L., Lim, M. S. C., & Skinner, S. R. (2022). Social Media Use and Health and Well-being of Lesbian, Gay, Bisexual, Transgender, and Queer

Youth: Systematic Review. Journal of medical Internet research, 24(9), e38449-e38449. https://doi.org/10.2196/38449

Berridge, Kent C., & Kringelbach, Morten L. (2015). Pleasure Systems in the Brain. *NEURON*, *86*(3), 646-664. https://doi.org/10.1016/j.neuron.2015.02.018

Berridge, K. C., & Robinson, T. E. (2011). Drug addiction as incentive sensitisation. In J. Poland & G. Graham (Eds.), *Addiction and responsibility* (pp. 21–54). MIT Press.

Berridge, K. C., & Robinson, T. E. (2016). Liking, wanting, and the incentive-sensitisation theory of addiction. *American Psychologist*, *71*(8), 670-679. https://doi.org/10.1037/amp0000059

Bielefeld, M., Drews, M., Putzig, I., Bottel, L., Steinbüchel, T., Dieris-Hirche, J.,…Theodor te Wildt, B. (2017). Comorbidity of Internet use disorder and attention deficit hyperactivity disorder: Two adult case–control studies. *Journal of Behavioural Addictions*, *6*(4), 490-504. https://doi.org/https://doi.org/10.1556/2006.6.2017.073

Billieux, J., Flayelle, M., Rumpf, H.-J., & Stein, D. J. (2019). High Involvement Versus Pathological Involvement in Video Games: a Crucial Distinction for Ensuring the Validity and Utility of Gaming Disorder. *Current Addiction Reports*, *6*(3), 323-330. https://doi.org/10.1007/s40429-019-00259-x

Billieux, J., Schimmenti, A., Khazaal, Y., Maurage, P., & Heeren, A. (2015). Are we overpathologizing everyday life? A tenable blueprint for behavioural addiction research. *J BEHAV ADDICT*, *4*(3), 119-123. https://doi.org/10.1556/2006.4.2015.009

Biondi, F. N., Saberi, B., Graf, F., Cort, J., Pillai, P., & Balasingam, B. (2023). Distracted worker: Using pupil size and blink rate to detect cognitive load during manufacturing tasks. *APPL ERGON*, *106*, 103867-103867. https://doi.org/10.1016/j.apergo.2022.103867

Blanco, C., Potenza, M. N., Kim, S. W., Ibáñez, A., Zaninelli, R., Saiz-Ruiz, J., & Grant, J. E. (2009). A pilot study of impulsivity and compulsivity in pathological gambling. *PSYCHIAT RES*, *167*(1), 161-168. https://doi.org/10.1016/j.psychres.2008.04.023

Block, J. J. (2008). Issues for DSM-V: Internet Addiction. *AM J PSYCHIAT*, *165*(3), 306-307. https://doi.org/10.1176/appi.ajp.2007.07101556

Blum, K., Thanos, P. K., & Gold, M. S. (2014). Dopamine and glucose, obesity, and reward deficiency syndrome. *FRONT PSYCHOL*, *5*, 919. https://doi.org/10.3389/fpsyg.2014.00919

Bollen, Z., D'Hondt, F., Dormal, V., Lannoy, S., Masson, N., & Maurage, P. (2021). Understanding Attentional Biases in Severe Alcohol Use Disorder: A Combined

Behavioural and Eye-Tracking Perspective. *ALCOHOL ALCOHOLISM*, *56*(1), 1-7. https://doi.org/10.1093/alcalc/agaa062

Boskovic, I., Biermans, A. J., Merten, T., Jelicic, M., Hope, L., & Merckelbach, H. (2018). The Modified Stroop Task Is Susceptible to Feigning: Stroop Performance and Symptom Over-endorsement in Feigned Test Anxiety. *FRONT PSYCHOL*, *9*, 1195-1195. https://doi.org/10.3389/fpsyg.2018.01195

Boyer, M., & Dickerson, M. (2003). Attentional bias and addictive behaviour: automaticity in a gambling-specific modified Stroop task. *Addiction*, *98*(1), 61-70. https://doi.org/10.1046/j.1360-0443.2003.00219.x

Bradley, B., Field, M., Mogg, K., & De Houwer, J. (2004). Attentional and evaluative biases for smoking cues in nicotine dependence: component processes of biases in visual orienting. *Behav Pharmacol*, *15*(1), 29-36. https://doi.org/10.1097/00008877-200402000-00004

Bradley, B. P., Field, M., Healy, H., & Mogg, K. (2008). Do the affective properties of smoking-related cues influence attentional and approach biases in cigarette smokers? *J PSYCHOPHARMACOL*, *22*(7), 737-745. https://doi.org/10.1177/0269881107083844

Bradley, B. P., Mogg, K., & Millar, N. H. (2000). Covert and overt orienting of attention to emotional faces in anxiety. *COGNITION EMOTION*, *14*(6), 789-808. https://doi.org/10.1080/02699930050156636

Bradley, B. P., Mogg, K., Wright, T., & Field, M. (2003). Attentional Bias in Drug Dependence: Vigilance for Cigarette-Related Cues in Smokers. *Psychol Addict Behav*, *17*(1), 66-72. https://doi.org/10.1037/0893-164X.17.1.66

Brand, M., Wegmann, E., Stark, R., Müller, A., Wölfling, K., Robbins, T. W., & Potenza, M. N. (2019). The Interaction of Person-Affect-Cognition-Execution (I-PACE) model for addictive behaviours: Update, generalization to addictive behaviours beyond internet-use disorders, and specification of the process character of addictive behaviours. *Neuroscience & Biobehavioural Reviews*, *104*, 1-10. https://doi.org/https://doi.org/10.1016/j.neubiorev.2019.06.032

Brevers, D., Cleeremans, A., Bechara, A., Laloyaux, C., Kornreich, C., Verbanck, P., & Noël, X. (2011). Time course of attentional bias for gambling information in problem gambling. *Psychology of Addictive Behaviours*, *25*(4), 675-682. https://doi.org/10.1037/a0024201

Brevers, D., & Turel, O. (2019). Strategies for self-controlling social media use: Classification and role in preventing social media addiction symptoms. *Journal of Behavioural Addictions*, *8*(3), 554-563. https://doi.org/10.1556/2006.8.2019.49

Bromberg-Martin, E. S., Matsumoto, M., & Hikosaka, O. (2010). Dopamine in Motivational Control: Rewarding, Aversive, and Alerting. *NEURON*, *68*(5), 815-834. https://doi.org/10.1016/j.neuron.2010.11.022

Brown, J., Beard, E., Kotz, D., Michie, S., & West, R. (2014). Real-world effectiveness of e-cigarettes when used to aid smoking cessation: a cross-sectional population study. *ADDICTION*, *109*(9), 1531-1540. https://doi.org/10.1111/add.12623

Bruce, G., & Jones, B. T. (2004). A pictorial Stroop paradigm reveals an alcohol attentional bias in heavier compared to lighter social drinkers. *J PSYCHOPHARMACOL*, *18*(4), 527-533. https://doi.org/10.1177/0269881104047280

Burt, J. S. (2002). Why do non-colour words interfere with colour naming? *J EXP PSYCHOL HUMAN*, *28*(5), 1019-1038. https://doi.org/10.1037//0096-1523.28.5.1019

Burén, J., Nutley, S. B., Sandberg, D., Ström Wiman, J., & Thorell, L. B. (2021). Gaming and Social Media Addiction in University Students: Sex Differences, Suitability of Symptoms, and Association With Psychosocial Difficulties. *FRONT PSYCHIATRY*, *12*, 740867-740867. https://doi.org/10.3389/fpsyt.2021.740867

Calluso, C., Pettorruso, M., Tosoni, A., Carenti, M. L., Cannito, L., Martinotti, G.,…Committeri, G. (2020). Cognitive dynamics of intertemporal choice in gambling disorder. *ADDICT BEHAV*, *109*, 106463-106463. https://doi.org/10.1016/j.addbeh.2020.106463

Calvo, M. G., & Nummenmaa, L. (2008). Detection of Emotional Faces: Salient Physical Features Guide Effective Visual Search. *J EXP PSYCHOL GEN*, *137*(3), 471-494. https://doi.org/10.1037/a0012771

Calvo, M. G., Nummenmaa, L., & Hyönä, J. (2008). Emotional Scenes in Peripheral Vision: Selective Orienting and Gist Processing, But Not Content Identification. *EMOTION*, *8*(1), 68-80. https://doi.org/10.1037/1528-3542.8.1.68

Cannito, L., Ceccato, I., Annunzi, E., Bortolotti, A., D'Intino, E., Palumbo, R.,…Palumbo, R. (2023). Bored with boredom? Trait boredom predicts internet addiction through the mediating role of attentional bias toward social networks. *FRONT HUM NEUROSCI*, *17*, 1179142-1179142. https://doi.org/10.3389/fnhum.2023.1179142

Carlson, J. M., & Fang, L. (2020). The stability and reliability of attentional bias measures in the dot-probe task: Evidence from both traditional mean bias scores and trial-level bias scores. *Motiv Emot*, *44*(5), 657-669. https://doi.org/10.1007/s11031-020-09834-6

Carter, B. L., & Tiffany, S. T. (1999). Meta-analysis of cue-reactivity in addiction research. *ADDICTION*, *94*(3), 327-340. https://doi.org/10.1046/j.1360-0443.1999.9433273.x

Casale, S., & Fioravanti, G. (2018). Why narcissists are at risk for developing Facebook addiction: The need to be admired and the need to belong. *Addictive Behaviours*, *76*, 312-318. https://doi.org/https://doi.org/10.1016/j.addbeh.2017.08.038

Casale, S., Fioravanti, G., & Rugai, L. (2016). Grandiose and Vulnerable Narcissists: Who Is at Higher Risk for Social Networking Addiction? *Cyberpsychology Behaviour and Social Networking*, *19*(8), 510-515. https://doi.org/10.1089/cyber.2016.0189

Cassimjee, N., & Maree, D. J. F. (2004). Change Detection in a Change Blindness Flicker Paradigm. *South African journal of psychology*, *34*(2), 222-236. https://doi.org/10.1177/008124630403400204

Casteau, S., & Smith, D. T. (2020). Covert attention beyond the range of eye-movements: Evidence for a dissociation between exogenous and endogenous orienting. *CORTEX*, *122*, 170-186. https://doi.org/10.1016/j.cortex.2018.11.007

Castro, D. C., & Berridge, K. C. (2014). Opioid Hedonic Hotspot in Nucleus Accumbens Shell: Mu, Delta, and Kappa Maps for Enhancement of Sweetness "Liking" and "Wanting". *J NEUROSCI*, *34*(12), 4239-4250. https://doi.org/10.1523/JNEUROSCI.4458-13.2014

Caudek, C., Ceccarini, F., & Sica, C. (2017). Facial expression movement enhances the measurement of temporal dynamics of attentional bias in the dot-probe task. *BEHAV RES THER*, *95*, 58-70. https://doi.org/10.1016/j.brat.2017.05.003

Chamberlain, S. R., Lochner, C., Stein, D. J., Goudriaan, A. E., van Holst, R. J., Zohar, J., & Grant, J. E. (2016). Behavioural addiction—A rising tide? *European Neuropsychopharmacology*, *26*(5), 841-855. https://doi.org/https://doi.org/10.1016/j.euroneuro.2015.08.013

Chambers, R. A., & Potenza, M. N. (2003). Neurodevelopment, Impulsivity, and Adolescent Gambling. *Journal of Gambling Studies*, *19*(1), 53-84.

Chanon, V. W., Sours, C. R., & Boettiger, C. A. (2010). Attentional bias toward cigarette cues in active smokers. *Psychopharmacology*, *212*(3), 309-320. https://doi.org/10.1007/s00213-010-1953-1

Chapman, A., Devue, C., & Grimshaw, G. M. (2019). Fleeting reliability in the dot-probe task. *Psychological Research*, *83*(2), 308-320. https://doi.org/10.1007/s00426-017-0947-6

Charlton, J. P., & Danforth, I. D. W. (2007a). Distinguishing addiction and high engagement in the context of online game playing. *Computers in Human Behaviour*, *23*(3), 1531-1548. https://doi.org/10.1016/j.chb.2005.07.002

Charlton, J. P., & Danforth, I. D. W. (2007b). Distinguishing addiction and high engagement in the context of online game playing. *Computers in Human Behaviour*, *23*(3), 1531-1548. https://doi.org/https://doi.org/10.1016/j.chb.2005.07.002

Charmaraman, L. (2022). Marginalized and Understudied Populations Using Digital Media. 188-214. https://doi.org/10.1017/9781108976237.011

Chen, S., & Epps, J. (2014). Using Task-Induced Pupil Diameter and Blink Rate to Infer Cognitive Load. *HUM-COMPUT INTERACT*, *29*(4), 390-413. https://doi.org/10.1080/07370024.2014.892428

Chun, M. M., Golomb, J. D., & Turk-Browne, N. B. (2011). A Taxonomy of external and internal attention. *ANNU REV PSYCHOL*, *62*(1), 73-101. https://doi.org/10.1146/annurev.psych.093008.100427

Chun, M. M., & Wolfe, J. M. (2001). Visual Attention. In E. B. Goldstein (Ed.), *Handbook of Experimental Psychology Series. Blackwell Handbook of Sensation and Perception* (pp. 272-310). Blackwell Publishing.

Ciccarelli, M., Nigro, G., Griffiths, M. D., Cosenza, M., & D'Olimpio, F. (2016). Attentional bias in non-problem gamblers, problem gamblers, and abstinent pathological gamblers: An experimental study. *Journal of Affective Disorders*, *206*, 9-16. https://doi.org/https://doi.org/10.1016/j.jad.2016.07.017

Cisler, J. M., Bacon, A. K., & Williams, N. L. (2009). Phenomenological Characteristics of Attentional Biases Towards Threat: A Critical Review. *Cogn Ther Res*, *33*(2), 221-234. https://doi.org/10.1007/s10608-007-9161-y

Cisler, J. M., & Koster, E. H. W. (2010). Mechanisms of attentional biases towards threat in anxiety disorders: An integrative review. *CLIN PSYCHOL REV*, *30*(2), 203-216. https://doi.org/10.1016/j.cpr.2009.11.003

Cohen, J. D., Dunbar, K., & McClelland, J. L. (1990). On the Control of Automatic Processes: A Parallel Distributed Processing Account of the Stroop Effect. *PSYCHOL REV*, *97*(3), 332-361. https://doi.org/10.1037/0033-295X.97.3.332

Cornoldi, C., & Giofre, D. (2014). The Crucial Role of Working Memory in Intellectual Functioning. *EUR PSYCHOL*, *19*(4), 260-268. https://doi.org/10.1027/1016-9040/a000183

Cousijn, J., Watson, P., Koenders, L., Vingerhoets, W. A. M., Goudriaan, A. E., & Wiers, R. W. (2013). Cannabis dependence, cognitive control and attentional bias for cannabis words. *ADDICT BEHAV*, *38*(12), 2825-2832. https://doi.org/10.1016/j.addbeh.2013.08.011

Cox, L. S., Tiffany, S. T., & Christen, A. G. (2001). Evaluation of the brief questionnaire of smoking urges (QSU-brief) in laboratory and clinical settings. *Nicotine & Tobacco Research*, *3*(1), 7-16. https://doi.org/10.1080/14622200124218

Cox, W. M., Brown, M. A., & Rowlands, L. J. (2003). The effects of alcohol cue exposure on non-dependent drinkers' attentional bias for alcohol-related stimuli. *Alcohol Alcohol*, *38*(1), 45-49. https://doi.org/10.1093/alcalc/agg010

Cox, W. M., Fadardi, J. S., & Pothos, E. M. (2006). The Addiction-Stroop Test: Theoretical Considerations and Procedural Recommendations. *Psychological Bulletin*, *132*(3), 443. https://doi.org/10.1037/0033-2909.132.3.443

Cox, W. M., & Klinger, E. (1988). A Motivational Model of Alcohol Use. *J Abnorm Psychol*, *97*(2), 168-180. https://doi.org/10.1037/0021-843X.97.2.168

Cox, W. M., Klinger, E., & Fadardi, J. S. (2006). Motivational basis of cognitive determinants of addiction. In M. Munafò & I. P. Albery (Eds.), *Cognition and addiction* (pp. 101-116). Oxford University Press.

Cox, W. M., Klinger, E., & Fadardi, J. S. (2017). Free will in addictive behaviours: A matter of definition. *Addictive Behaviours Reports*, *5*, 94-103. https://doi.org/https://doi.org/10.1016/j.abrep.2017.03.001

Coyne, S. M., Rogers, A. A., Zurcher, J. D., Stockdale, L., & Booth, M. (2020). Does time spent using social media impact mental health?: An eight year longitudinal study. *COMPUT HUM BEHAV*, *104*, 106160. https://doi.org/10.1016/j.chb.2019.106160

Crunelle, C. L., Veltman, D. J., Booij, J., Emmerik – van Oortmerssen, K., & den Brink, W. (2012). Substrates of neuropsychological functioning in stimulant dependence: a review of functional neuroimaging research. *BRAIN BEHAV*, *2*(4), 499-523. https://doi.org/10.1002/brb3.65

Dash, S., Yan, X., Wang, H., & Crawford, John D. (2015). Continuous Updating of Visuospatial Memory in Superior Colliculus during Slow Eye Movements. *Curr Biol*, *25*(3), 267-274. https://doi.org/10.1016/j.cub.2014.11.064

Davis, R. A. (2001). A cognitive-behavioural model of pathological Internet use. *Computers in Human Behaviour*, *17*(2), 187-195. https://doi.org/https://doi.org/10.1016/S0747-5632(00)00041-8

de Castro, V., Fong, T., Rosenthal, R. J., & Tavares, H. (2007). A comparison of craving and emotional states between pathological gamblers and alcoholics. *Addictive Behaviours*, *32*(8), 1555-1564. https://doi.org/https://doi.org/10.1016/j.addbeh.2006.11.014

Desimone, R., & Duncan, J. (1995). NEURAL MECHANISMS OF SELECTIVE VISUAL-ATTENTION. *ANNU REV NEUROSCI*, *18*, 193-222. https://doi.org/10.1146/annurev.neuro.18.1.193

DeVito, E. E., Kiluk, B. D., Nich, C., Mouratidis, M., & Carroll, K. M. (2018). Drug Stroop: Mechanisms of response to computerized cognitive behavioural therapy for cocaine dependence in a randomized clinical trial. *DRUG ALCOHOL DEPEN*, *183*, 162-168. https://doi.org/10.1016/j.drugalcdep.2017.10.022

Devoe, D. J., Alida, A., Anees, B., Manya, S., Scott, B. P., Andrea, S.,…Georgios, P. (2022). The Prevalence of Impulse Control Disorders and Behavioural Addictions in Eating Disorders: A Systematic Review and Meta-Analysis. *Frontiers in psychiatry*, *12*. https://doi.org/10.3389/fpsyt.2021.724034

Diana, M. (2011). The dopamine hypothesis of drug addiction and its potential therapeutic value. *Front Psychiatry*, *2*, 64-64. https://doi.org/10.3389/fpsyt.2011.00064

Dittmar, H., Long, K., & Bond, R. (2007). When a Better Self is Only a Button Click Away: Associations Between Materialistic Values, Emotional and Identity–Related Buying Motives, and Compulsive Buying Tendency Online. *J SOC CLIN PSYCHOL*, *26*(3), 334-361. https://doi.org/10.1521/jscp.2007.26.3.334

Dong, G., DeVito, E. E., Du, X., & Cui, Z. (2012). Impaired inhibitory control in 'internet addiction disorder': A functional magnetic resonance imaging study. *Psychiatry Res*, *203*(2), 153-158. https://doi.org/10.1016/j.pscychresns.2012.02.001

Drobes, D. J., Elibero, A., & Evans, D. E. (2006). Attentional Bias for Smoking and Affective Stimuli: A Stroop Task Study. *PSYCHOL ADDICT BEHAV*, *20*(4), 490-495. https://doi.org/10.1037/0893-164X.20.4.490

Drummond, D. C. (2000). What does cue-reactivity have to offer clinical research? *ADDICTION*, *95*(8s2), 129-144. https://doi.org/10.1046/j.1360-0443.95.8s2.2.x

Duka, T., & Townshend, J. M. (2004). The priming effect of alcohol pre-load on attentional bias to alcohol-related stimuli. *Psychopharmacology*, *176*(3), 353-361. https://doi.org/10.1007/s00213-004-1906-7

Duradoni, M., Innocenti, F., & Guazzini, A. (2020). Well-Being and Social Media: A Systematic Review of Bergen Addiction Scales. *FUTURE INTERNET*, *12*(2), 24. https://doi.org/10.3390/fi12020024

Ehrman, R. N., Robbins, S. J., Bromwell, M. A., Lankford, M. E., Monterosso, J. R., & O'Brien, C. P. (2002). Comparing attentional bias to smoking cues in current smokers, former smokers, and non-smokers using a dot-probe task. *Drug Alcohol Depend*, *67*(2), 185-191. https://doi.org/10.1016/s0376-8716(02)00065-0

Elton, A., Faulkner, M. L., Robinson, D. L., & Boettiger, C. A. (2021). Acute depletion of dopamine precursors in the human brain: effects on functional connectivity and alcohol attentional bias. *NEUROPSYCHOPHARMACOL*, *46*(8), 1421-1431. https://doi.org/10.1038/s41386-021-00993-9

Enez Darcin, A., Kose, S., Noyan, C. O., Nurmedov, S., Yılmaz, O., & Dilbaz, N. (2016). Smartphone addiction and its relationship with social anxiety and loneliness. *BEHAV INFORM TECHNOL*, *35*(7), 520-525. https://doi.org/10.1080/0144929X.2016.1158319

Enoch, M. A., & Goldman, D. (2002). Problem drinking and alcoholism: diagnosis and treatment. *Am Fam Physician*, *65*(3), 441-448.

Ersche, K. D., Bullmore, E. T., Craig, K. J., Shabbir, S. S., Abbott, S., Müller, U.,…Robbins, T. W. (2010). Influence of compulsivity of drug abuse on dopaminergic modulation of attentional bias in stimulant dependence. *Arch Gen Psychiatry*, *67*(6), 632-644. https://doi.org/10.1001/archgenpsychiatry.2010.60

Evans, T. C., & Britton, J. C. (2018). Improving the psychometric properties of dot-probe attention measures using response-based computation. *J BEHAV THER EXP PSY*, *60*, 95-103. https://doi.org/10.1016/j.jbtep.2018.01.009

Everitt, B. J., & Robbins, T. W. (2005). Neural systems of reinforcement for drug addiction: from actions to habits to compulsion. *NAT NEUROSCI*, *8*(11), 1481-1489. https://doi.org/10.1038/nn1579

Everitt, B. J., & Robbins, T. W. (2016). Drug Addiction: Updating Actions to Habits to Compulsions Ten Years On. *ANNU REV PSYCHOL*, *67*(1), 23-50. https://doi.org/10.1146/annurev-psych-122414-033457

Fackrell, K., Edmondson-Jones, M., & Hall, D. A. (2013). A Controlled Approach to the Emotional Dilution of the Stroop Effect. *PLOS ONE*, *8*(11), e80141-e80141. https://doi.org/10.1371/journal.pone.0080141

Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2009). Statistical power analyses using G*Power 3.1. *Behavior Research Methods, 41*(4), 1149–1160.

Faunce, G. J. (2002). Eating Disorders and Attentional Bias: A Review. *Eat Disord*, *10*(2), 125-139. https://doi.org/10.1080/10640260290081696

Favieri, F., Troisi, G., Forte, G., Corbo, I., Marselli, G., Blasutto, B.,…Casagrande, M. (2024). Effects of bottom-up and top-down attentional processes on change blindness for

COVID-related stimuli: influence of heart rate variability. *FRONT NEUROSCI-SWITZ*, *18*, 1458627. https://doi.org/10.3389/fnins.2024.1458627

Fernie, G., Cole, J. C., Goudie, A. J., & Field, M. (2010). Risk-taking but not response inhibition or delay discounting predict alcohol consumption in social drinkers. *DRUG ALCOHOL DEPEN*, *112*(1), 54-61. https://doi.org/10.1016/j.drugalcdep.2010.05.011

Field, M. (2006). Attentional biases in drug abuse and addiction: Cognitive mechanisms, causes, consequences and implications. In M. Munafò & I. P. Albery (Eds.), *Cognition and addiction.* (pp. 73-99). Oxford University Press.

Field, M., & Christiansen, P. (2012). Commentary on , 'Internal reliability of measures of substance-related cognitive bias'. *Drug Alcohol Depend*, *124*(3), 189-190. https://doi.org/10.1016/j.drugalcdep.2012.02.009

Field, M., & Cox, W. M. (2008). Attentional bias in addictive behaviours: A review of its development, causes, and consequences. *Drug and Alcohol Dependence*, *97*(1-2), 1-20. https://doi.org/https://doi.org/10.1016/j.drugalcdep.2008.03.030

Field, M., & Duka, T. (2002). Cues paired with a low dose of alcohol acquire conditioned incentive properties in social drinkers. *PSYCHOPHARMACOLOGY*, *159*(3), 325-334. https://doi.org/10.1007/s00213-001-0923-z

Field, M., Duka, T., Eastwood, B., Child, R., Santarcangelo, M., & Gayton, M. (2007). Experimental manipulation of attentional biases in heavy drinkers: Do the effects generalise? *PSYCHOPHARMACOLOGY*, *192*(4), 593-608. https://doi.org/10.1007/s00213-007-0760-9

Field, M., Munafò, M. R., & Franken, I. H. A. (2009a). A meta-analytic investigation of the relationship between attentional bias and subjective craving in substance abuse. *Psychological Bulletin*, *135*(4), 589-607. https://doi.org/10.1037/a0015843

Field, M., Duka, T., Tyler, E., & Schoenmakers, T. (2009b). Attentional bias modification in tobacco smokers. *Nicotine Tob Res*, *11*(7), 812-822. https://doi.org/10.1093/ntr/ntp067

Field, M., Hogarth, L., Bleasdale, D., Wright, P., Fernie, G., & Christiansen, P. (2011). Alcohol expectancy moderates attentional bias for alcohol cues in light drinkers. *ADDICTION*, *106*(6), 1097-1103. https://doi.org/10.1111/j.1360-0443.2011.03412.x

Field, M., Mogg, K., Zetteler, J., & Bradley, B. P. (2004a). Attentional biases for alcohol cues in heavy and light social drinkers: the roles of initial orienting and maintained attention. *Psychopharmacology*, *176*(1), 88-93. https://doi.org/10.1007/s00213-004-1855-1

Field, M., Mogg, K., & Bradley, B. P. (2004b). Cognitive bias and drug craving in recreational cannabis users. *Drug and Alcohol Dependence*, *74*(1), 105-111. https://doi.org/https://doi.org/10.1016/j.drugalcdep.2003.12.005

Field, M., Mogg, K., Mann, B., Bennett, G. A., & Bradley, B. P. (2013). Attentional biases in abstinent alcoholics and their association with craving. *PSYCHOL ADDICT BEHAV*, *27*(1), 71-80. https://doi.org/10.1037/a0029626

File, D., Petro, B., Kojouharova, P., Kővári, L., Gaál, Z. A., Demetrovics, Z., & Czigler, I. (2024). The imbalance of self-reported wanting and liking is associated with the degree of attentional bias toward smoking-related stimuli in low nicotine dependence smokers. *Front Psychol*, *15*, 1356434-1356434. https://doi.org/10.3389/fpsyg.2024.1356434

Fleming, K. A., Cofresí, R. U., & Bartholow, B. D. (2021). Transfer of incentive salience from a first-order alcohol cue to a novel second-order alcohol cue among individuals at risk for alcohol use disorder: electrophysiological evidence. *ADDICTION*, *116*(7), 1734-1746. https://doi.org/10.1111/add.15380

Fluharty, M., Taylor, A. E., Grabski, M., & Munafò, M. R. (2017). The Association of Cigarette Smoking With Depression and Anxiety: A Systematic Review. *NICOTINE TOB RES*, *19*(1), 3-13. https://doi.org/10.1093/ntr/ntw140

Folk, C. L., Remington, R. W., & Johnston, J. C. (1992). Involuntary Covert Orienting Is Contingent on Attentional Control Settings. *J Exp Psychol Hum Percept Perform*, *18*(4), 1030-1044. https://doi.org/10.1037/0096-1523.18.4.1030

Fong, T. C. T., Cui, K., & Yip, P. S. F. (2024). Interaction Effects Between Low Self-Control and Meaning in Life on Internet Gaming Disorder Symptoms and Functioning in Chinese Adolescents: Cross-Sectional Latent Moderated Structural Equation Modeling Study. *J Med Internet Res*, *26*(5), e59490. https://doi.org/10.2196/59490

Franken, I. H. A. (2003). Drug craving and addiction: integrating psychological and neuropsychopharmacological approaches. *Progress in Neuro-Psychopharmacology and Biological Psychiatry*, *27*(4), 563-579. https://doi.org/https://doi.org/10.1016/S0278-5846(03)00081-2

Franken, I. H. A., Booij, J., & van den Brink, W. (2005). The role of dopamine in human addiction: From reward to motivated attention. *EUR J PHARMACOL*, *526*(1), 199-206. https://doi.org/10.1016/j.ejphar.2005.09.025

Frewen, P. A., Dozois, D. J. A., Joanisse, M. F., & Neufeld, R. W. J. (2008). Selective attention to threat versus reward: Meta-analysis and neural-network modeling of the dot-probe task. *CLIN PSYCHOL REV*, *28*(2), 307-337. https://doi.org/10.1016/j.cpr.2007.05.006

Frings, C., & Wühr, P. (2012). Don't be afraid of irrelevant words: The emotional Stroop effect is confined to attended words. *COGNITION EMOTION*, *26*(6), 1056-1068. https://doi.org/10.1080/02699931.2011.638908

Frost, R. L., & Rickwood, D. J. (2017). A systematic review of the mental health outcomes associated with Facebook use. *Computers in Human Behaviour*, *76*, 576-600. https://doi.org/10.1016/j.chb.2017.08.001

Gainsbury, S. M. (2015). Online Gambling Addiction: the Relationship Between Internet Gambling and Disordered Gambling. *Curr Addict Rep*, *2*(2), 185-193. https://doi.org/10.1007/s40429-015-0057-8

Garbusow, M., Schad, D. J., Sebold, M., Friedel, E., Bernhardt, N., Koch, S. P.,…Heinz, A. (2016). Pavlovian-to-instrumental transfer effects in the nucleus accumbens relate to relapse in alcohol dependence. *ADDICT BIOL*, *21*(3), 719-731. https://doi.org/10.1111/adb.12243

Garland, E. L., Froeliger, B. E., Passik, S. D., & Howard, M. O. (2013). Attentional bias for prescription opioid cues among opioid dependent chronic pain patients. *J Behav Med*, *36*(6), 611-620. https://doi.org/10.1007/s10865-012-9455-8

Gibaldi, A., Vanegas, M., Bex, P. J., & Maiello, G. (2017). Evaluation of the Tobii EyeX Eye tracking controller and Matlab toolkit for research. *Behav Res*, *49*(3), 923-946. https://doi.org/10.3758/s13428-016-0762-9

Godijn, R., & Theeuwes, J. (2003). The Relationship Between Exogenous and Endogenous Saccades and Attention. In J. Hyönä, R. Radach, & H. Deubel (Eds.), *The Mind's Eye: Cognitive and Applied Aspects of Eye Movement Research* (pp. 3-26). Elsevier. https://doi.org/https://doi.org/10.1016/B978-044451020-4/50002-5

González-Marín, M. d. C., Coune, F., & Naassila, M. (2020). Vulnerability to ethanol sensitisation predicts higher intake and motivation to self-administer ethanol: Proof of the incentive salience sensitisation theory? *Addict Biol*, *25*(6), e12833-n/a. https://doi.org/10.1111/adb.12833

Goslar, M., Leibetseder, M., Muench, H. M., Hofmann, S. G., & Laireiter, A.-R. (2020). Treatments for internet addiction, sex addiction and compulsive buying: A meta-analysis. *J Behav Addict*, *9*(1), 14-43. https://doi.org/10.1556/2006.2020.00005

Grant, J. E., Potenza, M. N., Weinstein, A., & Gorelick, D. A. (2010). Introduction to Behavioural Addictions. *AM J DRUG ALCOHOL AB*, *36*(5), 233-241. https://doi.org/10.3109/00952990.2010.491884

Greenaway, R., Mogg, K., & Bradley, B. P. (2012). Attentional bias for smoking-related information in pregnant women: Relationships with smoking experience, smoking attitudes and perceived harm to foetus. *ADDICT BEHAV*, *37*(9), 1025-1028. https://doi.org/10.1016/j.addbeh.2012.04.005

Griffiths, M. (2005). A 'components' model of addiction within a biopsychosocial framework. In (pp. 191-197): Taylor & Francis.

Griffiths, M. (2019). The evolution of the 'components model of addiction' and the need for a confirmatory approach in conceptualising behavioural addictions. Dusunen Adam The Journal of Psychiatry and Neurological Sciences. *Dusunen Adam*, *32*, 179-184. https://doi.org/10.14744/DAJPNS.2019.00027

Griffiths, M., & Kuss, D. (2017). Adolescent social media addiction (revisited). *Education and Health*, *35*, 49-52.

Griffiths, M. D. (2010). The Role of Context in Online Gaming Excess and Addiction: Some Case Study Evidence [Article]. *International Journal of Mental Health & Addiction*, *8*(1), 119-125. https://doi.org/10.1007/s11469-009-9229-x

Griffiths, M. D., Kuss, D. J., & Demetrovics, Z. (2014). Chapter 6 - Social Networking Addiction:An Overview of Preliminary Findings. In K. P. Rosenberg & L. C. Feder (Eds.), *Behavioural Addictions: Criteria, Evidence, and Treatment* (pp. 119-141). Academic Press. https://doi.org/10.1016/B978-0-12-407724-9.00006-9

Grigutsch, L. A., Lewe, G., Rothermund, K., & Koranyi, N. (2019). Implicit 'wanting' without implicit 'liking': A test of incentive-sensitisation-theory in the context of smoking addiction using the wanting-implicit-association-test (W-IAT). *Journal of Behaviour Therapy and Experimental Psychiatry*, *64*, 9-14. https://doi.org/10.1016/j.jbtep.2019.01.002

Guo, J., Cheng, R., Zhang, W., & Xia, T. (2023). Influence of size and location of buttons on the usability of interface on large touch screens. *ERGONOMICS*, *66*(12), 2025-2038. https://doi.org/10.1080/00140139.2023.2179670

Gusev, A. N., Mikhaylova, O. A., & Utochkin, I. S. (2014). Stimulus determinants of the phenomenon of change blindness. *Psychology in Russia: State of the Art*, *7*(1), 122-134. https://doi.org/10.11621/pir.2014.0112

Haber, S. N. (2016). Corticostriatal circuitry. *DIALOGUES CLIN NEURO*, *18*(1), 7-21. https://doi.org/10.31887/DCNS.2016.18.1/shaber

Hawi, N. S., & Samaha, M. (2017). The Relations Among Social Media Addiction, Self-Esteem, and Life Satisfaction in University Students. *SOC SCI COMPUT REV*, *35*(5), 576-586. https://doi.org/10.1177/0894439316660340

Heffer, T., Good, M., Daly, O., MacDonell, E., & Willoughby, T. (2019). The Longitudinal Association Between Social-Media Use and Depressive Symptoms Among Adolescents and Young Adults: An Empirical Reply to Twenge et al. (2018). *CLIN PSYCHOL SCI*, *7*(3), 462-470. https://doi.org/10.1177/2167702618812727

Heitmann, J., Bennik, E. C., van Hemel-Ruiter, M. E., & de Jong, P. J. (2018). The effectiveness of attentional bias modification for substance use disorder symptoms in adults: a systematic review. *SYST REV-LONDON*, *7*(1), 160-160. https://doi.org/10.1186/s13643-018-0822-6

Hellberg, S. N., Abramowitz, J. S., Ojalehto, H. J., Butcher, M. W., Buchholz, J. L., & Riemann, B. C. (2022). Co-occurring depression and obsessive-compulsive disorder: A dimensional network approach. *Journal of Affective Disorders*, *317*, 417-426. https://doi.org/https://doi.org/10.1016/j.jad.2022.08.101

Hellström, C., Nilsson, K. W., Leppert, J., & Åslund, C. (2012). Influences of motives to play and time spent gaming on the negative consequences of adolescent online computer gaming. *COMPUT HUM BEHAV*, *28*(4), 1379-1387. https://doi.org/10.1016/j.chb.2012.02.023

Hickey, C., & Peelen, Marius V. (2015). Neural Mechanisms of Incentive Salience in Naturalistic Human Vision. *NEURON*, *85*(3), 512-518. https://doi.org/10.1016/j.neuron.2014.12.049

Ho, S. M. Y., Yeung, D., & Mak, C. W. Y. (2017). The interaction effect of attentional bias and attentional control on dispositional anxiety among adolescents. *BRIT J PSYCHOL*, *108*(3), 564-582. https://doi.org/10.1111/bjop.12225

Hobson, J., Bruce, G., & Butler, S. H. (2012). A flicker change blindness task employing eye tracking reveals an association with levels of craving not consumption. *Journal of Psychopharmacology*, *27*(1), 93-97. https://doi.org/10.1177/0269881112447990

Hogarth, L., Dickinson, A., Austin, A., Brown, C., & Duka, T. (2008). Attention and expectation in human predictive learning: The role of uncertainty. *The Quarterly Journal of Experimental Psychology*, *61*(11), 1658-1668. https://doi.org/10.1080/17470210701643439

Hogarth, L., Dickinson, A., & Duka, T. (2009). Detection versus sustained attention to drug cues have dissociable roles in mediating drug seeking behaviour. *Experimental and Clinical Psychopharmacology*, *17*(1), 21-30. https://doi.org/10.1037/a0014957

Hollingworth, A., Schrock, G., & Henderson, J. M. (2001). Change detection in the flicker paradigm: The role of fixation position within the scene. *Memory & Cognition*, *29*(2), 296-304. https://doi.org/10.3758/BF03194923

Hønsi, A., Mentzoni, R. A., Molde, H., & Pallesen, S. (2013). Attentional Bias in Problem Gambling: A Systematic Review. *J Gambl Stud*, *29*(3), 359-375. https://doi.org/10.1007/s10899-012-9315-z

Houghton, S., Lawrence, D., Hunter, S. C., Rosenberg, M., Zadow, C., Wood, L., & Shilton, T. (2018). Reciprocal Relationships between Trajectories of Depressive Symptoms and Screen Media Use during Adolescence. *J Youth Adolescence*, *47*(11), 2453-2467. https://doi.org/10.1007/s10964-018-0901-y

Huang, G., Han, C., Yang, J., Ye, C., Javed, I., Liu, F.,…Yang, M. (2023). Neural basis of the attention bias during addiction stroop task in methamphetamine-dependent patients with and without a history of psychosis: an ERP study. *FRONT PSYCHOL*, *14*, 1173711-1173711. https://doi.org/10.3389/fpsyg.2023.1173711

Hunt, M. G., Marx, R., Lipson, C., & Young, J. (2018). No More FOMO: Limiting Social Media Decreases Loneliness and Depression. Journal of Social and Clinical Psychology, 37(10), 751-768. doi:10.1521/jscp.2018.37.10.751

Jafarkarimi, H., Sim, A., Saadatdoost, R., & Hee, J. (2016). Facebook Addiction among Malaysian Students. *International Journal of Information and Education Technology 2010-3689*, *6*. https://doi.org/10.7763/IJIET.2016.V6.733

Jeromin, F., Nyenhuis, N., & Barke, A. (2016). Attentional bias in excessive Internet gamers: Experimental investigations using an addiction Stroop and a visual probe. *Journal of Behavioural Addictions*, *5*(1), 32-40. https://doi.org/10.1556/2006.5.2016.012

Jiang, Z., Zhao, X., & Li, C. (2017). Self-control predicts attentional bias assessed by online shopping-related Stroop in high online shopping addiction tendency college students. *Comprehensive Psychiatry*, *75*, 14-21. https://doi.org/https://doi.org/10.1016/j.comppsych.2017.02.007

Jones, B. C., Jones, B. T., Blundell, L., & Bruce, G. (2002). Social users of alcohol and cannabis who detect substance-related changes in a change blindness paradigm report higher levels of use than those detecting substance-neutral changes. *Psychopharmacology*, *165*(1), 93-96. https://doi.org/10.1007/s00213-002-1264-2

Jones, B. T., Bruce, G., Livingstone, S., & Reed, E. (2006). Alcohol-Related Attentional Bias in Problem Drinkers With the Flicker Change Blindness Paradigm. *Psychol Addict Behav*, *20*(2), 171-177. https://doi.org/10.1037/0893-164X.20.2.171

Jones, B. T., Jones, B. C., Smith, H., & Copley, N. (2003). A flicker paradigm for inducing change blindness reveals alcohol and cannabis information processing biases in social users. *Addiction*, *98*(2), 235-244. https://doi.org/10.1046/j.1360-0443.2003.00270.x

Kahan, T. A., & Hely, C. D. (2008). The role of valence and frequency in the emotional Stroop task. *Psychonomic Bulletin & Review*, *15*(5), 956-960. https://doi.org/10.3758/PBR.15.5.956

Kahneman, D. (2012). *Thinking, fast and slow*. Penguin

Kanwal, A., Munir, H., & Abrar, S. (2024). SMARTPHONE ADDICTION, PROBLEMATIC SOCIAL MEDIA USE & MENTAL HEALTH PROBLEMS AMONG YOUNG ADULTS. *The Gomal University journal of research*, *40*(4), 456-466. https://doi.org/10.51380/gujr-40-04-05

Kappenman, E. S., Farrens, J. L., Luck, S. J., & Proudfit, G. H. (2014). Behavioural and ERP measures of attentional bias to threat in the dot-probe task: poor reliability and lack of correlation with anxiety [10.3389/fpsyg.2014.01368]. *Frontiers in Psychology*, *5*, 1368.

Kappenman, E. S., MacNamara, A., & Proudfit, G. H. (2015). Electrocortical evidence for rapid allocation of attention to threat in the dot-probe task. *Social Cognitive and Affective Neuroscience*, *10*(4), 577-583. https://doi.org/10.1093/scan/nsu098

Kardefelt-Winther, D., Heeren, A., Schimmenti, A., van Rooij, A., Maurage, P., Carras, M.,…Billieux, J. (2017). How can we conceptualise behavioural addiction without pathologizing common behaviours? *Addiction*, *112*(10), 1709-1715. https://doi.org/10.1111/add.13763

Kavanagh, D. J., Andrade, J., & May, J. (2005). Imaginary Relish and Exquisite Torture: The Elaborated Intrusion Theory of Desire. *Psychological Review*, *112*(2), 446-467. https://doi.org/10.1037/0033-295X.112.2.446

Keles, B., McCrae, N., & Grealish, A. (2020). A systematic review: the influence of social media on depression, anxiety and psychological distress in adolescents. *INT J ADOLESC YOUTH*, *25*(1), 79-93. https://doi.org/10.1080/02673843.2019.1590851

Kennedy, A. P., Gross, R. E., Ely, T., Drexler, K. P. G., & Kilts, C. D. (2014). Clinical correlates of attentional bias to drug cues associated with cocaine dependence. *AM J ADDICTION*, *23*(5), 478-484. https://doi.org/10.1111/j.1521-0391.2014.12134.x

Kim, H. S., & Hodgins, D. C. (2018). Component model of addiction treatment: A pragmatic transdiagnostic treatment model of behavioural and substance addictions. *FRONT PSYCHIATRY*, *9*, 406-406. https://doi.org/10.3389/fpsyt.2018.00406

Kircaburun, K., & Griffiths, M. (2018). The dark side of internet: Preliminary evidence for the associations of dark personality traits with specific online activities and problematic internet use. *Journal of Behavioural Addictions*, *7*(4), 993-1003. https://doi.org/10.1556/2006.7.2018.109

Klinger, E. (1996). Emotional influences on cognitive processing, with implications for theories of both. In *The psychology of action: Linking cognition and motivation to behaviour.* (pp. 168-189). The Guilford Press.

Klinger, E., & Cox, W. (2008). Motivation and the Theory of Current Concerns. In E. Klinger & W. M. Cox (Eds.), *Handbook of Motivational Counseling: Concepts, Approaches, and Assessment.* (pp. 3-27). John Wiley & Sons Ltd. https://doi.org/10.1002/9780470713129.ch1

Klinger, D., Plener, P. L., Marboe, G., Karwautz, A., Kothgassner, O. D., & Dienlin, T. (2024). Exploring the relationship between media use and depressive symptoms among gender diverse youth: findings of the Mental Health Days Study. *Child and Adolescent Psychiatry and Mental Health*, *18*(1), 104. https://doi.org/10.1186/s13034-024-00797-x

Knight, H. C., Smith, D. T., Knight, D. C., & Ellison, A. (2018). Light social drinkers are more distracted by irrelevant information from an induced attentional bias than heavy social drinkers. *Psychopharmacology*, *235*(10), 2967-2978. https://doi.org/10.1007/s00213-018-4987-4

Konkolÿ Thege, B., Horwood, L., Slater, L., Tan, M. C., Hodgins, D. C., & Wild, T. C. (2017). Relationship between interpersonal trauma exposure and addictive behaviours: A systematic review. *BMC PSYCHIATRY*, *17*(1), 164-164. https://doi.org/10.1186/s12888-017-1323-1

Konkolÿ Thege, B., Woodin, E. M., Hodgins, D. C., & Williams, R. J. (2015). Natural course of behavioural addictions: a 5-year longitudinal study. *BMC PSYCHIATRY*, *15*(1), 4-4. https://doi.org/10.1186/s12888-015-0383-3

Kose, O. B., & Dogan, A. (2019). The Relationship between Social Media Addiction and Self-Esteem among Turkish University Students. *ADDICTA*, *6*(1), 175-190. https://doi.org/10.15805/addicta.2019.6.1.0036

Koster, E. H. W., Crombez, G., Verschuere, B., & De Houwer, J. (2004). Selective attention to threat in the dot probe paradigm: differentiating vigilance and difficulty to disengage. *BEHAV RES THER*, *42*(10), 1183-1192. https://doi.org/10.1016/j.brat.2003.08.001

Kraeplin, A. (2017). Conceptualising behavioural addiction in children and adolescents. *ADDICTION*, *112*(10), 1721-1723. https://doi.org/10.1111/add.13846

Kumalaratih, E., & Hendy Muagiri, M. (2023). Interaction of Person-Affect-Cognition-Execution (I-PACE) Model on Addictive Behaviour. *Jurnal Psikiatri Surabaya*, *12*(1), 12-19. https://doi.org/10.20473/jps.v12i1.28893

Kuss, D. J., & Griffiths, M. D. (2012). Internet Gaming Addiction: A Systematic Review of Empirical Research. *Int J Ment Health Addiction*, *10*(2), 278-296. https://doi.org/10.1007/s11469-011-9318-5

Kuss, D. J., & Griffiths, M. D. (2017). Social Networking Sites and Addiction: Ten Lessons Learned. *International Journal of Environmental Research and Public Health*, *14*(3), Article 311. https://doi.org/10.3390/ijerph14030311

Kuss, D. J., Griffiths, M. D., & Binder, J. F. (2013). Internet addiction in students: Prevalence and risk factors. *COMPUT HUM BEHAV*, *29*(3), 959-966. https://doi.org/10.1016/j.chb.2012.12.024

Kuss, D. J., & Lopez-Fernandez, O. (2016). Internet addiction and problematic Internet use: A systematic review of clinical research. *World J Psychiatry*, *6*(1), 143-176. https://doi.org/10.5498/wjp.v6.i1.143

Lane, B. R., Mulgrew, K. E., Mahar, D., White, M. J., & Loughnan, S. A. (2017). The effects of priming in a cued dot-probe task on appearance-related attentional biases in women. *INT J EAT DISORDER*, *50*(7), 817-825. https://doi.org/10.1002/eat.22699

Langner, R., Scharnowski, F., Ionta, S., Salmon, C. E. G., Piper, B. J., & Pamplona, G. S. P. (2023). Evaluation of the reliability and validity of computerized tests of attention. *PLoS One*, *18*(1), e0281196-e0281196. https://doi.org/10.1371/journal.pone.0281196

Langston, R. G., & Virmani, T. (2018). Use of a Modified STROOP Test to Assess Colour Discrimination Deficit in Parkinson's Disease. *FRONT NEUROL*, *9*, 765-765. https://doi.org/10.3389/fneur.2018.00765

Lervik-Olsen, L., Andreassen, T. W., & Fennis, B. M. (2023). When enough is not enough: behavioural and motivational paths to compulsive social media consumption. *EUR J MARKETING*, *58*(2), 519-547. https://doi.org/10.1108/EJM-12-2022-0898

Lin, L. Y., Sidani, J. E., Shensa, A., Radovic, A., Miller, E., Colditz, J. B.,…Primack, B. A. (2016). ASSOCIATION BETWEEN SOCIAL MEDIA USE AND DEPRESSION AMONG U.S. YOUNG ADULTS. *Depress Anxiety*, *33*(4), 323-331. https://doi.org/10.1002/da.22466

Liu, S., Lane, S. D., Schmitz, J. M., Waters, A. J., Cunningham, K. A., & Moeller, F. G. (2011). Relationship between attentional bias to cocaine-related stimuli and impulsivity in cocaine-dependent subjects. *AM J DRUG ALCOHOL AB*, *37*(2), 117-122. https://doi.org/10.3109/00952990.2010.543204

Liu, Y., Bengson, J., Huang, H., Mangun, G. R., & Ding, M. (2016). Top-down Modulation of Neural Activity in Anticipatory Visual Attention: Control Mechanisms Revealed by Simultaneous EEG-fMRI. *Cereb Cortex*, *26*(2), 517-529. https://doi.org/10.1093/cercor/bhu204

Lochbuehler, K., Wileyto, E. P., Tang, K. Z., Mercincavage, M., Cappella, J. N., & Strasser, A. A. (2018). Do current and former cigarette smokers have an attentional bias for e-cigarette cues? *J PSYCHOPHARMACOL*, *32*(3), 316-323. https://doi.org/10.1177/0269881117728418

Loh, Z., Hall, E. H., Cronin, D., & Henderson, J. M. (2023). Working memory control predicts fixation duration in scene-viewing. *Psychological Research*, *87*(4), 1143-1154. https://doi.org/10.1007/s00426-022-01694-8

Lopes, F. M., Viacava, K. R., & Bizarro, L. (2015). Attentional bias modification based on visual probe task: methodological issues, results and clinical relevance. *Trends Psychiatry Psychother*, *37*(4), 183-193. https://doi.org/10.1590/2237-6089-2015-0011

Lorenz, R. C., Krüger, J.-K., Neumann, B., Schott, B. H., Kaufmann, C., Heinz, A., & Wüstenberg, T. (2013). Cue reactivity and its inhibition in pathological computer game players. *ADDICT BIOL*, *18*(1), 134-146. https://doi.org/10.1111/j.1369-1600.2012.00491.x

Lovett, M. C. (2002). Modeling selective attention: Not just another model of Stroop (NJAMOS). *Cognitive systems research*, *3*(1), 67-76. https://doi.org/10.1016/S1389-0417(01)00045-6

Lovett, M. C. (2005). A Strategy-Based Interpretation of Stroop. *COGNITIVE SCI*, *29*(3), 493-524. https://doi.org/10.1207/s15516709cog0000_24

Luijten, M., Schellekens, A. F., Kühn, S., Machielse, M. W. J., & Sescousse, G. (2017). Disruption of reward-processing in addiction unravelled by image based meta-analysis of fMRI studies. *European neuropsychopharmacology*, *27*, S557. https://doi.org/10.1016/S0924-977X(17)31070-2

Luijten, M., Veltman, D. J., Hester, R., Smits, M., Pepplinkhuizen, L., & Franken, I. H. A. (2012). Brain activation associated with attentional bias in smokers is modulated by a dopamine antagonist. *Neuropsychopharmacology*, *37*(13), 2772-2779. https://doi.org/10.1038/npp.2012.143

Lusher, J., Chandler, C., & Ball, D. (2004). Alcohol dependence and the alcohol Stroop paradigm: evidence and issues. *DRUG ALCOHOL DEPEN*, *75*(3), 225-231. https://doi.org/10.1016/j.drugalcdep.2004.03.004

MacLeod, C., Mathews, A., & Tata, P. (1986). Attentional bias in emotional disorders. *J Abnorm Psychol*, *95*(1), 15-20. https://doi.org/10.1037//0021-843x.95.1.15

Mahler, S. V., Smith, K. S., & Berridge, K. C. (2007). Endocannabinoid Hedonic Hotspot for Sensory Pleasure: Anandamide in Nucleus Accumbens Shell Enhances 'Liking' of a Sweet Reward. *Neuropsychopharmacol*, *32*(11), 2267-2278. https://doi.org/10.1038/sj.npp.1301376

Manchery, L., Yarmush, D. E., Luehring-Jones, P., & Erblich, J. (2017). Attentional bias to alcohol stimuli predicts elevated cue-induced craving in young adult social drinkers. *ADDICT BEHAV*, *70*, 14-17. https://doi.org/10.1016/j.addbeh.2017.01.035

Marks, K. R., Alcorn, J. L., Stoops, W. W., & Rush, C. R. (2016). Cigarette Cue Attentional Bias in Cocaine-Smoking and Non-Cocaine-Using Cigarette Smokers. *Nicotine Tob Res*, *18*(9), 1915-1919. https://doi.org/10.1093/ntr/ntw026

Marlatt, G. A., VandenBos, G. R., & American Psychological, A. (1997). Addictive behaviours : readings on etiology, prevention, and treatment / [internet resource].

Marttila, E., Koivula, A., & Räsänen, P. (2021). Does excessive social media use decrease subjective well-being? A longitudinal analysis of the relationship between problematic use, loneliness and life satisfaction. *Telematics and Informatics*, *59*, 101556. https://doi.org/https://doi.org/10.1016/j.tele.2020.101556

McConkie, G., & Loschky, L. (2005). Change Blindness, Psychology of. *1*, 491-495. https://doi.org/10.1002/0470018860.s00492

McCrady, B. S., Zucker, R. A., Molina, B. S. G., Ammon, L., Ames, G. M., & Longabaugh, R. (2006). Social Environmental Influences on the Development and Resolution of Alcohol Problems. *ALCOHOL CLIN EXP RES*, *30*(4), 688-699. https://doi.org/10.1111/j.1530-0277.2006.00080.x

Mentzoni, R. A., Sætrevik, B., Molde, H., Wiium, N., Hetland, J., Fagerland, I.,…Pallesen, S. (2014). Attentional Bias in Snus Users: An Experimental Study. *PLOS ONE*, *9*(10), e108897. https://doi.org/10.1371/journal.pone.0108897

Miller, M. A., & Fillmore, M. T. (2010). The effect of image complexity on attentional bias towards alcohol-related images in adult drinkers [https://doi.org/10.1111/j.1360-0443.2009.02860.x]. *Addiction*, *105*(5), 883-890. https://doi.org/https://doi.org/10.1111/j.1360-0443.2009.02860.x

Mogg, K., Bradley, B. P., Field, M., & De Houwer, J. (2003). Eye movements to smoking-related pictures in smokers: relationship between attentional biases and implicit and explicit measures of stimulus valence. *Addiction*, *98*(6), 825-836. https://doi.org/10.1046/j.1360-0443.2003.00392.x

Mogg, K., Field, M., & Bradley, B. P. (2005). Attentional and approach biases for smoking cues in smokers: an investigation of competing theoretical views of addiction. *PSYCHOPHARMACOLOGY*, *180*(2), 333-341. https://doi.org/10.1007/s00213-005-2158-x

Monem, R., & Fillmore, M. T. (2019). Alcohol Administration Reduces Attentional Bias to Alcohol-Related but Not Food-Related Cues: Evidence for a Satiety Hypothesis. *PSYCHOL ADDICT BEHAV*, *33*(8), 677-684. https://doi.org/10.1037/adb0000522

Moretta, T., Franceschini, C., & Musetti, A. (2023). Loneliness and problematic social networking sites use in young adults with poor vs. good sleep quality: The moderating role of gender. *Addictive Behaviours*, *142*, 107687. https://doi.org/https://doi.org/10.1016/j.addbeh.2023.107687

Moss, A. C., Albery, I. P., & Sharma, D. (2011). Development of a repeated measures affective change blindness task. *Behav Res*, *43*(3), 826-833. https://doi.org/10.3758/s13428-011-0072-1

Müller, A., Mitchell, J. E., & de Zwaan, M. (2015). Compulsive buying. *Am J Addict*, *24*(2), 132-137. https://doi.org/10.1111/ajad.12111

Munafò, M., Mogg, K., Roberts, S., Bradley, B. P., & Murphy, M. (2003). Selective Processing of Smoking-Related Cues in Current Smokers, Ex-Smokers and Never-Smokers on the Modified Stroop Task. *J PSYCHOPHARMACOL*, *17*(3), 310-316. https://doi.org/10.1177/02698811030173013

Nees, F., Diener, C., Smolka, M. N., & Flor, H. (2012). The role of context in the processing of alcohol-relevant cues. *Addict Biol*, *17*(2), 441-451. https://doi.org/10.1111/j.1369-1600.2011.00347.x

Nesi, J. (2020). The Impact of Social Media on Youth Mental Health: Challenges and Opportunities. *N C Med J*, *81*(2), 116-121. https://doi.org/10.18043/ncm.81.2.116

Nikolaidou, M., Fraser, D. S., & Hinvest, N. (2019). Attentional bias in Internet users with problematic use of social networking sites. *Journal of Behavioural Addictions*, *8*(4), 733-742. https://doi.org/10.1556/2006.8.2019.60

Niziolek, C. A., Lin, K. R., Beach, S. D., Quillen, I. A., & Kiran, S. (2017). Speech acoustics can be modulated by cognitive interference in a vowel-modified Stroop task. *The Journal of the Acoustical Society of America*, *141*(5), 3582-3582. https://doi.org/10.1121/1.4987641

Noël, X., Brevers, D., & Bechara, A. (2013). A Triadic Neurocognitive Approach to Addiction for Clinical Interventions. *Front Psychiatry*, *4*, 179-179. https://doi.org/10.3389/fpsyt.2013.00179

Olasina, G., & Kheswa, S. (2021). Exploring the factors of excessive smartphone use by undergraduate students. *Knowledge management & e-learning*, *13*(1), 118-141. https://doi.org/10.34105/j.kmel.2021.13.007

Olney, J. J., Warlow, S. M., Naffziger, E. E., & Berridge, K. C. (2018). Current perspectives on incentive salience and applications to clinical disorders. *CURR OPIN BEHAV SCI*, *22*, 59-69. https://doi.org/10.1016/j.cobeha.2018.01.007

Ostlund, S. B., LeBlanc, K. H., Kosheleff, A. R., Wassum, K. M., & Maidment, N. T. (2014). Phasic Mesolimbic Dopamine Signaling Encodes the Facilitation of Incentive Motivation Produced by Repeated Cocaine Exposure. *NEUROPSYCHOPHARMACOL*, *39*(10), 2441-2449. https://doi.org/10.1038/npp.2014.96

Panksepp, J. (2023). *Affective neuroscience: the foundations of human and animal emotions*. Oxford University Press

Papachristou, H., Nederkoorn, C., Giesen, J. C. A. H., & Jansen, A. (2014). Cue reactivity during treatment, and not impulsivity, predicts an initial lapse after treatment in alcohol use disorders. *ADDICT BEHAV*, *39*(3), 737-739. https://doi.org/10.1016/j.addbeh.2013.11.027

Parris, B. A., Augustinova, M., & Ferrand, L. (2019). Editorial: The Locus of the Stroop Effect. *FRONT PSYCHOL*, *10*, 2860-2860. https://doi.org/10.3389/fpsyg.2019.02860

Parsons, S., Kruijt, A.-W., & Fox, E. (2019). Psychological Science Needs a Standard Practice of Reporting the Reliability of Cognitive-Behavioural Measurements. *Advances in Methods and Practices in Psychological Science*, *2*(4), 378-395. https://doi.org/10.1177/2515245919879695

Paschke, K., Austermann, M. I., & Thomasius, R. (2021). ICD-11-Based Assessment of Social Media Use Disorder in Adolescents: Development and Validation of the Social Media Use Disorder Scale for Adolescents. *FRONT PSYCHIATRY*, *12*, 661483-661483. https://doi.org/10.3389/fpsyt.2021.661483

Paulhus, D. L. (1991). Measurement and control of response bias. In J. P. Robinson, P. R. Shaver, & L. S. Wrightsman (Eds.), *Measures of personality and social psychological* *attitudes* (pp. 17–59). Academic Press. https://doi.org/10.1016/B978-0-12-590241-0.50006-X

Peciña, S., & Berridge, K. C. (2013). Dopamine or opioid stimulation of nucleus accumbens similarly amplify cue-triggered 'wanting' for reward: entire core and medial shell mapped as substrates for PIT enhancement. *EUR J NEUROSCI*, *37*(9), 1529-1540. https://doi.org/10.1111/ejn.12174

Pekal, J., Laier, C., Snagowski, J., Stark, R., & Brand, M. (2018). Tendencies toward Internet-pornography-use disorder: Differences in men and women regarding attentional biases to pornographic stimuli. *J BEHAV ADDICT*, *7*(3), 574-583. https://doi.org/10.1556/2006.7.2018.70

Pennington, C. R., Shaw, D. J., Adams, J., Kavanagh, P., Reed, H., Robinson, M.,…White, H. (2020). Where's the wine? Heavy social drinkers show attentional bias towards alcohol in a visual conjunction search task. *ADDICTION*, *115*(9), 1650-1659. https://doi.org/10.1111/add.14997

Petry, N. M., & Weiss, L. (2009). Social Support is Associated with Gambling Treatment Outcomes in Pathological Gamblers. *AM J ADDICTION*, *18*(5), 402-408. https://doi.org/10.1080/10550490903077861

Petry, N. M., Zajac, K., & Ginley, M. K. (2018). Behavioural Addictions as Mental Disorders: To Be or Not To Be? *Annu Rev Clin Psychol*, *14*(1), 399-423. https://doi.org/10.1146/annurev-clinpsy-032816-045120

Poole, J. C., Kim, H. S., Dobson, K. S., & Hodgins, D. C. (2017). Adverse Childhood Experiences and Disordered Gambling: Assessing the Mediating Role of Emotion Dysregulation. *J Gambl Stud*, *33*(4), 1187-1200. https://doi.org/10.1007/s10899-017-9680-8

Posner, M. I., & Petersen, S. E. (1990). The Attention System of the Human Brain. *Annu Rev Neurosci*, *13*(1), 25-42. https://doi.org/10.1146/annurev.ne.13.030190.000325

Posner, M. I., & Rothbart, M. K. (2007). Research on attention networks as a model for the integration of psychological science. *ANNU REV PSYCHOL*, *58*(1), 1-23. https://doi.org/10.1146/annurev.psych.58.110405.085516

Posner, M. I., Snyder, C. R., & Davidson, B. J. (1980). Attention and the detection of signals. *J EXP PSYCHOL GEN*, *109*(2), 160-174. https://doi.org/10.1037/0096-3445.109.2.160

Potenza, M. N. (2018). Searching for Replicable Dopamine-Related Findings in Gambling Disorder. *Biol Psychiatry*, *83*(12), 984-986. https://doi.org/10.1016/j.biopsych.2018.04.011

Prolific. (2021). *Easily collect high-quality data from real people*. Prolific. http://www.prolific.com/

Przybylski, A. K., Murayama, K., DeHaan, C. R., & Gladwell, V. (2013). Motivational, emotional, and behavioural correlates of fear of missing out. *Computers in human behaviour*, *29*(4), 1841-1848. https://doi.org/10.1016/j.chb.2013.02.014

Psychology Software Tools. (2020). *E-prime go: Psychology software tools*. Psychology Software Tools | Solutions for Research, Assessment, and Education. https://pstnet.com/eprime-go/

Qualtrics. (2021). *Qualtrics XM - experience management software*. Qualtrics. https://www.qualtrics.com/

Ramirez, J. J., Monti, P. M., & Colwill, R. M. (2015). Alcohol-Cue Exposure Effects on Craving and Attentional Bias in Underage College-Student Drinkers. *PSYCHOL ADDICT BEHAV*, *29*(2), 317-322. https://doi.org/10.1037/adb0000028

Redish, A. D., Jensen, S., & Johnson, A. (2008). A unified framework for addiction: Vulnerabilities in the decision process. *BEHAV BRAIN SCI*, *31*(4), 415-437. https://doi.org/10.1017/S0140525X0800472X

Rehbein, F., & Baier, D. (2013). Family-, Media-, and School-Related Risk Factors of Video Game Addiction: A 5-Year Longitudinal Study. *J MEDIA PSYCHOL-GER*, *25*(3), 118-128. https://doi.org/10.1027/1864-1105/a000093

Rehme, A. K., Bey, K., Frommann, I., Mogg, K., Bradley, B. P., Bludau, J.,…Wagner, M. (2018). Selective attention to smoking cues in former smokers. *EUR NEUROPSYCHOPHARM*, *28*(2), 276-284. https://doi.org/10.1016/j.euroneuro.2017.12.003

Rensink, R. A. (2000). The Dynamic Representation of Scenes. *Visual cognition*, *7*(1-3), 17-42. https://doi.org/10.1080/135062800394667

Rensink, R. A., O'Regan, J. K., & Clark, J. J. (1997). To See or not to See: The Need for Attention to Perceive Changes in Scenes. *Psychological Science*, *8*(5), 368-373. https://doi.org/10.1111/j.1467-9280.1997.tb00427.x

Robbins, S. J., & Ehrman, R. N. (2004). The role of attentional bias in substance abuse. *Behavioural and Cognitive Neuroscience Reviews*, *3*(4), 243-260.

Roberts, J. A., Yaya, L. H. P., & Manolis, C. (2014). The invisible addiction: Cell-phone activities and addiction among male and female college students. *J BEHAV ADDICT*, *3*(4), 254-265. https://doi.org/10.1556/jba.3.2014.015

Robinson, J. D., Cui, Y., Linares Abrego, P., Engelmann, J. M., Prokhorov, A. V., Vidrine, D. J.,…Cinciripini, P. M. (2022). Sustained Reduction of Attentional Bias to Smoking Cues by Smartphone-Delivered Attentional Bias Modification Training for Smokers. *PSYCHOL ADDICT BEHAV*, *36*(7), 906-919. https://doi.org/10.1037/adb0000805

Robinson, T. E., & Berridge, K. C. (1993). The neural basis of drug craving: An incentive-sensitisation theory of addiction. *Brain Research Reviews*, *18*(3), 247-291. https://doi.org/10.1016/0165-0173(93)90013-P

Robinson, T. E., & Berridge, K. C. (2000). The psychology and neurobiology of addiction: an incentive–sensitisation view. *Addiction*, *95*(8s2), 91-117. https://doi.org/10.1046/j.1360-0443.95.8s2.19.x

Robinson, T. E., & Berridge, K. C. (2001). Incentive-sensitisation and addiction. *Addiction*, *96*(1), 103-114. https://doi.org/10.1046/j.1360-0443.2001.9611038.x

Robinson, T. E., & Berridge, K. C. (2008a). The incentive sensitisation theory of addiction: some current issues. *Philosophical Transactions of the Royal Society B-Biological Sciences*, *363*(1507), 3137-3146. https://doi.org/10.1098/rstb.2008.0093

Robinson, T. E., & Berridge, K. C. (2008b). The Incentive Sensitisation Theory of Addiction: Some Current Issues. *Philosophical Transactions: Biological Sciences*, *363*(1507), 3137-3146.

Roy-Charland, A., Plamondon, A., Homeniuk, A. S., Flesch, C. A., Klein, R. M., & Stewart, S. H. (2017). Attentional bias toward alcohol-related stimuli in heavy drinkers: evidence from dynamic eye movement recording. *AM J DRUG ALCOHOL AB*, *43*(3), 332-340. https://doi.org/10.1080/00952990.2016.1209511

Ryan, T., Chester, A., Reece, J., & Xenos, S. (2014). The uses and abuses of Facebook: A review of Facebook addiction. *Journal of Behavioural Addictions*, *3*(3), 133-148. https://doi.org/10.1556/jba.3.2014.016

Rømer Thomsen, K., Fjorback, L. O., Møller, A., & Lou, H. C. (2014). Applying incentive sensitisation models to behavioural addiction. *Neuroscience & Biobehavioural Reviews*, *45*, 343-349. https://doi.org/https://doi.org/10.1016/j.neubiorev.2014.07.009

Savci, M., & Griffiths, M. D. (2021). The Development of the Turkish Social Media Craving Scale (SMCS): a Validation Study. *Int J Ment Health Addiction*, *19*(2), 359-373. https://doi.org/10.1007/s11469-019-00062-9

Scarpina, F., & Tagini, S. (2017). The Stroop Colour and Word Test. *FRONT PSYCHOL*, *8*, 557-557. https://doi.org/10.3389/fpsyg.2017.00557

Schmukle, S. C. (2005). Unreliability of the dot probe task. *EUR J PERSONALITY*, *19*(7), 595-605. https://doi.org/10.1002/per.554

Schoenmakers, T., Wiers, R. W., & Field, M. (2008). Effects of a low dose of alcohol on cognitive biases and craving in heavy drinkers. *Psychopharmacology*, *197*(1), 169-178. https://doi.org/10.1007/s00213-007-1023-5

Schreiber, L. R. N., Grant, J. E., & Odlaug, B. L. (2013). The overlap between binge eating disorder and substance use disorders: Diagnosis and neurobiology. *J BEHAV ADDICT*, *2*(4), 191-198. https://doi.org/10.1556/JBA.2.2013.015

Shaffer, H. J., Hall, M. N., & Bilt, J. V. (2000). "Computer Addiction": A Critical Consideration. *AM J ORTHOPSYCHIAT*, *70*(2), 162-168. https://doi.org/10.1037/h0087741

Sharma, D., Albery, I. P., & Cook, C. (2001). Selective attentional bias to alcohol related stimuli in problem drinkers and non-problem drinkers. *ADDICTION*, *96*(2), 285-295. https://doi.org/10.1046/j.1360-0443.2001.96228512.x

Sherman, L. E., Greenfield, P. M., Hernandez, L. M., & Dapretto, M. (2018). Peer Influence Via Instagram: Effects on Brain and Behaviour in Adolescence and Young Adulthood. *CHILD DEV*, *89*(1), 37-47. https://doi.org/10.1111/cdev.12838

Shensa, A., Escobar-Viera, C. G., Sidani, J. E., Bowman, N. D., Marshal, M. P., & Primack, B. A. (2017). Problematic social media use and depressive symptoms among U.S. young adults: A nationally-representative study. *SOC SCI MED*, *182*, 150-157. https://doi.org/10.1016/j.socscimed.2017.03.061

Simons, D. J., Franconeri, S. L., & Reimer, R. L. (2000). Change Blindness in the Absence of a Visual Disruption. *PERCEPTION*, *29*(10), 1143-1154. https://doi.org/10.1068/p3104

Slutske, W. S. (2006). Natural Recovery and Treatment-Seeking in Pathological Gambling: Results of Two U.S. National Surveys. *American Journal of Psychiatry*, *163*(2), 297-302. https://doi.org/10.1176/appi.ajp.163.2.297

Smith, K. S., Mahler, S. V., Pecina, S., & Berridge, K. C. (2011). Hedonic hotspots: Generating sensory pleasure in the brain. In Kringelbach, M. L. & Berridge, K. C. (Eds.), *Pleasures of the brain* (pp. 27–49). Oxford University Press. https://doi.org/10.1016/S0278-2626(03)00014-9

Sofuoglu, M., & Kosten, T. R. (2006). Emerging pharmacological strategies in the fight against cocaine addiction. *Expert Opin Emerg Drugs*, *11*(1), 91-98. https://doi.org/10.1517/14728214.11.1.91

Spiegelhalder, K., Jähne, A., Kyle, S. D., Beil, M., Doll, C., Feige, B., & Riemann, D. (2011). Is Smoking-related Attentional Bias a Useful Marker for Treatment Effects? *BEHAV MED*, *37*(1), 26-34. https://doi.org/10.1080/08964289.2010.543195

Stanesby, O., Labhart, F., Dietze, P., Wright, C. J. C., & Kuntsche, E. (2019). The contexts of heavy drinking: A systematic review of the combinations of context-related factors associated with heavy drinking occasions. *PLOS ONE*, *14*(7), e0218465-e0218465. https://doi.org/10.1371/journal.pone.0218465

Starcevic, V. (2016). Tolerance and withdrawal symptoms may not be helpful to enhance understanding of behavioural addictions. *ADDICTION*, *111*(7), 1307-1308. https://doi.org/10.1111/add.13381

Starzomska, M. (2017). Applications of the dot probe task in attentional bias research in eating disorders: A review. *PSICOLOGICA*, *38*(2), 283-346.

Statista. (2020). Social Media Usage Worldwide. Statista. https://www.statista.com/study/12393/social-networks-statista- dossier/

Staugaard, S. R. (2009). Reliability of two versions of the dot-probe task using photographic faces. *Psychology science*, *51*(3), 339.

Tang, C. S.-K., Koh, Y. W., & Gan, Y. (2017). Addiction to Internet Use, Online Gaming, and Online Social Networking Among Young Adults in China, Singapore, and the United States. *Asia-Pacific Journal of Public Health*, *29*(8), 673-682. https://doi.org/10.1177/1010539517739558

Tejero, P., Perea, M., & Jiménez, M. (2014). Is there a genuine advantage to the upper part of words during lexical access? Evidence from the Stroop task. *Mem Cogn*, *42*(5), 834-841. https://doi.org/10.3758/s13421-013-0390-x

Thomas, T. A., Joshi, M., Trotzke, P., Steins-Loeber, S., & Müller, A. (2023). Cognitive Functions in Compulsive Buying-Shopping Disorder: a Systematic Review. *Curr Behav Neurosci Rep*, *10*(1), 1-19. https://doi.org/10.1007/s40473-023-00255-6

Thomson, K., Hunter, S. C., Butler, S. H., & Robertson, D. J. (2021). Social media ‘addiction’: The absence of an attentional bias to social media stimuli. *J BEHAV ADDICT*, *10*(2), 302-313. https://doi.org/10.1556/2006.2021.00011

Tibber, M. S., & Silver, E. (2022). A trans-diagnostic cognitive behavioural conceptualisation of the positive and negative roles of social media use in adolescents’ mental health and wellbeing. *tCBT*, *15*. https://doi.org/10.1017/S1754470X22000034

Tiffany, S. T., & Drobes, D. J. (1991). The development and initial validation of a questionnaire on smoking urges. *Br J Addict*, *86*(11), 1467-1476. https://doi.org/10.1111/j.1360-0443.1991.tb01732.x

Türkoğlu, S., Amado, S., Gönül, A. S., & Eker, Ç. d. (2022). Comparison of Alcohol Attentional Bias and Alcohol Craving Among Alcohol Abusers and Non-Abusers. *Current Approaches in Psychiatry*, *14*(Suppl. 1), 75-82. https://doi.org/10.18863/pgy.1095312

Uyaroğlu, A. K., Ergin, E., Tosun, A. S., & Erdem, Ö. (2022). A cross-sectional study of social media addiction and social and emotional loneliness in university students in Turkey [https://doi.org/10.1111/ppc.13056]. *Perspectives in Psychiatric Care*, *n/a*(n/a). https://doi.org/https://doi.org/10.1111/ppc.13056

van den Eijnden, R. J. J. M., Lemmens, J. S., & Valkenburg, P. M. (2016). The Social Media Disorder Scale. *Computers in Human Behaviour*, *61*, 478-487. https://doi.org/https://doi.org/10.1016/j.chb.2016.03.038

van Holst, R. J. M. S., Lemmens, J. S. P. D., Valkenburg, P. M. P. D., Peter, J. P. D., Veltman, D. J. M. D. P. D., & Goudriaan, A. E. P. D. (2012). Attentional Bias and Disinhibition Toward Gaming Cues Are Related to Problem Gaming in Male Adolescents. *J ADOLESCENT HEALTH*, *50*(6), 541-546. https://doi.org/10.1016/j.jadohealth.2011.07.006

van Laarhoven, A. I. M., Becker, J. M., van Ryckeghem, D. M. L., Van Damme, S., Crombez, G., & Wiers, R. W. H. J. (2021). Attentional Bias Modification Training for Itch: A Proof-of-Principle Study in Healthy Individuals. *FRONT MED-LAUSANNE*, *8*. https://doi.org/10.3389/fmed.2021.627593

van Rooij, A. J., & Prause, N. (2014). A critical review of "Internet addiction" criteria with suggestions for the future. *J BEHAV ADDICT*, *3*(4), 203-213. https://doi.org/10.1556/JBA.3.2014.4.1

Varakin, D., Tolliver, J., & Miller, A. (2021). Gaze cues from the past can attenuate change blindness in the flicker paradigm. *Journal of vision (Charlottesville, Va.)*, *21*(9), 2625. https://doi.org/10.1167/jov.21.9.2625

Varona, M. N., Muela, A., & Machimbarrena, J. M. (2022). Problematic use or addiction? A scoping review on conceptual and operational definitions of negative social networking sites use in adolescents. *ADDICT BEHAV*, *134*, 107400-107400. https://doi.org/10.1016/j.addbeh.2022.107400

Villardefrancos, E., & Otero-López, J. M. (2016). Compulsive buying in university students: its prevalence and relationships with materialism, psychological distress symptoms, and subjective well-being. *COMPR PSYCHIAT*, *65*, 128-135. https://doi.org/10.1016/j.comppsych.2015.11.007

Vogels, E. A., & Gelles-Watnick, R. (2023). Teens and social media: Key findings from Pew Research Center surveys. *Policy File*.

Volkow, N. D., Koob, G. F., & McLellan, A. T. (2016). Neurobiologic Advances from the Brain Disease Model of Addiction. *NEW ENGL J MED*, *374*(4), 363-371. https://doi.org/10.1056/NEJMra1511480

Vollstädt-Klein, S., Loeber, S., Richter, A., Kirsch, M., Bach, P., von der Goltz, C.,…Kiefer, F. (2012). Validating incentive salience with functional magnetic resonance imaging: association between mesolimbic cue reactivity and attentional bias in alcohol-dependent patients. *ADDICT BIOL*, *17*(4), 807-816. https://doi.org/10.1111/j.1369-1600.2011.00352.x

Waechter, S., Nelson, A. L., Wright, C., Hyatt, A., & Oakman, J. (2014). Measuring Attentional Bias to Threat: Reliability of Dot Probe and Eye Movement Indices. *Cogn Ther Res*, *38*(3), 313-333. https://doi.org/10.1007/s10608-013-9588-2

Wang, J., Tang, H., & Deng, Y. (2016). Novel Symbol Learning-Induced Stroop Effect: Evidence for a Strategy-Based, Utility Learning Model. *J Psycholinguist Res*, *45*(5), 1161-1171. https://doi.org/10.1007/s10936-015-9397-8

Wartberg, L., Kriston, L., & Kammerl, R. (2017). Associations of Social Support, Friends Only Known Through the Internet, and Health-Related Quality of Life with Internet Gaming Disorder in Adolescence. *Cyberpsychol Behav Soc Netw*, *20*(7), 436-441. https://doi.org/10.1089/cyber.2016.0535

Waters, A. J., Shiffman, S., Sayette, M. A., Paty, J. A., Gwaltney, C. J., & Balabanis, M. H. (2003). Attentional Bias Predicts Outcome in Smoking Cessation. *HEALTH PSYCHOL*, *22*(4), 378-387. https://doi.org/10.1037/0278-6133.22.4.378

Waters, A. J., Shiffman, S., Sayette, M. A., Paty, J. A., Gwaltney, C. J., & Balabanis, M. H. (2004). Cue-Provoked Craving and Nicotine Replacement Therapy in Smoking Cessation. *J CONSULT CLIN PSYCH*, *72*(6), 1136-1143. https://doi.org/10.1037/0022-006X.72.6.1136

Waters, A. J., Szeto, E. H., Wetter, D. W., Cinciripini, P. M., Robinson, J. D., & Li, Y. (2013). Cognition and Craving During Smoking Cessation: An Ecological Momentary Assessment Study. *Nicotine & Tobacco Research*, *16*(Suppl_2), S111-S118. https://doi.org/10.1093/ntr/ntt108

Wegmann, E., Müller, S. M., Turel, O., & Brand, M. (2020). Interactions of impulsivity, general executive functions, and specific inhibitory control explain symptoms of social-networks-use disorder: An experimental study. *Sci Rep*, *10*(1), 3866-3866. https://doi.org/10.1038/s41598-020-60819-4

Wegmann, E., Stodt, B., & Brand, M. (2015). Addictive use of social networking sites can be explained by the interaction of Internet use expectancies, Internet literacy, and psychopathological symptoms. *Journal of Behavioural Addictions*, *4*(3), 155-162. https://doi.org/10.1556/2006.4.2015.021

Weinstein, E. (2018). The social media see-saw: Positive and negative influences on adolescents' affective well-being. *NEW MEDIA SOC*, *20*(10), 3597-3623. https://doi.org/10.1177/1461444818755634

Werthmann, J., Jansen, A., Vreugdenhil, A. C. E., Nederkoorn, C., Schyns, G., & Roefs, A. (2015). Food Through the Child's Eye: An Eye-Tracking Study on Attentional Bias for Food in Healthy-Weight Children and Children With Obesity. *HEALTH PSYCHOL*, *34*(12), 1123-1132. https://doi.org/10.1037/hea0000225

Whiting, A., & Williams, D. (2013). Why people use social media: a uses and gratifications approach. *QUAL MARK RES*, *16*(4), 362-369. https://doi.org/10.1108/QMR-06-2013-0041

Wiers, C. E., Gladwin, T. E., Ludwig, V. U., Groepper, S., Stuke, H., Gawron, C. K.,…Bermpohl, F. (2017). Comparing three cognitive biases for alcohol cues in alcohol dependence. *ALCOHOL ALCOHOLISM*, *52*(2), 242-248. https://doi.org/10.1093/alcalc/agw063

Wiers, R. W., Ames, S. L., Hofmann, W., Krank, M., & Stacy, A. W. (2010). Impulsivity, impulsive and reflective processes and the development of alcohol use and misuse in adolescents and young adults. *FRONT PSYCHOL*, *1*, 144-144. https://doi.org/10.3389/fpsyg.2010.00144

Wiers, R. W., Bartholow, B. D., van den Wildenberg, E., Thush, C., Engels, R. C. M. E., Sher, K. J.,…Stacy, A. W. (2007). Automatic and controlled processes and the development of addictive behaviours in adolescents: A review and a model. *PHARMACOL BIOCHEM BE*, *86*(2), 263-283. https://doi.org/10.1016/j.pbb.2006.09.021

Wilcockson, T. D. W., Pothos, E. M., Osborne, A. M., & Crawford, T. J. (2021). Top-down and bottom-up attentional biases for smoking-related stimuli: Comparing dependent and non-dependent smokers. *ADDICT BEHAV*, *118*, 106886-106886. https://doi.org/10.1016/j.addbeh.2021.106886

Wiley, K., Berger, P., Achim Friehs, M., & Lee Mandryk, R. (2024). Measuring the Reliability of a Gamified Stroop Task: Quantitative Experiment. *JMIR Serious Games*, *12*(1), e50315-e50315. https://doi.org/10.2196/50315

Williams, A. D., & Grisham, J. R. (2012). Impulsivity, Emotion Regulation, and Mindful Attentional Focus in Compulsive Buying. *Cogn Ther Res*, *36*(5), 451-457. https://doi.org/10.1007/s10608-011-9384-9

Winkler, M. H., Weyers, P., Mucha, R. F., Stippekohl, B., Stark, R., & Pauli, P. (2011). Conditioned cues for smoking elicit preparatory responses in healthy smokers. *Psychopharmacology*, *213*(4), 781-789. https://doi.org/10.1007/s00213-010-2033-2

Witteman, J., Post, H., Tarvainen, M., de Bruijn, A., Perna Ede, S., Ramaekers, J. G., & Wiers, R. W. (2015). Cue reactivity and its relation to craving and relapse in alcohol dependence: a combined laboratory and field study. *Psychopharmacology (Berl)*, *232*(20), 3685-3696. https://doi.org/10.1007/s00213-015-4027-6

Woods, H. C., & Scott, H. (2016). Sleepyteens: Social media use in adolescence is associated with poor sleep quality, anxiety, depression and low self-esteem. *J ADOLESCENCE*, *51*(1), 41-49. https://doi.org/10.1016/j.adolescence.2016.05.008

World Health Organization. (2018). *International classification of diseases for mortality and morbidity statistics (11th Revision)*. World Health Organization. https://icd.who.int/en/

Wright, M., Green, A., & Baker, S. (2000). Limitations for Change Detection in Multiple Gabor Targets. *Visual Cognition*, *7*(1-3), 237-252. https://doi.org/10.1080/135062800394784

Yaxley, R. H., & Zwaan, R. A. (2005). Attentional bias affects change detection. *Psychonomic Bulletin & Review*, *12*(6), 1106-1111. https://doi.org/10.3758/BF03206451

Yellowlees, P. M., & Marks, S. (2007). Problematic Internet use or Internet addiction? *COMPUT HUM BEHAV*, *23*(3), 1447-1453. https://doi.org/10.1016/j.chb.2005.05.004

Yoon, E. J., Choi, J. S., Kim, H., Sohn, B. K., Jung, H. Y., Lee, J. Y.,…Kim, Y. K. (2017). Altered hippocampal volume and functional connectivity in males with Internet gaming disorder comparing to those with alcohol use disorder. *Sci Rep*, *7*(1), 5744-5712. https://doi.org/10.1038/s41598-017-06057-7

Young, K. S. (1998). Internet addiction: The emergence of a new clinical disorder. *CyberPsychology & Behaviour*, *1*(3), 237-244. https://doi.org/10.1089/cpb.1998.1.237

Zafar, H., & Mobin, M. B. (2024). Excessive usage of social media: A potential threat to mental health in Pakistan. *J Pak Med Assoc*, *74*(1), 201-201. https://doi.org/10.47391/JPMA.9907

Zamani, S. N., Mansouri, H., Fazilatpour, M., & Shamsai, Z. (2014). A Comparison of Attentional Bias Towards Drug Cues in Addicts and Non-Addicts. *Int J High Risk Behav Addict*, *3*(3), e18669-e18669. https://doi.org/10.5812/ijhrba.18669

Zhang, M., Ying, J., Amron, S. B., Mahreen, Z., Song, G., Fung, D. S., & Smith, H. (2018). A Smartphone Attention Bias Intervention for Individuals With Addictive Disorders: Protocol for a Feasibility Study. *JMIR research protocols*, *7*(11), e11822-e11822. https://doi.org/10.2196/11822

Zhao, J., Zhou, Z., Sun, B., Zhang, X., Zhang, L., & Fu, S. (2022). Attentional Bias Is Associated with Negative Emotions in Problematic Users of Social Media as Measured by a Dot-Probe Task. *INT J ENV RES PUB HE*, *19*(24), 16938. https://doi.org/10.3390/ijerph192416938

Zhao, Q., Li, H., Hu, B., Li, Y., Gillebert, C. R., Mantini, D., & Liu, Q. (2018). Neural Correlates of Drug-Related Attentional Bias in Heroin Dependence. *FRONT HUM NEUROSCI*, *11*, 646-646. https://doi.org/10.3389/fnhum.2017.00646

Zhu, L., & Lv, J. (2023). Review of Studies on User Research Based on EEG and Eye Tracking. *Applied sciences*, *13*(11), 6502. https://doi.org/10.3390/app13116502

Appendix A

Ratings Task for Stimuli Used in Experiment 1

We are doing this Instagram rating task to see if the images that will be used for the Change Blindness experiment are similar in familiarity and closeness to social media, and looking at how well the images grab your attention. There will be three different types of stimuli employed in this study: social media related stimuli (Appendix A1) refers to images related to things like Instagram, Facebook, Twitter, TikTok, etc., this experiment will use icons, screenshots, and different Instagram symbols, control stimuli (Appendix A2) which is non-social images refers to images that are like books, cars, nature, etc., and neutral images (Appendix A3) which is images of neutral events.

Methods

Participants

The participants were 35 volunteers (*M* age=21.80, *SD*=2.72) from the Prolific online participant recruitment for surveys and marketing (Prolific, 2021). Of the 35 participants, 28 were females (*M*=21.93, *SD*=2.99) and 7 were males (*M*=21.29, *SD*=1.11). Participants were advised that the aim of the study was to investigate whether they associated certain images with social media and if they are familiar with some of the images used for social media. The eligibility criteria for inclusion in the study were a) participants should be 18 and older, and b) have normal or corrected to normal vision, d) have no colour vision deficiency/colour blindness. This study was conducted under ethical approval, granted by the Ethics Committee of the University of Strathclyde School of Psychological Sciences and Health.

Apparatus and materials

Socio-demographics. The task included questions concerning age and gender to obtain a profile of the participants' socio-demographic features.

Social Media Familiarity. Participants were asked to respond to each image presented with the question "To what extent do you think this image grabs your attention?". Using a self-report questionnaire, with 62 images assigned to the familiarity subscale being social media related, control, and neutral images. Each image is rated on a 9-point Likert scale from 1 (*not at all*) to 9 (*very much*).

Social Media Association. Participants were asked to respond to each image presented with the question "To what extent do you associate this image with social media?". Using a self-report questionnaire, with 62 images assigned to the association subscale being social media related, control, and neutral images. Each image is rated on a 9-point Likert scale from 1 (*not at all related*) to 9 (*very related*).

Stimuli Used (images). Three different types of stimuli were employed in the study: social media related stimuli (Appendix A1) and control stimuli (Appendix A2), and neutral stimuli

(Appendix A3)[3]. The 48 Instagram images included different icons and screenshot images related to Instagram, including the application icon, the Instagram messenger icon, follow symbol (e.g., the like button), etc. Using different stimuli allowed the images to include a wider range of colours rather than just using the standard blue Instagram symbol. The 58 control images included different icons and desktop screenshots from non-social media images. These icons resembled application icons that you would see on a smartphone or tablet device, and the screenshots were taken from a desktop computer. Neutral images included 35 different images of neutral events (e.g., neutral faces, household objects, places, etc.), were taken from International Affective Picture System (IAPS).

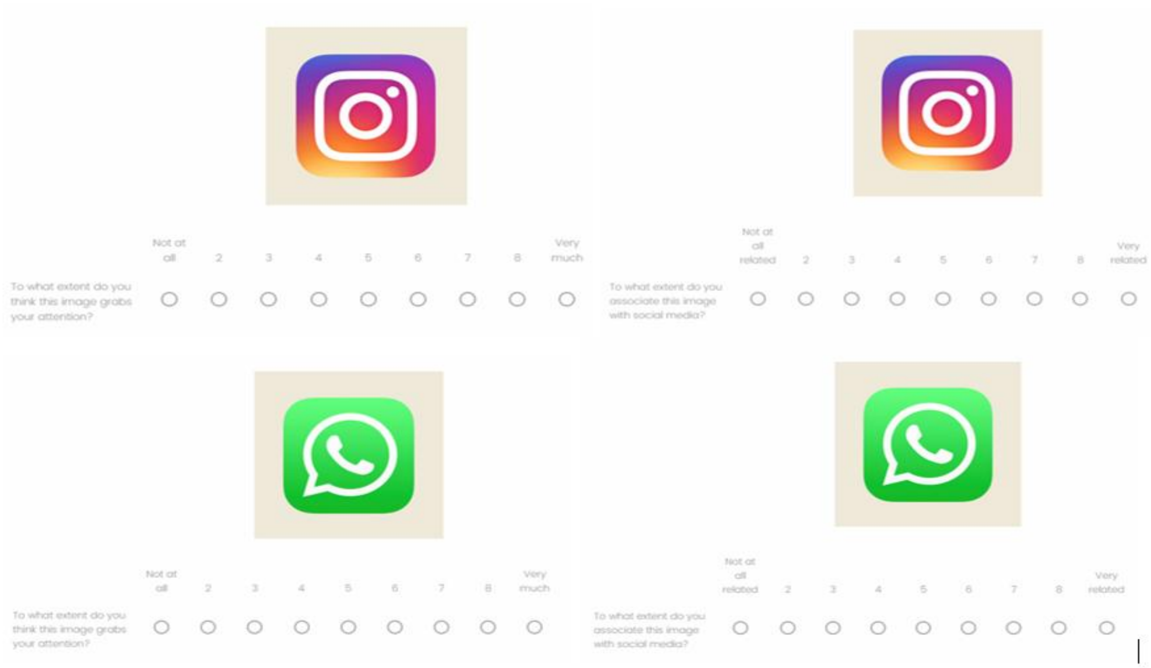
Procedure

Participants were provided informed consent through Qualtrics and did the survey on Qualtrics (Qualtrics, 2021). Participants are asked not to use a smartphone to do the survey, only a desktop computer, laptop, or reasonably sized tablet. The 48 Instagram images, and 58 control images were presented randomly for a total of 106 trials. All the images were shown two times each, requiring a response on familiarity and association (*Figure A1*).

Figure A1

Stimulus Familiarity and Association Ratings

[3] The numbers of IAPS (Kappenman et al., 2015; Kappenman et al., 2014) pictures used were as follows. Neutral: 2038, 2191, 2410, 2445, 2446, 2745.1, 5390, 5510, 5740, 6150, 7000, 7002, 7004, 7006, 7030, 7041, 7493, 7546, 7009, 7025, 7034, 7036, 7038, 7057, 7090, 7100, 7150, 7175, 7211, 7547, 7595, 7620, 7700, 7710, 7920



Note. Examples of stimuli presented during the image evaluation phase of the study. Each image (e.g., Instagram and WhatsApp logos) was shown twice—once for each of two rating tasks. Participants were asked to rate the extent to which the image grabbed their attention and how strongly they associated it with social media. *(*7-point Likert scale, not at all to very much)*.

Results

Data analysis

Stimulus Analysis

The ratings task had 42 stimulus in the Instagram stimuli set (social media related), 58 stimulus in the Control stimuli set, and 35 stimulus in the Neutral stimuli set. The three different stimuli set where placed in 12 images selected for Instagram related stimuli, 12 images selected for control stimuli, and 12 images for neutral stimuli. The three different stimuli used in this study will be broken down into 12 images per set by looking at the mean for each group for attention grabbing and the mean for each group for association relatedness. We aiming to statistically ensure similar levels of rating across the three stimuli sets should satisfy the following: To what extent does this image grab your attention (here we want to have the three sets of images not be statistically different in terms of their mean ratings) see *Table A1* and To what extent do you associate this image with social media (here we want to have three sets of images were images in set A (social media stimuli) is significantly different (e.g. higher) than the B (control) and C (neutral) sets, additionally, we would want an analysis of the comparison statistically of sets B and C too) see *Table A2*. Making sure that the mean across the 3 groups for each setting was close in mean rating.

Table A1

Mean Ratings of Image Stimuli on Attention-Grabbing Quality

	Stimuli A	Stimuli B	Stimuli C
	6.69	4.28	4.94
	6.06	4.36	4.94
	6.46	4.39	5.33
	6.49	5.06	5.47
	4.14	5.03	5.22
	3.37	4.94	4.50
	3.26	5.03	4.58
	4.11	4.69	3.78
	3.06	4.94	4.11
	4.11	4.94	5.00
	6.69	5.19	5.00
	4.11	4.06	5.03
Mean total	4.88	4.74	4.83

Note. Displays overall participant ratings for three types of visual stimuli (A, B, and C) for 12 images based on how attention-grabbing each image was perceived to be. Here Stimuli A (social media stimuli), Stimuli B (control), and Stimuli C (neutral) are not statistically different in terms of their mean ratings.

Table A2

Mean Ratings of Image Stimuli on Social Media Association

	Stimuli A	Stimuli B	Stimuli C
	7.71	2.61	3.00
	7.11	2.72	2.86
	7.29	2.86	2.81
	7.83	2.75	2.78
	8.2	3.03	2.69
	8.2	2.89	2.61
	8.14	4.39	2.58
	8.11	3.25	2.56
	8.11	3.58	2.47
	8.09	3.78	2.44
	7.49	3.89	2.39
	8.06	3.61	2.36
Mean total	7.86	3.28	2.63

Note. Displays the overall ratings for three types of visual stimuli (A, B, and C) for 12 images based on how strongly each is associated with social media. Here Stimuli A (social media stimuli) are statistically different (e.g. higher) than Stimuli B (control) and Stimuli C (neutral). The results show that Stimulus A was consistently rated as highly associated with social media, while Stimuli

B and C received substantially lower ratings, suggesting that Stimulus A was perceived as a social media-related image more strongly than the others.

In the first round of analysis, we were looking at "To what extent does this image grab your attention?" when looking at the mean ratings for Stimuli A to B, a paired-sample t-test was conducted to compare ratings one gives to an image regarding the images perceived degree of attention to social media in Stimuli A and Stimuli B conditions (*Table A3*).

Table A3

Analysis of Image Stimuli on Attention-Grabbing Quality

	Attention Grabbing	
	M	*SD*
Stimuli A	4.88	1.46
Stimuli B	4.74	.374
Stimuli C	4.83	.498

Note. Summarises the mean ratings (*M*) and standard deviations (*SD*) for three visual stimuli (A, B, and C) in terms of how attention-grabbing participants perceived them to be.

When looking at the analysis of comparison of Stimuli A to B. There was no significant difference in the scores for Stimuli A and Stimuli B conditions; $t(11)=.297$, $p=.772$. These results suggests that Stimuli A and Stimuli B have no difference when looking at the mean ratings for social media familiarity. For Stimuli B to C, a paired-sample t-test was conducted to compare social media awareness in social media familiarity in Stimuli B and Stimuli C conditions. There was no significant difference in the scores for Stimuli B and Stimuli C conditions; $t(11)=-.439$, $p=.669$. These results suggests that Stimuli B and Stimuli C have no difference when looking at the mean ratings for social media familiarity. For Stimuli A to C, a paired-sample t-test was conducted to compare social media awareness in social media familiarity in Stimuli A and Stimuli C conditions. There was no significant difference in the scores for Stimuli A and Stimuli C conditions; $t(11)=.153$, $p=.881$. These results suggests that Stimuli A and Stimuli C have no difference when looking at the mean ratings for social media familiarity.

We were looking at the data the participants provided related to their ratings of images upon this question "To what extent do you associate this image with social media?" when looking at the mean ratings for Stimuli A to B, a paired-sample t-test was conducted to compare ratings gives to an image regarding the perceived degree of awareness to social media compared to degree of association in Stimuli A and Stimuli B conditions (*Table A4*).

Table A4

Analysis of Image Stimuli on Social Media Association

	Association	
	M	*SD*

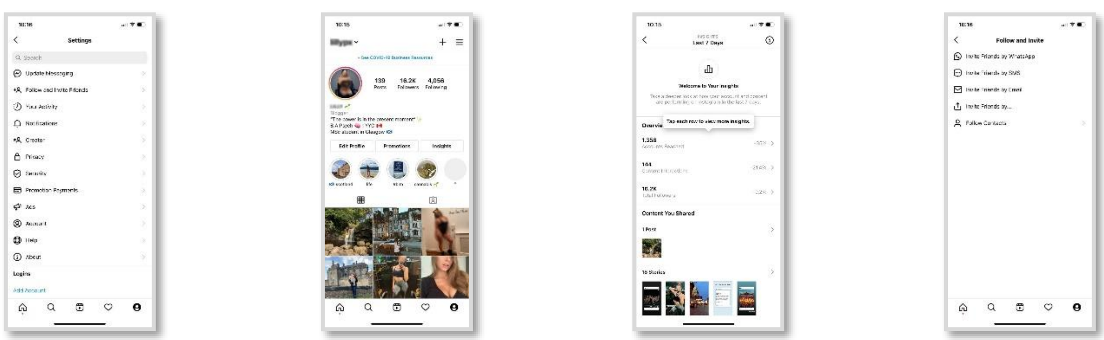
Stimuli A	7.86	.378
Stimuli B	3.28	.563
Stimuli C	2.63	.202

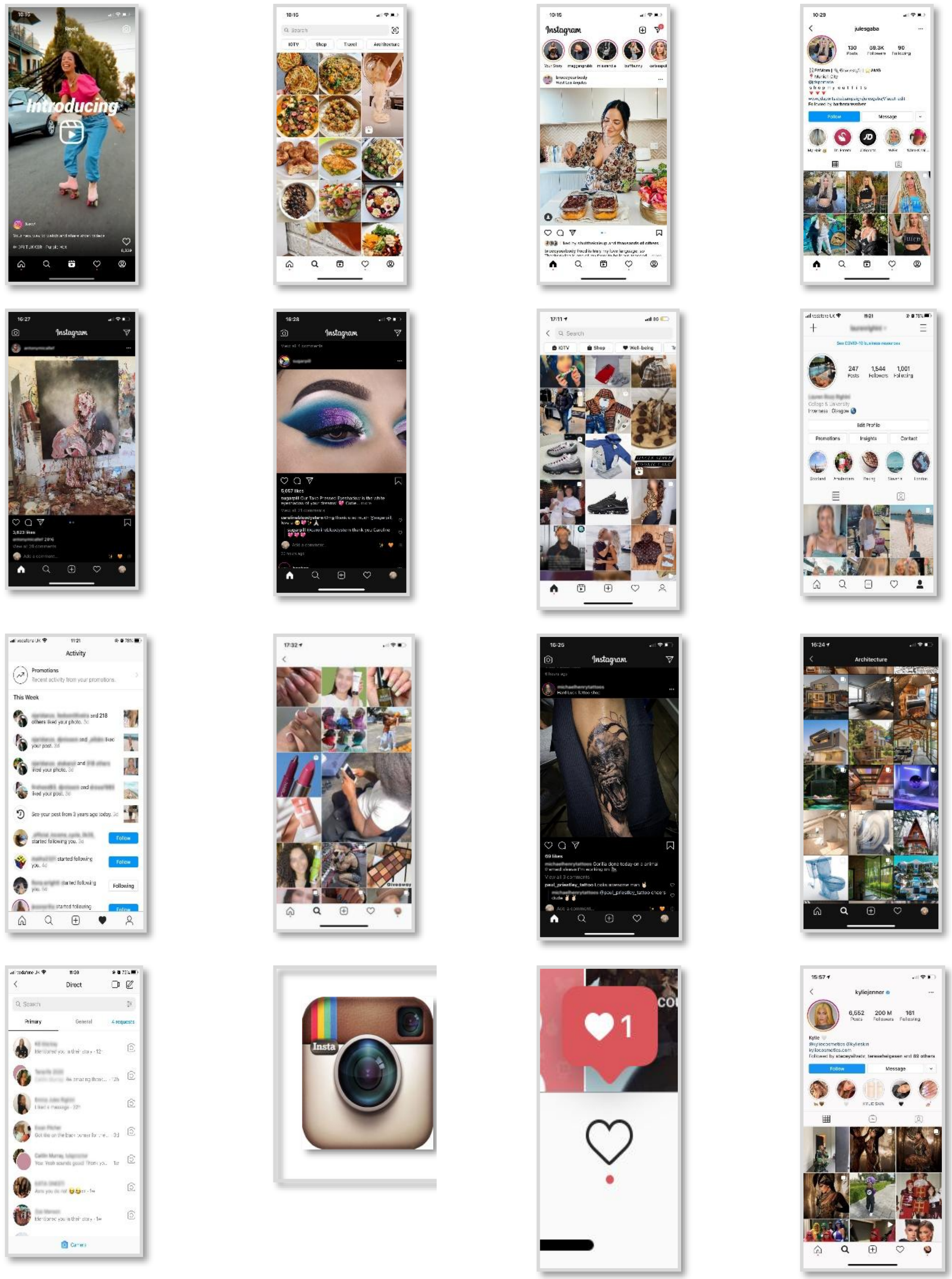
Note. Summarises the mean ratings (*M*) and standard deviations (*SD*) for three image stimuli (A, B, and C) regarding their perceived association with social media. The results indicate that Stimulus A was rated as highly associated with social media, while Stimuli B and C were rated significantly lower, suggesting that Stimulus A was most recognisable as a social media-related image.

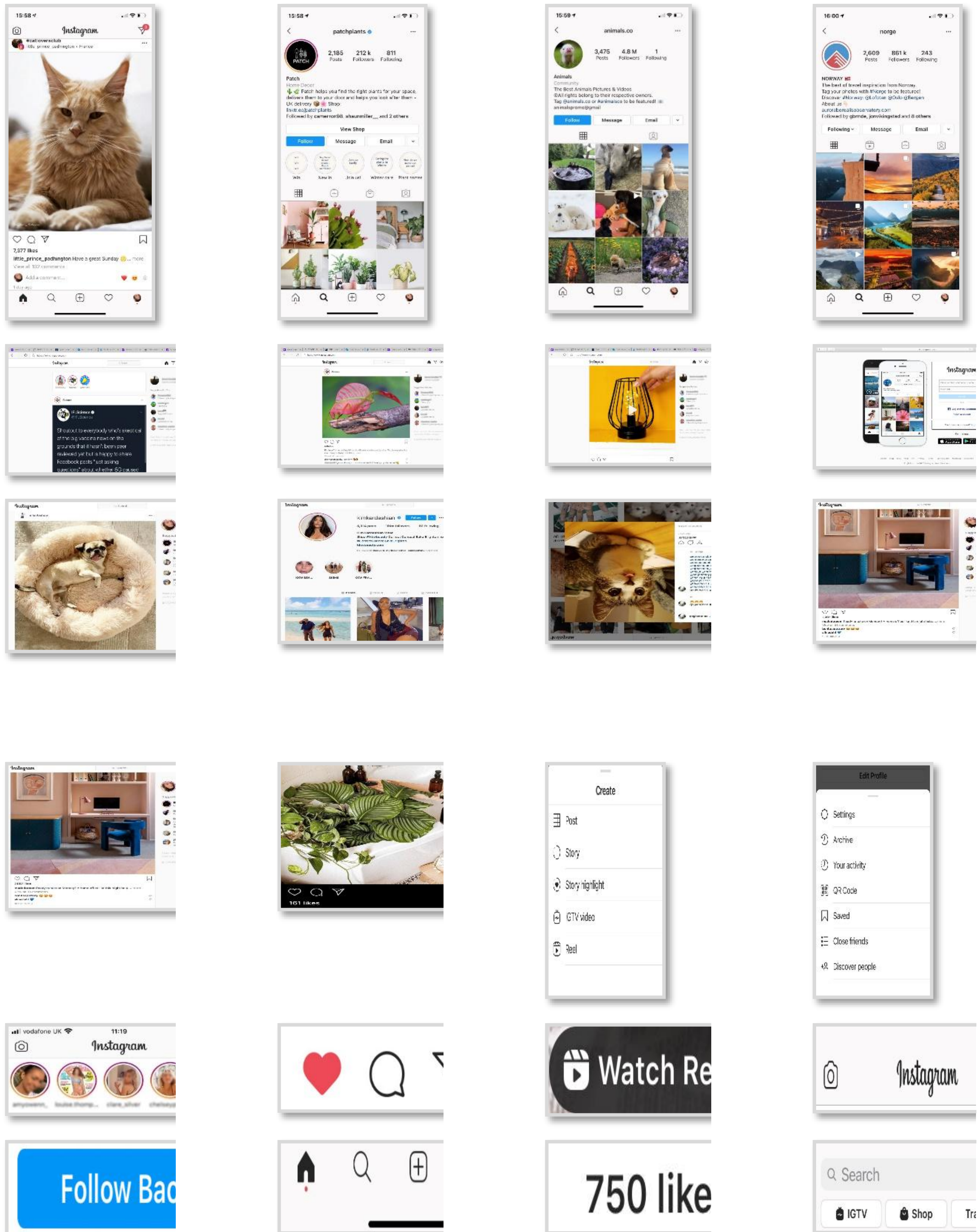
When looking at the analysis of comparison of Stimuli A to B. There was a significant difference in the scores for Stimuli A and Stimuli B conditions; $t(11)=29.07$, $p<.05$. These results suggests that Stimuli A and Stimuli B have difference when looking at the mean ratings for association to social media. For Stimuli A to C, a paired-sample t-test was conducted to compare social media awareness in social media association in Stimuli A and Stimuli C conditions. There was a significant difference in the scores for Stimuli A and Stimuli C conditions; $t(11)=35.75$, $p<.05$. These results suggests that Stimuli A and Stimuli C have difference when looking at the mean ratings for association to social media. For Stimuli B to C, a paired-sample t-test was conducted to compare social media awareness in social media association in Stimuli B and Stimuli C conditions. There was a significant difference in the scores for Stimuli B and Stimuli C conditions; $t(11)=3.08$, $p<.05$. These results suggest that Stimuli B and Stimuli C differ significantly in their mean ratings for social media association.

Appendix A1

Social Media Related Stimuli



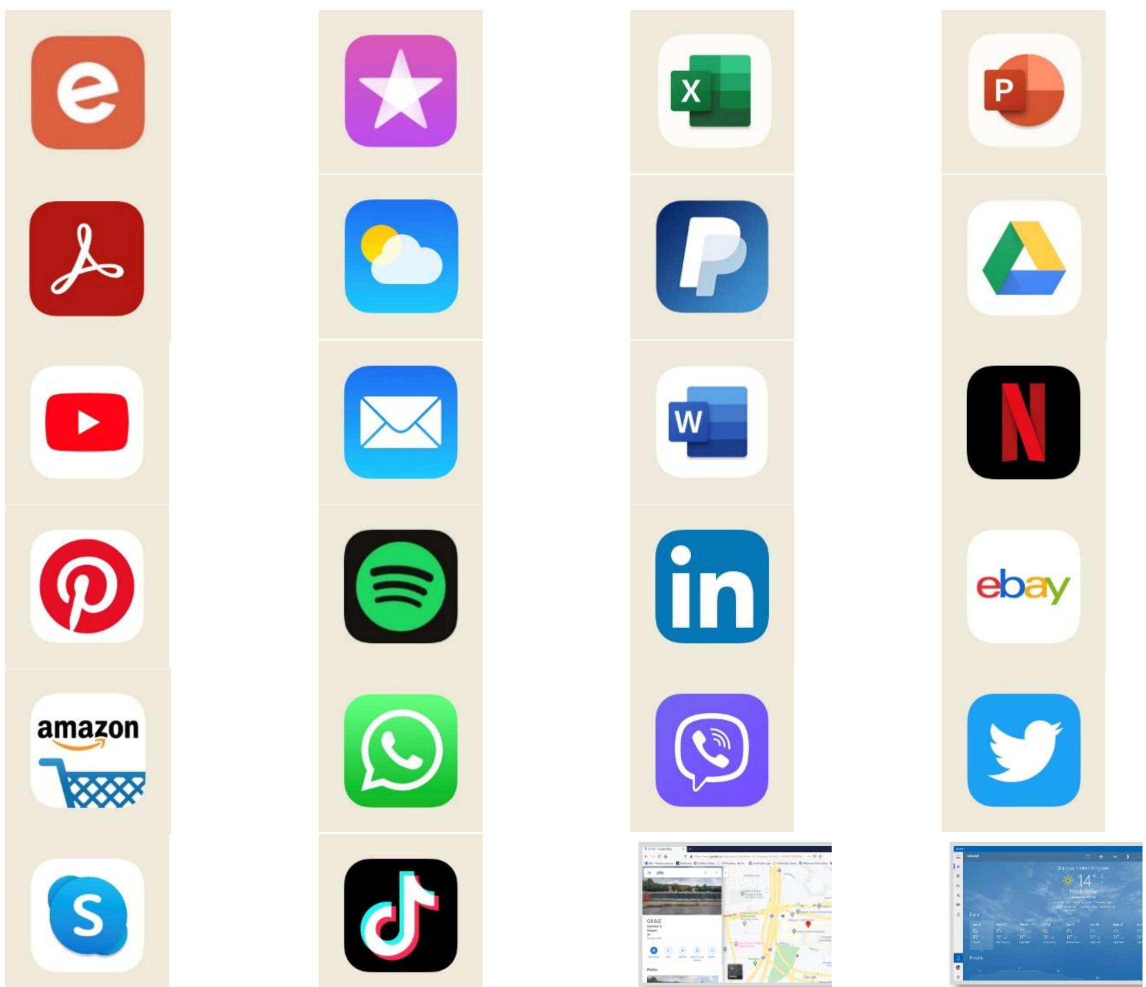


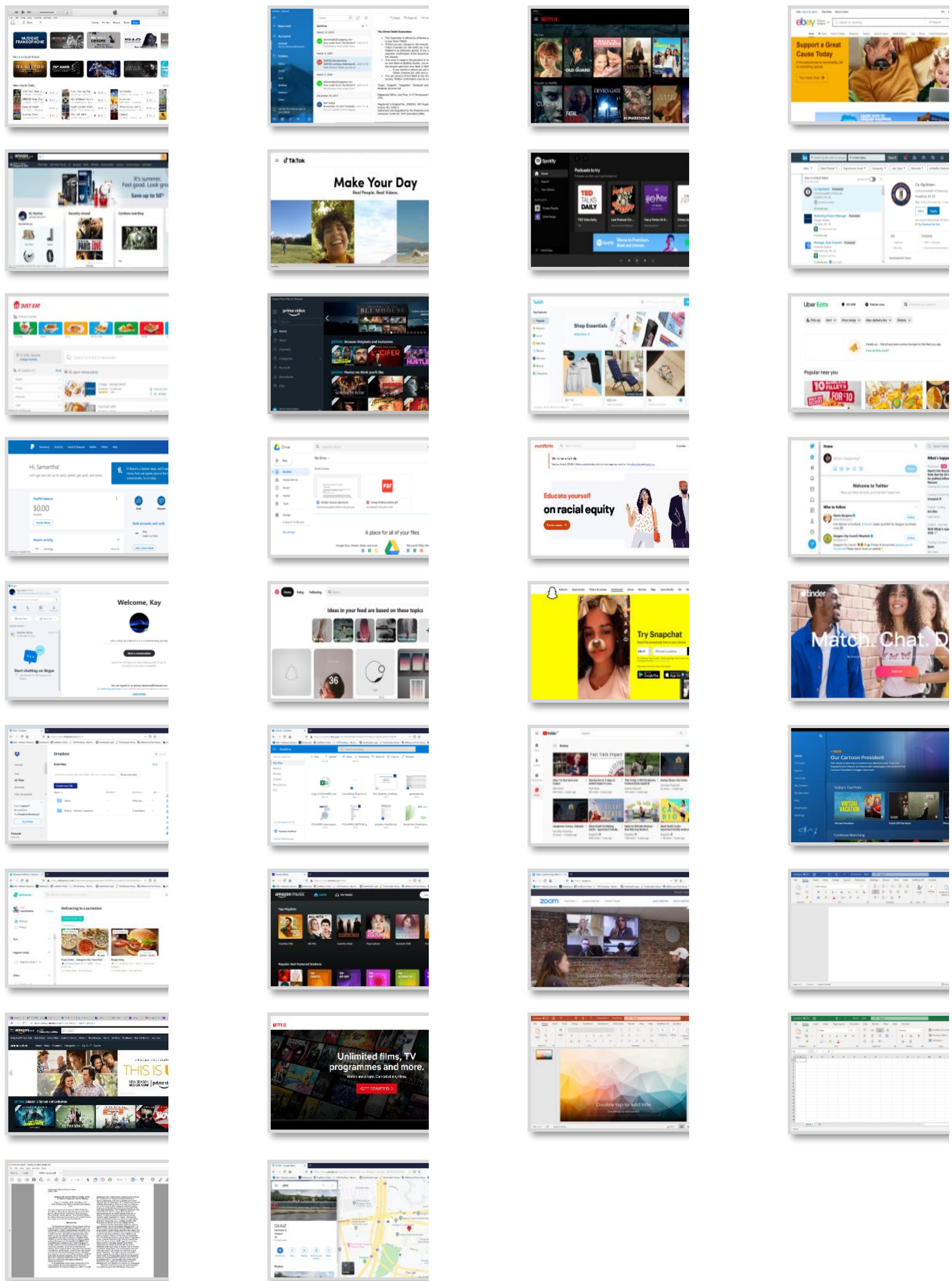

Instagram
Create
Post
Story
Story highlight
IGTV video
Reel
Edit Profile
Settings
Archive
Your activity
QR Code
Saved
Close friends
Discover people
Instagram
Watch Re
Instagram
Follow Bac
750 like
Search
IGTV
Shop

Note. 48 Instagram images included different icons and screenshot images related to Instagram, including the application icon, the Instagram messenger icon, follow symbol (e.g., the like button), etc.

Appendix A2

Control Stimuli

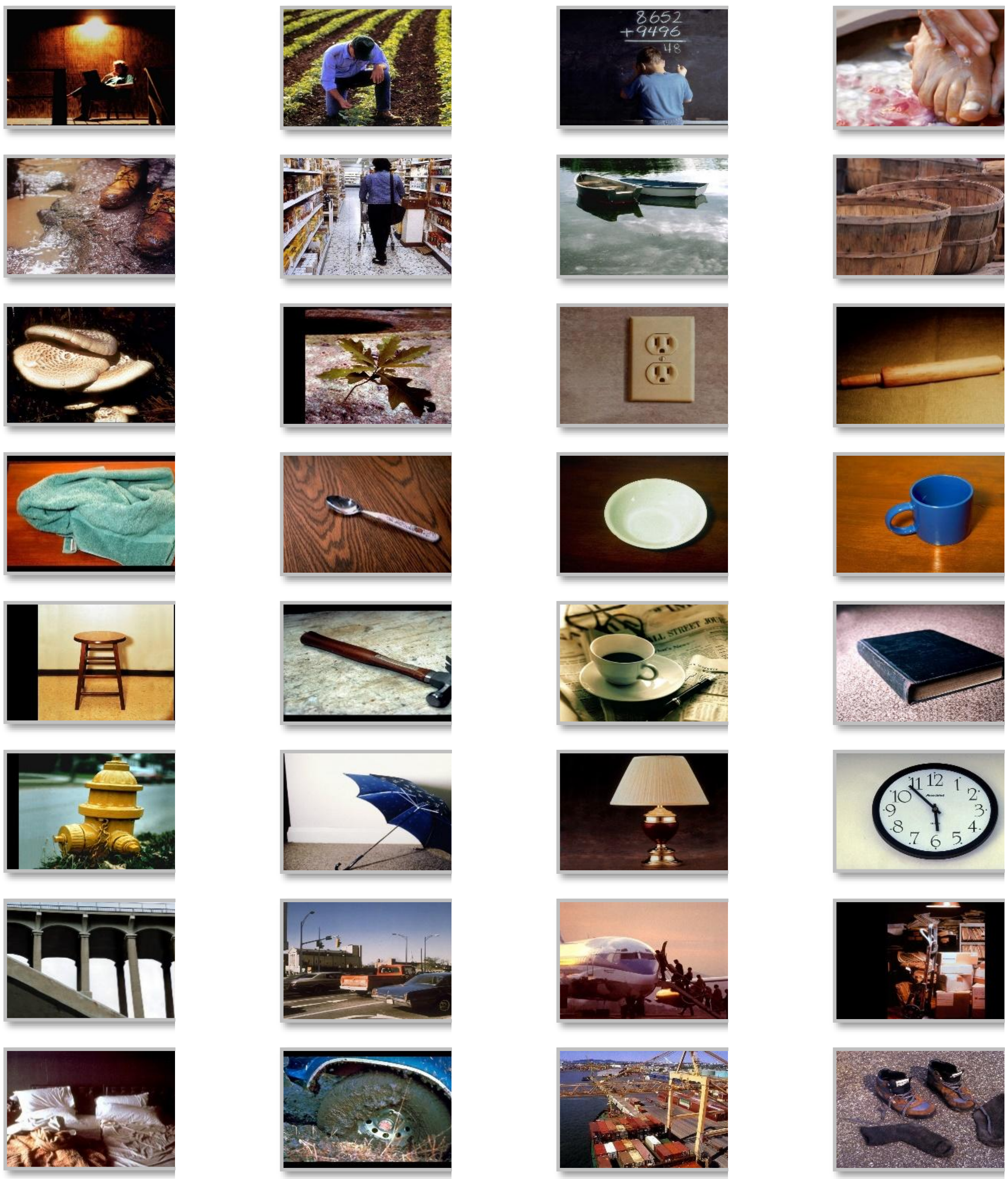



Make Your Day
Support a Great Cause Today
Shop Essentials
Popular near you
Hi, Samantha
$0.00
A place for all of your files
Educate yourself
on racial equity
Welcome, Kay
Ideas in your feed are based on these topics
Try Snapchat
Our Cartoon President
Unlimited films, TV programmes and more.

Note. 58 control images included different icons and desktop screenshots from non-social media images. These icons resembled application icons that you would see on a smartphone or tablet device, and the screenshots were taken from a desktop computer.

Appendix A3

Neutral Stimuli



Note. 35 neutral images of neutral events (e.g., neutral faces, household objects, places, etc.), taken from International Affective Picture System (IAPS)

Appendix B

Ratings Task for Stimuli Used in Experiment 2

We are doing this Instagram rating task to see if the images that will be used for the Dot Probe experiment are similar in familiarity and closeness to social media, and looking at how well the images grab your attention. There will be three different types of stimuli employed in this study: social media related stimuli (Appendix B1) refers to images related to things like Instagram, this experiment will use icons, screenshots, and different Instagram symbols, control stimuli (Appendix B2) which is non-social images refers to images that are like books, cars, nature, etc., and neutral images (Appendix B3) which is images of neutral events.

Methods

Participants

The three different types of stimuli employed in this study went through a rating task where a between-subjects design was employed. The participants were 23 (who did not participate in experiment 2 dot probe task) volunteers (*M* age=20.39, *SD*=1.90). Of the 23 participants, 14 were females (*M*=20.50, *SD*=1.99) and 9 were males (*M*=20.22, *SD*=1.86). Participants were advised that the aim of the study was to investigate the understanding of how social media network usage influences attention through a series of computer tasks. The eligibility criteria for inclusion in the study were a) participants should be 18 and older, and b) have normal or corrected to normal vision, d) have no colour vision deficiency/colour blindness. This study was conducted under ethical approval, granted by the Ethics Committee of the University of Strathclyde School of Psychological Sciences and Health.

Apparatus and materials

Socio-demographics. The task included questions concerning age and gender to obtain a profile of the participants' socio-demographic features.

Social Media Familiarity. Participants were asked to respond to each image presented with the question "When this image is displayed on a computer screen, how much does it grab your attention?". Using a self-report questionnaire, with 56 images assigned to the familiarity subscale being social media related, control, and neutral images. Each image is rated on a 9-point Likert scale from 1 (*not at all*) to 9 (*extremely*).

Social Media Association. Participants were asked to respond to each image presented with the question "To what extent do you associate this image with Instagram?". Using a self-report questionnaire, with 56 images assigned to the association subscale being social media related, control, and neutral images. Each image is rated on a 9-point Likert scale from 1 (*not at all*) to 9 (*extremely*).

Image Similarity. Participants were shown images paired together and were asked to respond to each pairing presented with the question "To what extent do you think these two images are similar?". Using a self-report questionnaire, with 28 pairing of images assigned to the similarity subscale being social media related, control, and neutral images. Each image is rated on a 9-point Likert scale from 1 (*not at all*) to 9 (*extremely*).

Stimuli Used (images). Three different types of stimuli were employed in the study: Instagram related stimuli (Appendix B1), control stimuli (Appendix B2), and filler stimuli (Appendix B3) [4]. The 20 Instagram images included the application icon, the Instagram messenger icon, etc. The 20 control images included images of words and desktop screenshots from non-social media images. These icons resembled application icons that you would see on a smartphone or tablet device, and the screenshots were taken from a desktop computer. Filler images included 40 different images of neutral events (e.g., neutral faces, household objects, places, etc.), were taken from International Affective Picture System (IAPS).

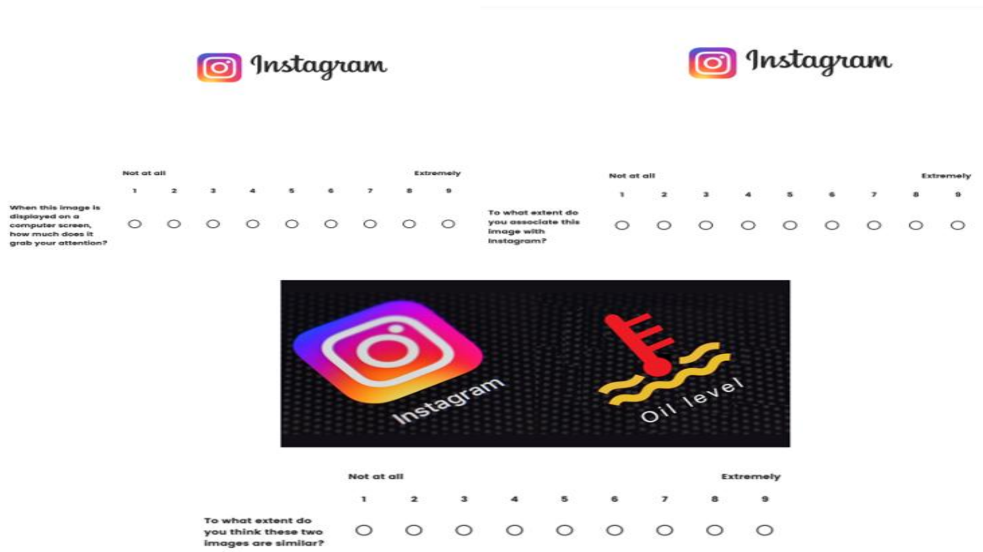
Procedure

Participants were provided informed consent through Qualtrics and did the survey on Qualtrics (Qualtrics, 2021). Participants are asked not to use a smartphone to do the survey, only a desktop computer, laptop, or reasonably sized tablet. The 20 Instagram images, and 20 control images were presented randomly for a total of 160 trials. All the images were shown two times each, requiring a response on familiarity, association, and similarity (*Figure B1*).

Figure B1

Stimulus Familiarity and Association Ratings

[4] The numbers of IAPS (Kappenman et al., 2015; Kappenman et al., 2014) pictures used were as follows. Neutral: 2038, 2102, 2190, 2393, 2397, 2840, 2880, 2890, 5510, 5534, 6150, 7000, 7002, 7004, 7006, 7009, 7010, 7020, 7034, 7035, 7036, 7038, 7041, 7050, 7055, 7056, 7059, 7090, 7160, 7161, 7170, 7175, 7179, 7185, 7187, 7217, 7233, 7235, 7491, and 7950



Note. Example stimulus pairs for stimulus rating task, the top left and right images show the social media related images for both questions "When this image is displayed on a computer screen, how much does it grab your attention?" (social media familiarity) and "To what extent do you associate this image with Instagram?" (social media association). The bottom image shows pairing of the social media stimuli with the control stimuli with the question "To what extent do you think these two images are similar?" (similarity).

Results

Data analysis

Stimulus analysis

The study process involved selecting a subset of images from the Instagram Rating Task. The selection process was undertaken using R program. The primary objective involved identifying a specific subset with predetermined criteria associated with participants' ratings. More importantly, this study ensured that the mean rating for the two sets of 28 images was statistically similar in relation to attention-grabbing, regardless of whether they were related to Instagram or control stimuli. Each stimulus condition consisted of 28 images: one set of Instagram-related stimuli and one set of control stimuli, forming the basis for the three experimental stimulus comparisons. These images will all have a rating for "When this image is displayed on a computer screen, how much does it grab your attention?" and "To what extent do you associate this image with Instagram?" The mean rating for each stimulus was used to make sure that the two sets of images should satisfy the following: how much does it grab your attention (here, we want to have two sets of 28 images that are not statistically different in terms of their mean rating) and To what extent do you associate this image with Instagram (here we want to have two sets of 28 images were images in set A is significantly different (e.g. higher) than the B set. We ran the 56 images through the R program, and it came up with 10 sets of images with 20 Instagram images and 20 control images that were not statistically significant for how much the image grabs your attention and statistically significant for to what extent do you associate this image with Instagram. Out of the 10 sets, set number 6 was chosen for the images to incorporate into the Dot Probe E-Prime Task. In part, set 6 met the set criteria since there were no demonstrable statistically significant variations in attention towards images grabbed or their Instagram between these two sets. Thus, set 6 meets the requirements for inclusion into the Dot Probe E-Prime Task since the selected images align with the researcher's objectives (*Table B1*).

Table B1

Mean Ratings of Social Media and Control Stimuli on Attention-Grabbing Quality and Social Media Association

	Attention Grabbing		*Association*	
Stimuli	Social media related	Control	Social media related	Control
	M	*M*	*M*	*M*
SM2_C2	5.74	5.65	7.52	3.17
SM3_C3	6.57	5.91	8.57	5.22
SM5_C5	4.48	5.00	6.30	2.43
SM6_C6	3.52	2.78	4.35	1.35
SM7_C7	3.78	3.48	6.7	1.09
SM8_C8	4.78	4.65	8.22	1.57
SM9_C9	6.09	5.61	8.48	2.87
SM12_C12	4.26	4.13	7.87	3.26
SM13_C13	4.65	4.17	7.83	2.30
SM14_C14	3.96	2.30	7.17	1.70
SM15_C15	4.83	4.74	7.61	2.35
SM17_C17	3.57	4.35	3.57	2.22
SM19_C19	5.09	4.30	7.91	1.96
SM20_C20	4.96	4.65	6.30	2.39
SM21_C21	3.87	3.52	7.70	2.09
SM22_C22	4.39	5.00	8.00	2.09
SM23_C23	5.09	4.52	8.39	1.78
SM24_C24	4.04	4.17	6.70	1.83
SM25_C25	3.65	4.13	6.87	2.52
SM27_C27	6.26	5.74	8.57	2.26

Note. Displays the mean ratings for pairs of visual stimuli—each pair comprising a social media-related image (SM) and a matched control image (C)—across two dimensions: Attention-Grabbing Quality and Association with Social Media.

In the first round of analysis, we were looking at "When this image is displayed on a computer screen, how much does it grab your attention?" when looking at the mean ratings for Stimuli A to B, a paired-sample t-test was conducted to compare ratings one gives to an image regarding the images perceived degree of attention to social media in Stimuli A and Stimuli B conditions (*Table B2*).

Table B2

Analysis of Image Stimuli on Attention-Grabbing Quality

	Attention Grabbing	
	M	*SD*
Stimuli A	4.68	.917
Stimuli B	4.44	.945

Note. Shows the mean ratings (M) and standard deviations (SD) for two visual stimuli (A and B) in terms of how attention-grabbing participants found them.

When looking at the analysis of comparison of Stimuli A to B. There was a significant difference in the scores for Stimuli A and Stimuli B conditions; $t(19)=1.88$, $p=.038<.05$. These results suggest that Stimuli A and Stimuli B differed significantly in their ability to capture participants' attention.

We were looking at the data the participants provided related to their ratings of images upon this question "To what extent do you associate this image with Instagram?" when looking at the mean ratings for Stimuli A to B, a paired-sample t-test was conducted to compare ratings one gives to an image regarding the images perceived degree of association to Instagram in Stimuli A and Stimuli B conditions (*Table B3*).

Table B3

Analysis of Image Stimuli on Social Media Association

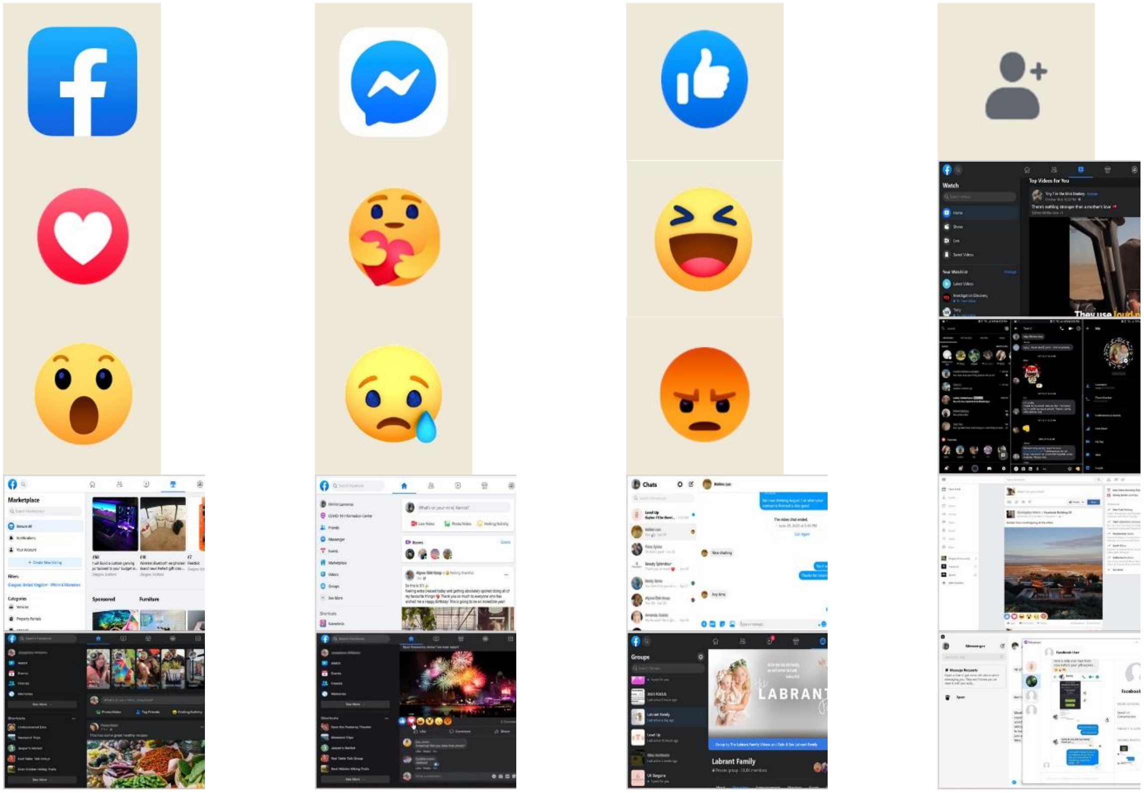
	Association	
	M	*SD*
Stimuli A	7.23	1.34
Stimuli B	2.32	.875

Note. Presents the mean (M) and standard deviation (SD) of participant ratings for two image stimuli (A and B) on the dimension of social media association.

When looking at the analysis of comparison of Stimuli A to B. There was a significant difference in the scores for Stimuli A and Stimuli B conditions; $t(19)=16.46$, $p=.001<.05$. These results suggests that Stimuli A and Stimuli B have difference when looking at the mean ratings for association to Instagram.

Appendix B1

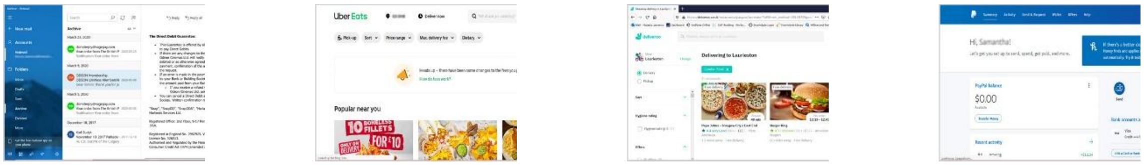
Instagram Stimuli



Note. 20 Instagram images included the application icon, the Instagram messenger icon, etc.

Appendix B2

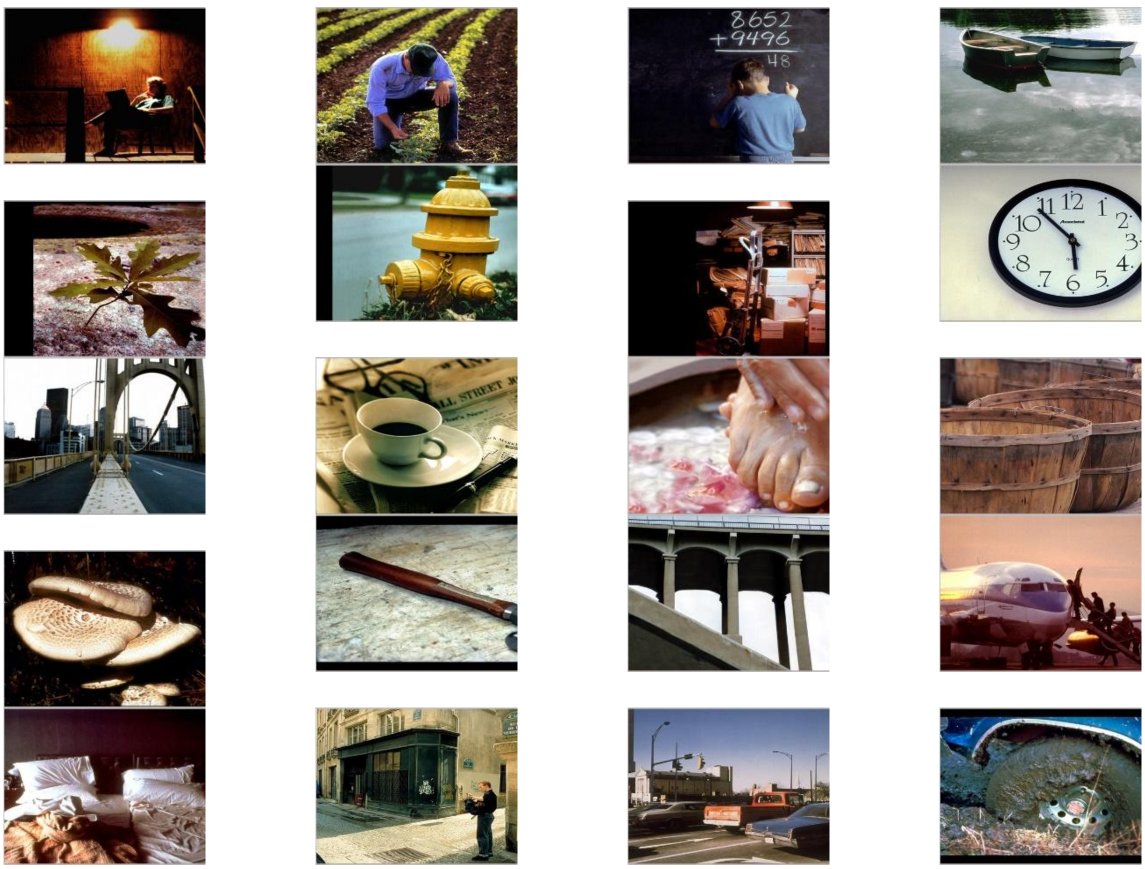
Control Stimuli



Note. 20 control images included images of words and desktop screenshots from non-social media images. These icons resembled application icons that you would see on a smartphone or tablet device, and the screenshots were taken from a desktop computer.

Appendix B3

Neutral Stimuli



Note. 40 Filler images of neutral events (e.g., neutral faces, household objects, places, etc.), taken from International Affective Picture System (IAPS).

Appendix C

Ratings Task for Stimuli Used in Experiment 3

We are doing this Instagram rating task to see if the images that will be used for the Dot Probe experiment are similar in familiarity and closeness to social media, and looking at how well the images grab your attention. There will be three different types of stimuli employed in this study: social media related stimuli (Appendix C1) refers to images related to things like Instagram, this experiment will use icons, screenshots, and different Instagram symbols, control stimuli (Appendix C2) which is non-social images refers to images that are like books, cars, nature, etc., and neutral images (Appendix C3) which is images of neutral events.

Methods

Participants

The three different types of stimuli employed in this study went through a rating task where a between-subjects design was employed. The participants were 23 (who did not participate in experiment 3 dot probe task) volunteers (*M* age=20.39, *SD*=1.90). Of the 23 participants, 14 were females (*M*=20.50, *SD*=1.99) and 9 were males (*M*=20.22, *SD*=1.86). Participants were advised that the aim of the study was to investigate the understanding of how social media network usage influences attention through a series of computer tasks. The eligibility criteria for inclusion in the study were a) participants should be 18 and older, and b) have normal or corrected to normal vision, d) have no colour vision deficiency/colour blindness. This study was conducted under ethical approval, granted by the Ethics Committee of the University of Strathclyde School of Psychological Sciences and Health.

Apparatus and materials

Socio-demographics. The task included questions concerning age and gender to obtain a profile of the participants' socio-demographic features.

Social Media Familiarity. Participants were asked to respond to each image presented with the question "When this image is displayed on a computer screen, how much does it grab your attention?". Using a self-report questionnaire, with 56 images assigned to the familiarity subscale being social media related, control, and neutral images. Each image is rated on a 9-point Likert scale from 1 (*not at all*) to 9 (*extremely*).

Social Media Association. Participants were asked to respond to each image presented with the question "To what extent do you associate this image with Instagram?". Using a self-report questionnaire, with 56 images assigned to the association subscale being social media related, control, and neutral images. Each image is rated on a 9-point Likert scale from 1 (*not at all*) to 9 (*extremely*).

Image Similarity. Participants were shown images paired together and were asked to respond to each pairing presented with the question "To what extent do you think these two images are similar?". Using a self-report questionnaire, with 28 pairing of images assigned to the similarity subscale being social media related, control, and neutral images. Each image is rated on a 9-point Likert scale from 1 (*not at all*) to 9 (*extremely*).

Stimuli Used (images). Three different types of stimuli were employed in the study: Instagram related stimuli (Appendix C1), control stimuli (Appendix C2), and filler stimuli (Appendix C3) [5]. The 10 Instagram images included the application icon, the Instagram messenger icon, etc. Using different stimuli allowed the images to include a wider range of colours rather than just using the standard blue Instagram symbol. The words and modern digital branding elements, including icons/logos and recognizable branding (e.g., Polaroid, Community Fund, an Instagram-like colour gradient). Filler images included 20 different images of neutral events (e.g., neutral faces, household objects, places, etc.), were taken from International Affective Picture System (IAPS).

Procedure

Participants were provided informed consent through Qualtrics and did the survey on Qualtrics (Qualtrics, 2021). Participants are asked not to use a smartphone to do the survey, only a desktop computer, laptop, or reasonably sized tablet. The 10 Instagram images, 10 control images, and 20 filler images were repeated randomly for a total of 80 trials.

Results

Data analysis

Stimulus analysis

Out of the 10 sets, set number 6 was chosen for the images to incorporate into the Dot Probe E-Prime Task. In part, set 6 met the set criteria since there were no demonstrable statistically significant variations in attention towards images grabbed or their Instagram between these two sets. Thus, set 6 meets the requirements for inclusion into the Dot Probe E-Prime Task since the selected images align with the researcher's objectives. A smaller stimuli size was used in this experiment as even with smaller stimuli set the results should not be affected (Choo et al., 2022; Caudek, Ceccarini & Sica, 2017; Wilcockson et al., 2021; Nikolaidou, Fraser & Hinvest, 2019; Robinson et al., 2022). Using set 6, out of the 20 Instagram images and 20 control images only 10 of each were used, the 10 stimuli chosen was based on the images that were not statistically significant for how much the image grabs your attention and statistically significant for to what extent do you associate this image with Instagram (*Table C1*).

[5] The numbers of IAPS (Kappenman et al., 2015; Kappenman et al., 2014) pictures used were as follows. Neutral: 2190, 2397, 2840, 7000, 7004, 7006, 7010, 7020, 7035, 7041, 7050, 7059, 7090, 7175, 7185, 7187, 7217, 7233, 7491, and 7950

Table C1

Mean Ratings of Social Media and Control Stimuli on Attention-Grabbing Quality and Social Media Association

	Attention Grabbing		*Association*	
Stimuli	Social media related	Control	Social media related	Control
	M	*M*	*M*	*M*
SM2_C2	5.74	5.65	7.52	3.17
SM3_C3	6.57	5.91	8.57	5.22
SM8_C8	4.78	4.65	8.22	1.57
SM9_C9	6.09	5.61	8.48	2.87
SM12_C12	4.26	4.13	7.87	3.26
SM13_C13	4.65	4.17	7.83	2.30
SM19_C19	5.09	4.30	7.91	1.96
SM22_C22	4.39	5.00	8.00	2.09
SM23_C23	5.09	4.52	8.39	1.78
SM27_C27	6.26	5.74	8.57	2.26

Note. Presents the mean ratings (M) for selected pairs of stimuli, each consisting of a social media-related image and a matched control image, across two dimensions: Attention-Grabbing Quality and Association with Social Media.

In the first round of analysis, we were looking at "When this image is displayed on a computer screen, how much does it grab your attention?" when looking at the mean ratings for Stimuli A to B, a paired-sample t-test was conducted to compare ratings one gives to an image regarding the images perceived degree of attention to social media in Stimuli A and Stimuli B conditions (*Table C2*).

Table C2

Analysis of Image Stimuli on Attention-Grabbing Quality

	Attention Grabbing	
	M	*SD*
Stimuli A	4.78	1.03
Stimuli B	4.37	1.24

Note. Presents the mean (M) and standard deviation (SD) of participant ratings for two image stimuli (A and B) on the dimension of attention-grabbing quality. The results show that Stimulus A received a slightly higher mean rating compared to Stimulus B, suggesting it was perceived as marginally more attention-grabbing.

When looking at the analysis of comparison of Stimuli A to B. There was a significant difference in the scores for Stimuli A and Stimuli B conditions; $t(9)=2.32$, $p=.023<.05$. These results suggests that Stimuli A and Stimuli B grabbed the participants attention.

We were looking at the data the participants provided related to their ratings of images upon this question "To what extent do you associate this image with Instagram?" when looking at the mean ratings for Stimuli A to B, a paired-sample t-test was conducted to compare ratings one gives to an image regarding the images perceived degree of association to Instagram in Stimuli A and Stimuli B conditions (*Table C3*).

Table C3

Analysis of Image Stimuli on Social Media Association

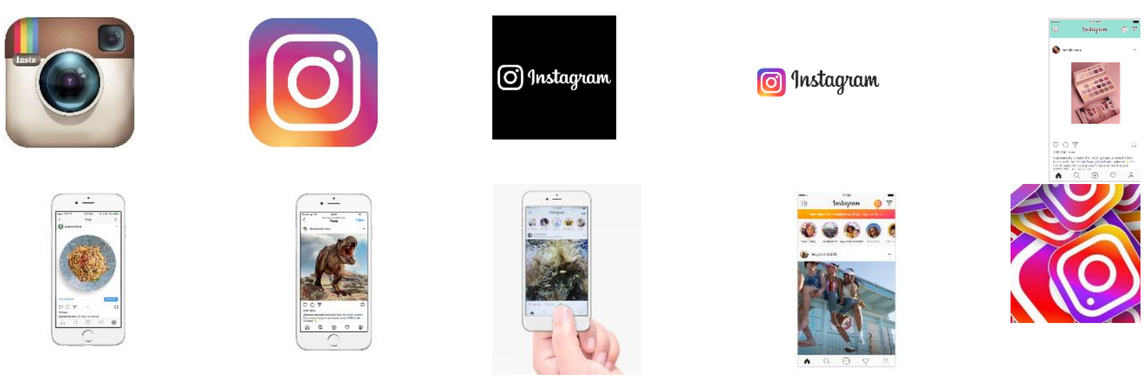
	Association	
	M	*SD*
Stimuli A	7.30	1.27
Stimuli B	2.50	1.22

Note. Displays the mean (M) and standard deviation (SD) of participant ratings for two image stimuli (A and B) on their association with social media. The results indicate that Stimulus A was perceived as being strongly associated with social media, while Stimulus B was perceived as only weakly associated.

When looking at the analysis of comparison of Stimuli A to B. There was a significant difference in the scores for Stimuli A and Stimuli B conditions; $t(9)=13.07$, $p=.001<.05$. These results suggests that Stimuli A and Stimuli B have difference when looking at the mean ratings for association to Instagram.

Appendix C1

Instagram Stimuli



Note. 10 Instagram images included the application icon, the Instagram messenger icon, etc.

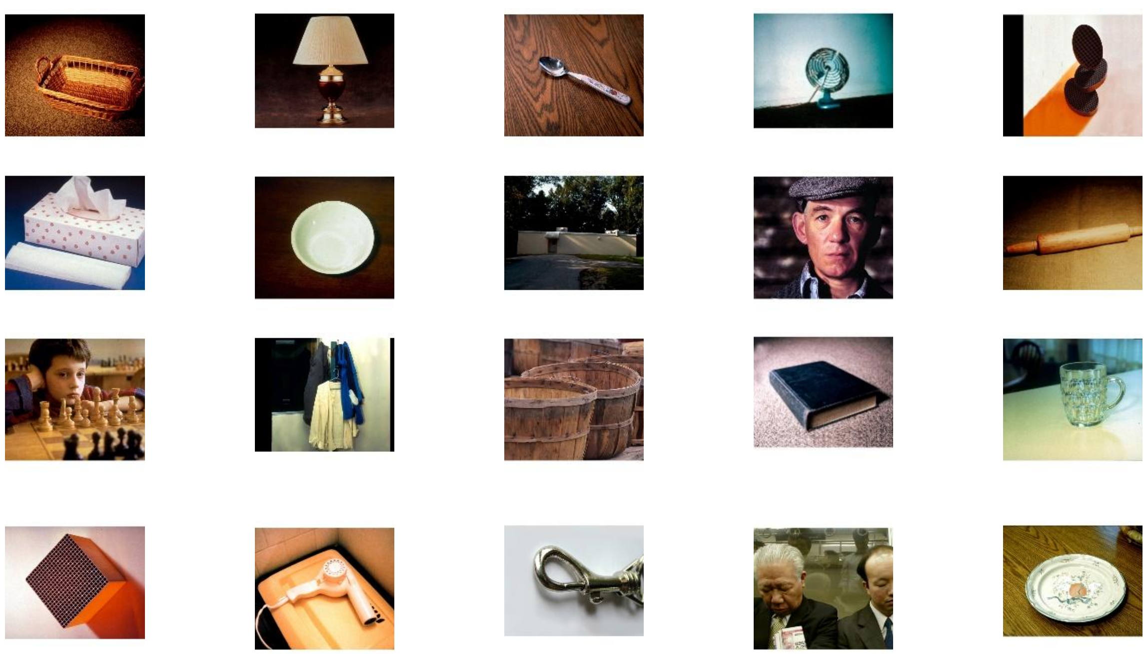
Appendix C2

Control Stimuli

Note. 10 control images included images of words and modern digital branding elements, including icons/logos and recognizable branding (e.g., Polaroid, Community Fund, an Instagram-like colour gradient).

Appendix C3

Neutral Stimuli



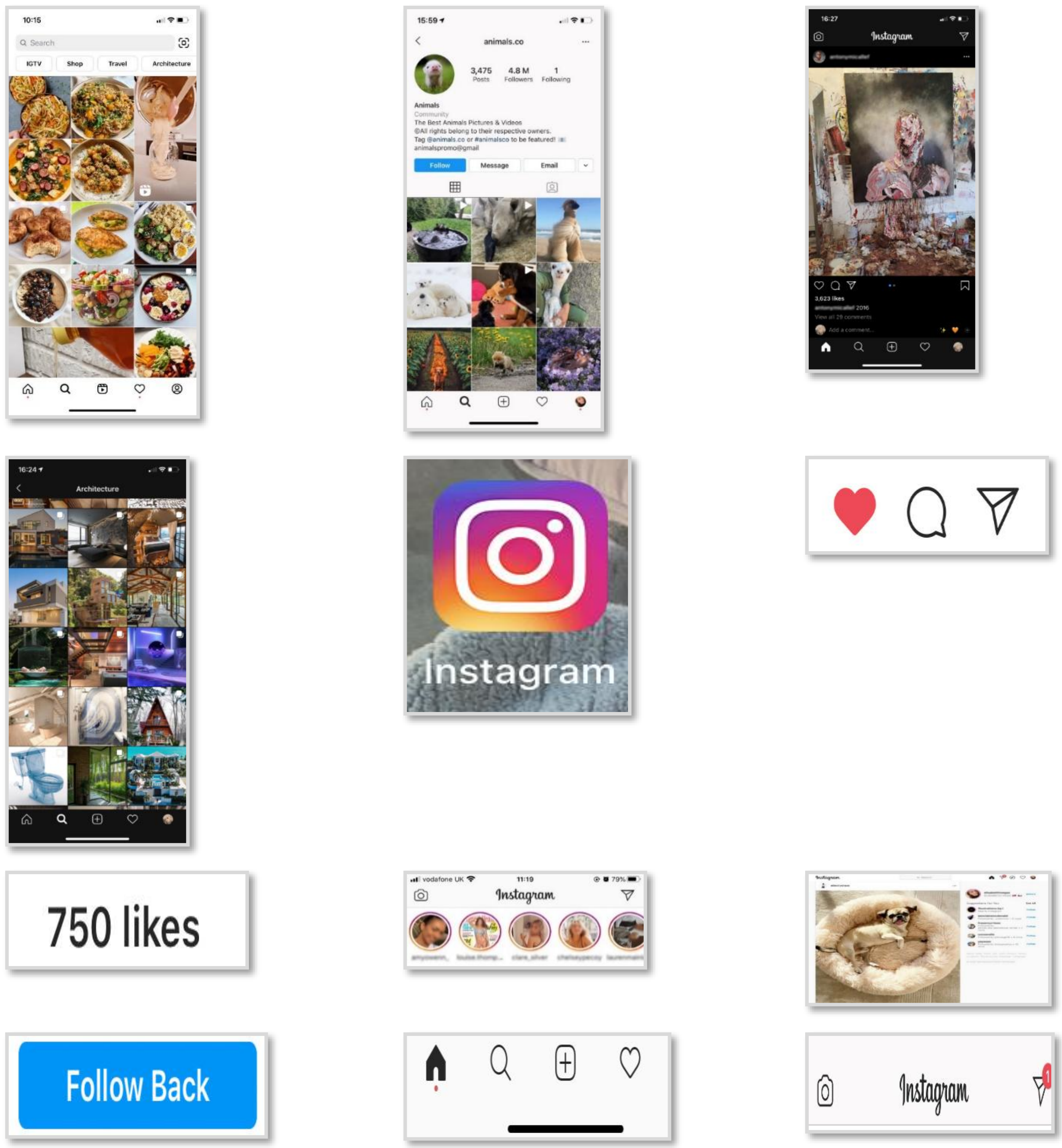
Note. 20 filler images of neutral events (e.g., neutral faces, household objects, places, etc.), taken from International Affective Picture System (IAPS).

Appendix D

Stimuli Used in Experiment 1

Figure D1

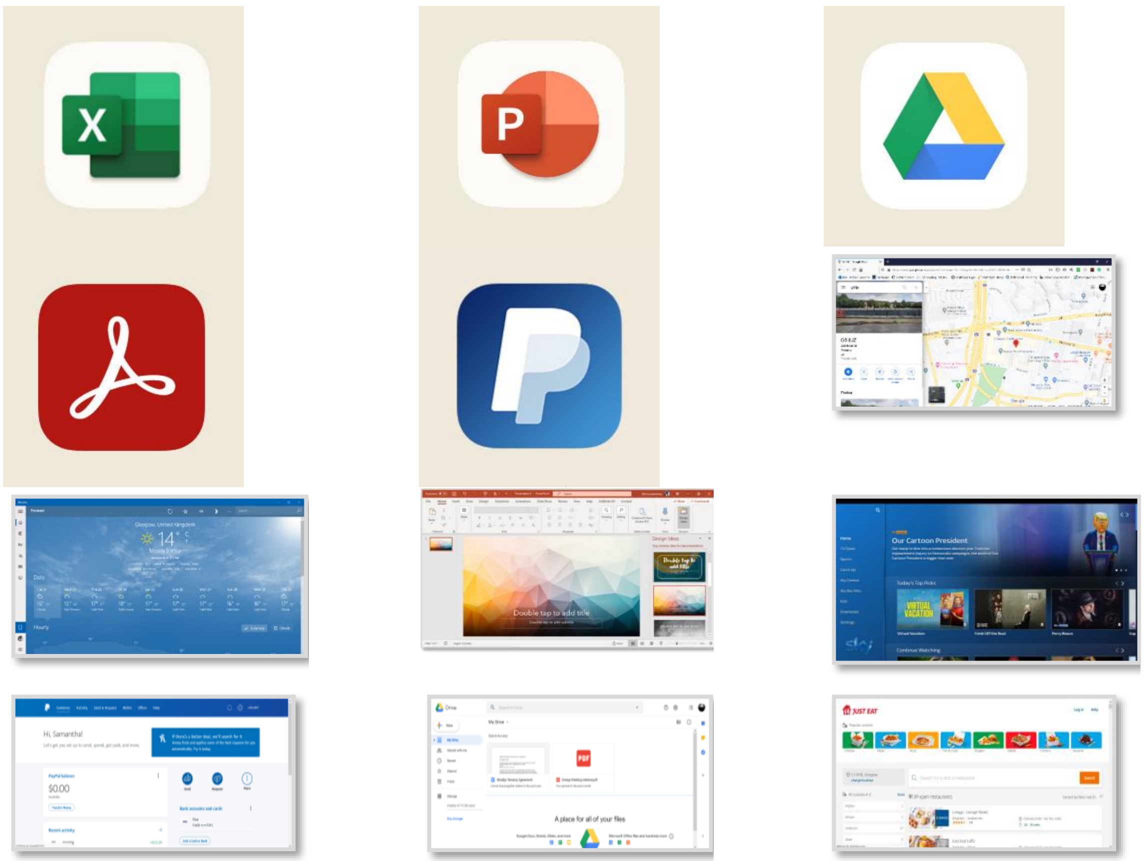
Social Media Related Stimuli



Note. 12 Instagram images included different icons and screenshot images related to Instagram, including the application icon, the like symbol, the follow back, the heart symbol, etc.

Figure D2

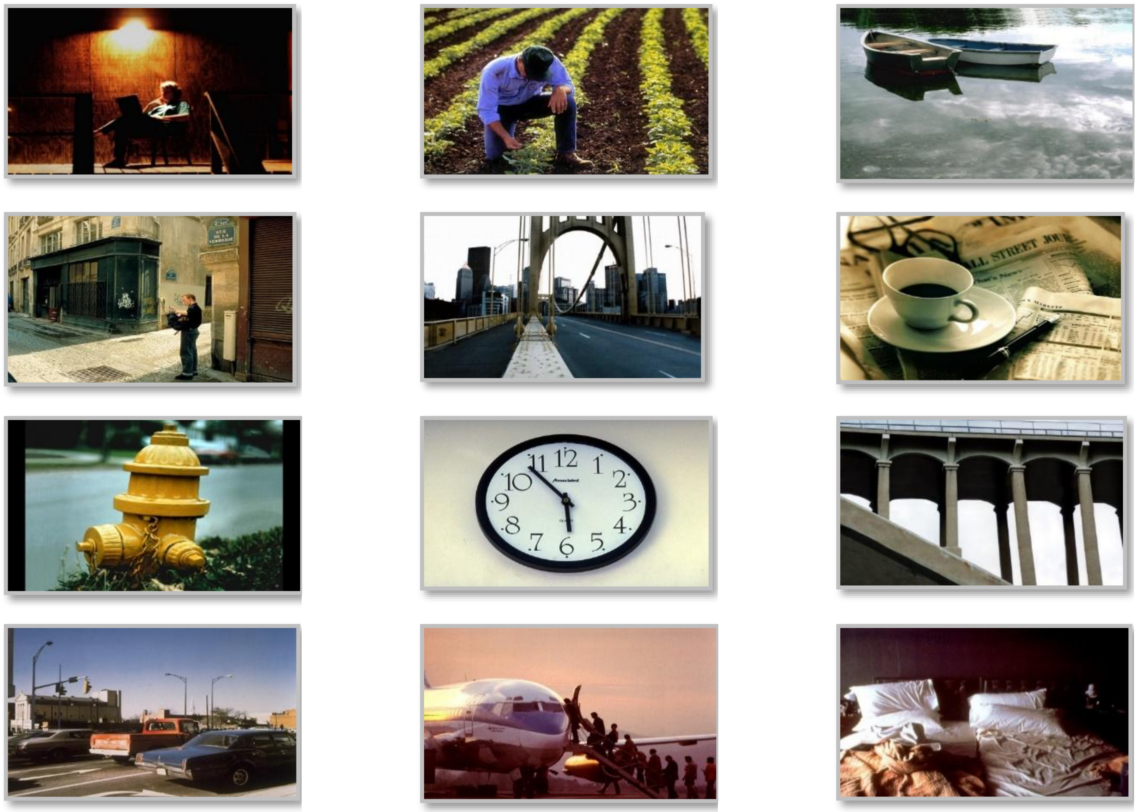
Control Stimuli



Note. 12 control images included different icons and desktop screenshots from familiar applications. These icons resembled application icons that you would see on a smartphone or tablet device, and the screenshots were taken from a desktop computer.

Figure D3

Neutral Stimuli



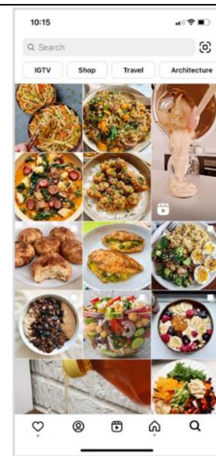
Note. 12 neutral images included different images of neutral events (e.g., neutral faces, household objects, places, etc.), taken from International Affective Picture System (IAPS).

Appendix D1

Trials Changes for Each Stimuli

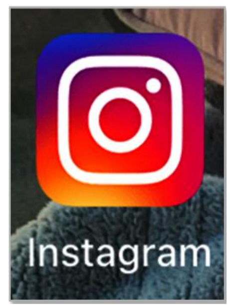
Trial Image	Changing Image 1	Location of Change 1	Changing Image 2	Location of Change 2

Stimuli7a_mod
(top left)



Stimuli22a_mod
(bottom left)

Stimuli8b_mod
(top middle)



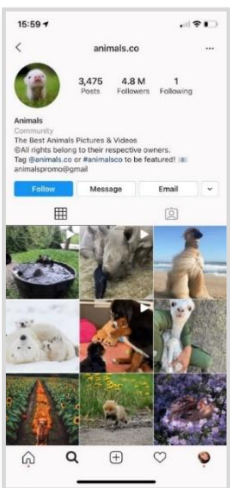
Stimuli23b_mod
(bottom middle)

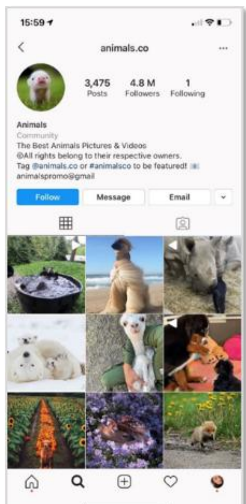
Stimuli9c_mod
(top right)

Stimuli24c_mod
(bottom right)

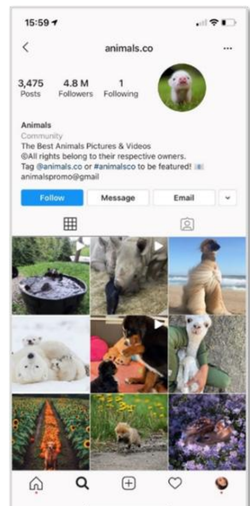
Stimuli10a_mod (bottom left)

Stimuli19a_mod (top left)

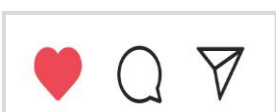


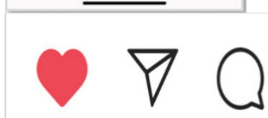


Stimuli11b_mod (bottom middle)

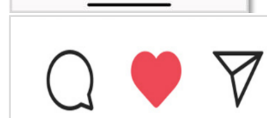


Stimuli20b_mod (top middle)

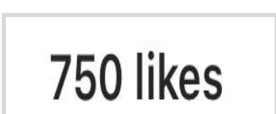




Stimuli12c_mod (bottom right)

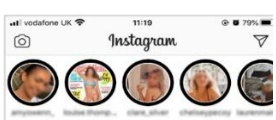


Stimuli21c_mod (top right)

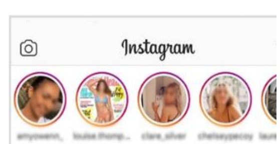


Stimuli1a_mod(top left)

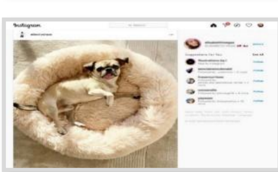
Stimuli16a_mod (bottom left)

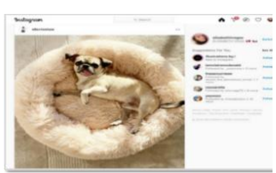


Stimuli2b_mod (top middle)

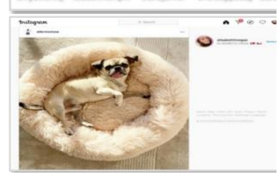


Stimuli17b_mod (bottom middle)

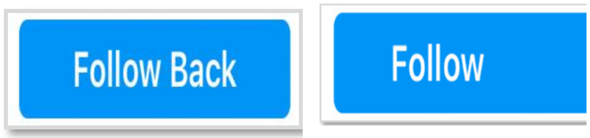




Stimuli3c_mod (top right)

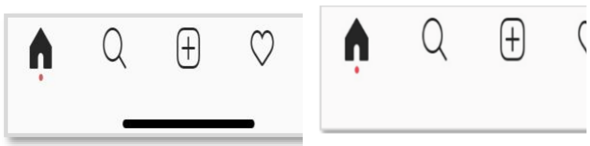


Stimuli18c_mod (bottom right)

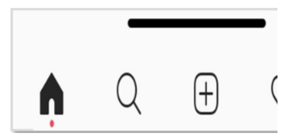


Stimuli4a_mod
(bottom left)

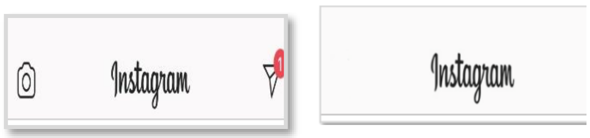
Stimuli13a_mod
(top left)



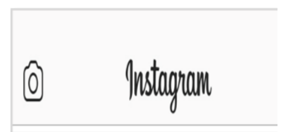
Stimuli5b_mod
(bottom middle)



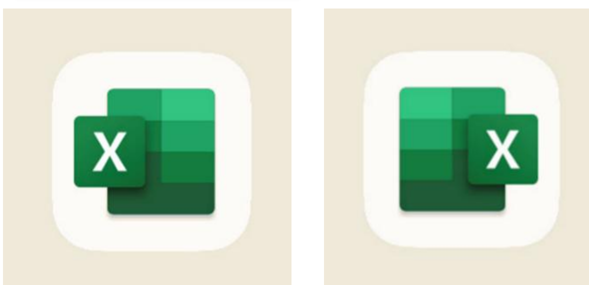
Stimuli14b_mod
(top middle)



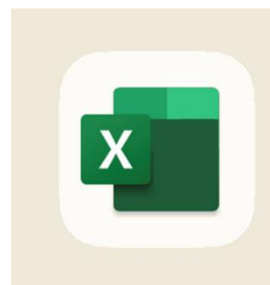
Stimuli6c_mod
(bottom right)



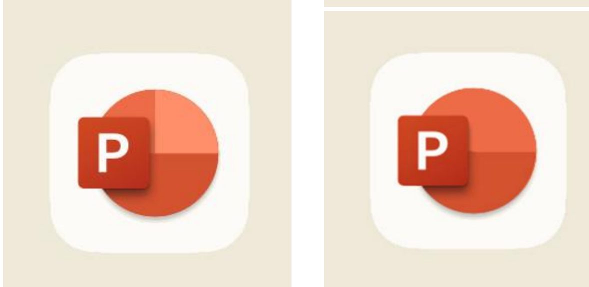
Stimuli15c_mod
(top right)



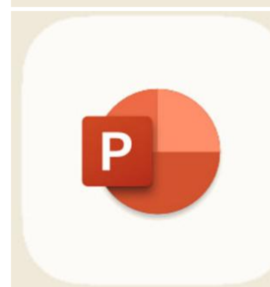
Stimuli7b_mod
(top left)



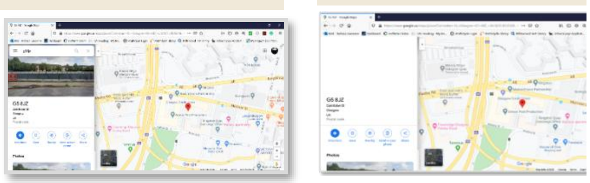
Stimuli22b_mod
(bottom left)



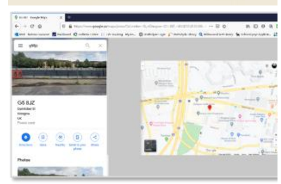
Stimuli8c_mod
(top middle)



Stimuli23c_mod
(bottom middle)

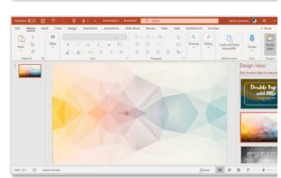


Stimuli9a_mod
(top right)

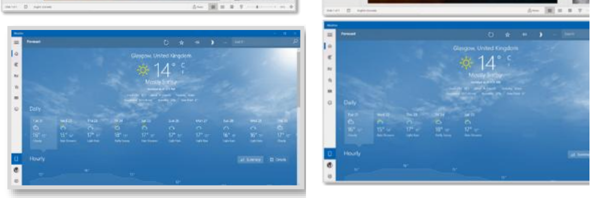


Stimuli24a_mod
(bottom right)

Stimuli10b_mod
(bottom left)



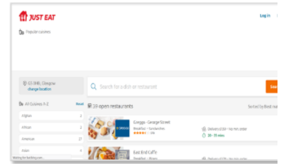
Stimuli19b_mod
(top left)



Stimuli11c_mod
(bottom middle)

Stimuli20c_mod
(top middle)


Stimuli12a_mod
(bottom right)



Stimuli21a_mod
(top right)

Stimuli1b_mod
(top left)

Stimuli16b_mod
(bottom left)

Stimuli2c_mod
(top middle)

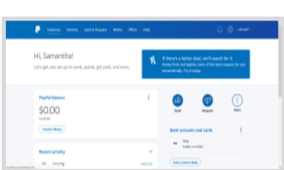
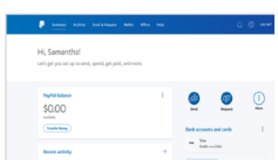
Stimuli17c_mod
(bottom middle)

Stimuli3a_mod
(top right)

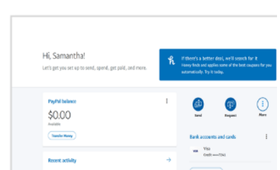
Stimuli18a_mod
(bottom right)


Stimuli4b_mod
(bottom left)

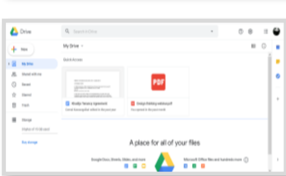
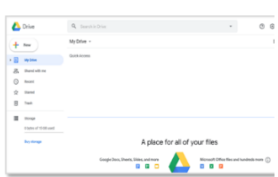
Stimuli13b_mod
(top left)

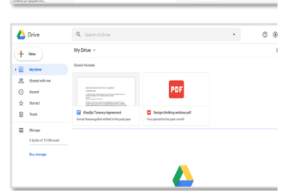
Stimuli5c_mod
(bottom middle)



Stimuli14c_mod
(top middle)

Stimuli6a_mod
(bottom right)



Stimuli15a_mod
(top right)



Stimuli7c_mod
(top left)

Stimuli22c_mod
(bottom left)



Stimuli8a_mod
(top middle)

Stimuli23a_mod
(bottom middle)



Stimuli9b_mod
(top right)

Stimuli24b_mod
(bottom right)



Stimuli10c_mod
(bottom left)

Stimuli19c_mod
(top left)



Stimuli11a_mod
(bottom middle)

Stimuli20a_mod
(top middle)



Stimuli12b_mod
(bottom right)

Stimuli21b_mod
(top right)



Stimuli1c_mod
(top left)

Stimuli16c_mod
(bottom left)



Stimuli2a_mod
(top middle)

Stimuli17a_mod
(bottom middle)


Stimuli3b_mod (top right)

Stimuli18b_mod (bottom right)


Stimuli4c_mod (bottom left)

Stimuli13c_mod (top left)


Stimuli5a_mod (bottom middle)

Stimuli14a_mod (top middle)


Stimuli6b_mod (bottom right)

Stimuli15b_mod (top right)

Note. How each stimuli was changed and placed in the experiment

Appendix D2

Questionnaires Used in Experiment 1

Table D1

QIUU

Questionnaire on Internet Use Urges (QIUU)
• I have a desire to be online right now.
• Nothing would be better than being online right now.
• If it were possible, I probably would be online now.
• I could control things better right now if I could be online.
• All I want right now is to be online.
• I have an urge to be online.
• Being online would feel good now.
• I would do almost anything to be online now.
• Being online would make me less depressed.
• I am going to be online as soon as possible.

Note. *(*7-point Likert scale, strongly agree to strongly disagree*)

Table D2

AEQ

Addiction-Engagement Questionnaire (AEQ)

Factor 1 – *Addiction*

- I sometimes neglect important things because of an interest in social media
- My social life has sometimes suffered because of my social media internet use
- Being on social media has sometimes interfered with my work
- When I am not on social media I often feel agitated
- I have made unsuccessful attempts to reduce the time I spend on social media
- I am sometimes late for engagements because I am on social media
- Arguments have sometimes arisen at home because of the time I spend on social media
- I think that I am addicted to social media
- I often fail to get enough sleep because of social media
- I never miss meals because of social media
- I have never used social media as an escape from socialising
- I feel a sense of power when I am on social media
- I often feel that I spend more money than I can afford on social media

Factor 2 – *(Low) Engagement*

- It would not matter to me if I never went on social media again
- I feel happy at the thought of being on social media The less I have to do with social media, the better
- Social media is unimportant in my life
- I would hate to go without social media for more than a few days
- I spend little of my spare time on social media
- When I see social media, I feel drawn towards it
- I rarely think about social media when I am not using a computer

- I pay little attention when people talk about social media
- I tend to want to spend increasing amounts of time on social media
- It is important to me to be good at social media
- I often experience a buzz of excitement while on social media
- I like the challenge that learning social media presents
- I try to make my social media last as long as possible
- Social media jargon sounds stupid to me
- I can't understand why people like social media

Note. *(*7-point Likert scale, completely agree to completely disagree*)

Table D3

BSMAS

Bergen Social Media Addiction Scale (BSMAS)

How often during the last week have you . . .?

Salience

- BFAS1*Spent a lot of time thinking about social media or planned use of social media?
- BFAS2 Thought about how you could free more time to spend on social media?
- BFAS3 Thought a lot about what has happened on social media recently?

Tolerance

- BFAS4 Spent more time on social media than initially intended?
- BFAS5* Felt an urge to use social media more and more?
- BFAS6 Felt that you had to use social media more and more in order to get the same pleasure from it?

Mood modification

- BFAS7* Used social media in order to forget about personal problems?
- BFAS8 Used social media to reduce feelings of guilt, anxiety, helplessness, and depression?
- BFAS9 Used social media in order to reduce restlessness?

Relapse

- BFAS10 Experienced that others have told you to reduce your use of social media but not listened to them?
- BFAS11* Tried to cut down on the use of social media without success?
- BFAS12 Decided to use social media less frequently, but not managed to do so?

Withdrawal

- BFAS13* Become restless or troubled if you have been prohibited from using social media?
- BFAS14 Become irritable if you have been prohibited from using social media?
- BFAS15 Felt bad if you, for different reasons, could not log on to social media for some time?

Conflict

- BFAS16* Used social media so much that it has had a negative impact on your job/studies?
- BFAS17 Given less priority to hobbies, leisure activities, and exercise because of social media?
- BFAS18 Ignored your partner, family members, or friends because of social media?

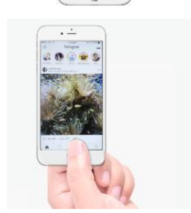
Note. *(*5-point Likert scale, very rarely to very often*)

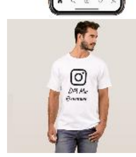
Appendix E

Stimuli Used in Experiment 2

Figure E1

Instagram Stimuli

SM2 (S 11)	instagramoldicon	
SM3 (S 13)	newinstaicon	
SM8 (S 23)	instablacklogo	
SM9 (S 25)	instalogo	
SM12 (S 32)	instaeyemakeup	
SM13 (S 34)	instanoodles	
SM19 (S 46)	instadino	
SM22 (S 142)	instahand	

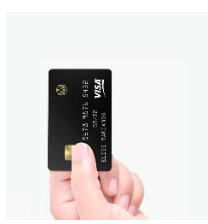
SM23 (S 144)	instagroup	
SM27 (S 152)	instaiconpile	
SM5 (S 17)	instagramshare	
SM6 (S18)	Billalawnmower	Lawnmower
SM7 (S 20)	wordinstagram	**Instagram**
SM14 (S 36)	instahouse	
SM15 (S 38)	instajurassic	
SM17 (S 41)	instasearch	
SM20 (S 47)	instafootball	
SM21 (S 49)	instacar	
SM24 (S 146)	instatshirt	

SM25 (S 148)	instabag	

Note. 20 Instagram images included the application icon, the Instagram messenger icon, etc.

Figure E2

Control Stimuli

C2 (S 10)	camera	
C3 (S 12)	rainbow	
C8 (S 22)	communityfund	
C9 (S 26)	polaroid	
C12 (S 31)	makeuplogo	
C13 (S 33)	noodles	
C19 (S 45)	dino	
C22 (S 141)	creditcard	

C23 (S 143) group

C27 (S 151) chipspile

C5 (S 16) chanel

C6 (S 19) TNRlawnmower

Lawnmower

C7 (S 21) newspaper

Newspaper

C14 (S 35) house

C15 (S 37) jurassic

C17 (S 42) male

C20 (S 48) football

C21 (S 50) car

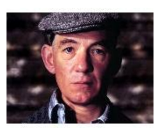
C24 (S 145) tshirt

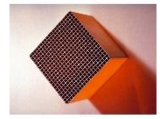
C25 (S 147) chanelbag 

Note. 20 control images included images of words and modern digital branding elements, including icons/logos and recognizable branding (e.g., Polaroid, Community Fund, an Instagram-like colour gradient).

Figure E3

Neutral Stimuli

f1a	basket		f1b	lamp	
f2a	spoon		f2b	fan	
f3a	woodenovals		f3b	kleenexbox	
f4a	bowl		f4b	building	
f5a	gandulf		f5b	rollingpin	
f6a	chess		f6b	clothesrack	
f7a	woodenbuckets		f7b	book	

f8a glasscup  f8b cube 

f9a hairdryer  f9b clip 

f10a peopleontrain  f10b plate 

f11a mushrooms  f11b chair 

f12a manworking  f12b carpet 

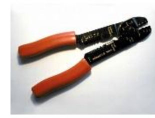
f13a mansittingunderlight  f13b twins 

f14a shadowofman  f14b pole 

f15a bluecup  f15b workshoes 

f16a manreading  f16b lightbulb 

f17a hammer  f17b scarf 

f18a	mushrooms2		f18b	pliers	
f19a	towel		f19b	lightbulbon	
f20a	socket		f20b	shippingyard	

Note. 40 filler images of neutral events (e.g., neutral faces, household objects, places, etc.), taken from International Affective Picture System (IAPS).

Appendix E1

How Stimuli Were Placed Together in Experiment 2

Table E1

How Stimuli were placed together

Instagram-Images	*Control-Images*
instagramoldicon	camera
newinstaicon	rainbow
instagramshare	chanel
Billalawnmower	TNRlawnmower
wordinstagram	newspaper
instablacklogo	communityfund
instalogo	polaroid
instaeyemakeup	makeuplogo
instanoodles	noodles
instahouse	house
instajurassic	jurassic
instasearch	male
a	dino
instafootball	football
instacar	car
instahand	creditcard
instagroup	group
instatshirt	tshirt
instabag	chanelbag
instaiconpile	chipspile

Appendix E2

Questionnaires Used in Experiment 2

Table E2

QIUU

Questionnaire on Internet Use Urges (QIUU)
• I have a desire to be online right now.
• Nothing would be better than being online right now.
• If it were possible, I probably would be online now.
• I could control things better right now if I could be online.
• All I want right now is to be online.
• I have an urge to be online.
• Being online would feel good now.
• I would do almost anything to be online now.
• Being online would make me less depressed.
• I am going to be online as soon as possible.

Note. *(*7-point Likert scale, strongly agree to strongly disagree*)

Table E3

SMAQ

Social Media Addiction Questionnaire (SMAQ)
• I often think about Instagram when I am not using it
• I often use Instagram for no particular reason
• Arguments have arisen with others because of my Instagram use
• I interrupt whatever else I am doing when I feel the need to access Instagram
• I feel connected to others when I use Instagram
• I lose track of how much I am using Instagram

- The thought of not being able to access Instagram makes me feel distressed
- I have been unable to reduce my Instagram use
- I have been unable to reduce my Instagram use

Note. *(*7-point Likert scale, strongly disagree to strongly agree*)

Table E4

BSMAS

Bergen Social Media Addiction Scale (BSMAS)
• How often during the last year have you...... Spent a lot of time thinking about Instagram or planned use of Instagram?
• How often during the last year have you...... Felt an urge to use Instagram more and more?
• How often during the last year have you...... Used Instagram in order to forget about personal problems?
• How often during the last year have you...... Tried to cut down on the use of Instagram without success?
• How often during the last year have you...... Become restless or troubled if you have been prohibited from using Instagram?
• How often during the last year have you...... Used Instagram so much that it has had a negative impact on your job/studies?

Note. *(*5-point Likert scale, very rarely to very often*)

Table E5

SMES

Social Media Engagement Scale (SMES)
• Please reflect on how you used Instagram in the past week (i.e. the previous seven days) and report the number of times you used it...... within 15 min of waking up?

- Please reflect on how you used Instagram in the past week (i.e. the previous seven days) and report the number of times you used it......

  when eating breakfast?

- Please reflect on how you used Instagram in the past week (i.e. the previous seven days) and report the number of times you used it......

  when eating lunch?

- Please reflect on how you used Instagram in the past week (i.e. the previous seven days) and report the number of times you used it......

  when eating dinner?

- Please reflect on how you used Instagram in the past week (i.e. the previous seven days) and report the number of times you used it......

  within 15 min of going to sleep?

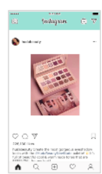
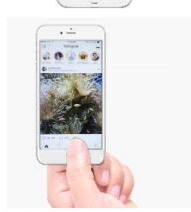
Note. *(*8-point Likert scale, not one day last week to every day last week*)

Appendix F

Stimuli Used in Experiment 3

Figure F1

Instagram Stimuli

SM2 (S 11)	instagramoldicon	
SM3 (S 13)	newinstaicon	
SM8 (S 23)	instablacklogo	
SM9 (S 25)	instalogo	
SM12 (S 32)	instaeyemakeup	
SM13 (S 34)	instanoodles	
SM19 (S 46)	instadino	
SM22 (S 142)	instahand	

SM23 (S 144) instagroup

SM27 (S 152) instaiconpile

Note. 10 Instagram images included the application icon, the Instagram messenger icon, etc.

Figure F2

Control Stimuli

C2 (S 10) camera

C3 (S 12) rainbow

C8 (S 22) communityfund

C9 (S 26) polaroid

C12 (S 31) makeuplogo

C13 (S 33) noodles

C19 (S 45) dino

C22 (S 141) creditcard

C23 (S 143) group

C27 (S 151) chipspile

Note. 10 control images included images of words and modern digital branding elements, including icons/logos and recognizable branding (e.g., Polaroid, Community Fund, an Instagram-like colour gradient).

Figure F3

Neutral Stimuli

f1a basket

f1b lamp

f2a spoon

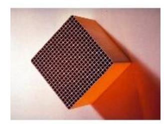
f2b fan

f3a woodenovals

f3b kleenexbox

f4a bowl

f4b building

f5a	gandulf		f5b	rollingpin	
f6a	chess		f6b	clothesrack	
f7a	woodenbuckets		f7b	book	
f8a	glasscup		f8b	cube	
f9a	hairdryer		f9b	clip	
f10a	peopleontrain		f10b	plate	

Note. 20 filler images of neutral events (e.g., neutral faces, household objects, places, etc.), taken from International Affective Picture System (IAPS).

Appendix F1

How Stimuli Were Placed Together in Experiment 3

Table F1

How Stimuli were placed together

Instagram-Images	*Control-Images*
instagramoldicon	camera
newinstaicon	rainbow
instablacklogo	communityfund
instalogo	polaroid
instaeyemakeup	makeuplogo

instanoodles	noodles
instadino	dino
instahand	creditcard
instagroup	group
instaiconpile	chipspile

Appendix F2

Questionnaires Used in Experiment 3

Table F2

QIUU

Questionnaire on Internet Use Urges (QIUU)
• I have a desire to be online right now.
• Nothing would be better than being online right now.
• If it were possible, I probably would be online now.
• I could control things better right now if I could be online.
• All I want right now is to be online.
• I have an urge to be online.
• Being online would feel good now.
• I would do almost anything to be online now.
• Being online would make me less depressed.
• I am going to be online as soon as possible.

Note. Do a description. *(*7-point Likert scale, strongly agree to strongly disagree*)

Table F3

SMAQ

Social Media Addiction Questionnaire (SMAQ)
• I often think about Instagram when I am not using it
• I often use Instagram for no particular reason
• Arguments have arisen with others because of my Instagram use

- I interrupt whatever else I am doing when I feel the need to access Instagram
- I feel connected to others when I use Instagram
- I lose track of how much I am using Instagram
- The thought of not being able to access Instagram makes me feel distressed
- I have been unable to reduce my Instagram use
- I have been unable to reduce my Instagram use

Note. Do a description *(*7-point Likert scale, strongly disagree to strongly agree*)

Table F4

BSMAS

Bergen Social Media Addiction Scale (BSMAS)

- How often during the last year have you......

  Spent a lot of time thinking about Instagram or planned use of Instagram?
- How often during the last year have you......

  Felt an urge to use Instagram more and more?
- How often during the last year have you......

  Used Instagram in order to forget about personal problems?
- How often during the last year have you......

  Tried to cut down on the use of Instagram without success?
- How often during the last year have you......

  Become restless or troubled if you have been prohibited from using Instagram?
- How often during the last year have you......

  Used Instagram so much that it has had a negative impact on your job/studies?

Note. Do a description *(*5-point Likert scale, very rarely to very often*)

Table F5

SMES

Social Media Engagement Scale (SMES)

- Please reflect on how you used Instagram in the past week (i.e. the previous seven days) and report the number of times you used it......

  within 15 min of waking up?

- Please reflect on how you used Instagram in the past week (i.e. the previous seven days) and report the number of times you used it......

  when eating breakfast?

- Please reflect on how you used Instagram in the past week (i.e. the previous seven days) and report the number of times you used it......

  when eating lunch?

- Please reflect on how you used Instagram in the past week (i.e. the previous seven days) and report the number of times you used it......

  when eating dinner?

- Please reflect on how you used Instagram in the past week (i.e. the previous seven days) and report the number of times you used it......

  within 15 min of going to sleep?

Note. Do a description *(*8-point Likert scale, not one day last week to every day last week*)