An Exploration of Social Media and Physiological Stress Recovery: A Preliminary Investigation Within a Biopsychosocial Framework

DUKE, LIAM,MICHAEL

An Exploration of Social Media and Physiological Stress Recovery: A Preliminary Investigation Within a Biopsychosocial Framework

Author: Liam Michael Duke.
Supervised by Dr Thuy-Vy Nguyen, Dr Niklas Ihssen, and Dr Jonathon McPhetres
Department of Psychology, Durham University

Originally Submitted: September 29th, 2025
Last Revised: February 14th, 2026

Dissertation submitted in fulfilment of the requirements for MSc (by Research) in Psychology.

Contributor Role Taxonomy (CRediT) Statement

Liam Duke was responsible for the conceptualisation and methodology of the present study (the choosing of experimental inventories and variables to explore, as well as the specific data analyses to conduct) contained within the larger study context, which was designed and conceptualised by Dr Jonathon McPhetres and Dr Thuy-Vy Nguyen. Liam Duke along with the other members of the wider study context laboratory, contributed equally to the curation and investigation (data collection) of physiological, individual-difference, and social media variables. While the task of cleaning and processing physiological data was shared equally amongst Liam Duke and the other members of the wider study laboratory team, social media and individual difference data were processed solely by Liam Duke. Liam Duke solely contributed to the formal analysis and interpretation of the present study's data. Liam Duke prepared the original draft and revised version writing for this dissertation, including any visualisations of data.

Dr. Jonathan McPhetres, Dr. Thuy-Vy Nguyen, and Dr. Nikklas Ihsen contributed through academic supervision, methodological feedback, and draft feedback on the dissertation. Dr. Nikklas Ihsen also provided both methodological and practical guidance on the revised version of this dissertation.

Acknowledgements

I would like to thank Dr Thuy-Vy Nguyen, Dr Nikklas Ihssen, and Dr Jonathon McPhetres for their supervision at various points during this project. Also, a thank you to the other members of the study team for their collaboration.

I would like to extend a heartfelt thank you to all the friends I have made during this past year at Durham. In light of many personal challenges faced this past year, having your support throughout this year has been invaluable for maintaining my resolve. Indeed, getting to know so many unique and friendly people has been a truly precious experience. I would like to personally thank my dear friends Tabs, Aisha, and Myth for their genuine hospitality in welcoming me into their friend groups as a Postgraduate student, and, of course, for being such wonderful, enthusiastic, and empathetic friends. Furthermore, I must thank all the lovely people at the Eco Society and Wizard Society (Yeah, you read that right) here at the University. It has been an honour to connect with such diverse and caring souls, and I appreciate the unique experiences and new skills learnt through my time with these societies. I hope we all stay in contact, regardless of whether I decide to stay or leave Durham.

Beyond this, I would like to extend further appreciation to the friends formed at both York and Peterborough. Without you, I would not have been able to get to this point. Likewise, I hold much appreciation to my long-time online friends, particularly Marley, for listening to me complain and rave frantically about things throughout the years, specifically about the challenges faced during this course with limitless patience and understanding. Finally, the same goes for my mother, for spending many a phone calls listening to me ramble on and on about this course. There are many more that I could name but for the sake of brevity, I hope you will understand that my thanks go without saying.

An Exploration of Social Media and Physiological Stress Recovery: A Preliminary Investigation within a Biopsychosocial Framework

ABSTRACT

Billions use social media apps (SM), which function to connect people. Despite good intentions, researchers have expressed concern about potential psychosocial impacts. Indeed, previously detected links between stress recovery deficits and SM remain contested in the literature, with substantial gaps in mechanistic knowledge. Many studies observe direct manipulations of SM use but fail to consider longer-term trends of habitual use. Accordingly, we sought to employ a design informed by the biopsychosocial challenge and threat, as well as the multi-channel approach frameworks of SM research, to conduct a comprehensive exploration of habitual SM's link to stress recovery. This study investigated whether reward sensitivity, perceived information overload, daily average screen time, and valence predicted cardiovascular recovery following an acute social stressor. Participants (N = 24) completed self-report scales and had screen time data recorded. Subsequently, participants underwent a Trier Social Stress Test, after which they recovered in isolation. We recorded cardiovascular data at baseline, stress, and recovery, from which we derived proportional recovery indices. The present paper suffered from low power. As such, no inferential, confirmatory effects were detected, except for an association between reward sensitivity and SM valence. However, when exploring descriptive patterns, several preliminary effects appear to have emerged. Firstly, reward sensitivity appeared to negatively associate with daily mean screen time. Similarly, preliminary patterns suggested a negative association between screen time and certain stress recovery indices, and that both PIO and Reward sensitivity may moderate associations between valence and stress recovery indices. These preliminary findings suggest that there may be complex processes underlying social media stress. However, we recognise that, due to the underpowered and methodologically constrained nature of this study, definitive conclusions about effects or their lack cannot be definitively drawn. The study highlights directions for further investigation into the psychosocial and physiological consequences of SM use.

CONTENTS

ABBREVIATIONS

AI – Artificial Intelligence

ANS – Autonomic Nervous System

BAS – Behavioural Activation Scale

BIS – Behavioural Inhibition Scale

BP – Blood Pressure

BPS – Biopsychosocial

BPS-CT – Biopsychosocial Model of Challenge and Threat

CLT – Cognitive Load Theory

CMC – Computer-Mediated Communication

CNS – Central Nervous System

CO – Cardiac Output

DBP – Diastolic Blood Pressure

ECG - Electrocardiogram

EEG - Electroencephalogram

HPA - Hypothalamic-Pituitary-Adrenal axis

HR – Heart Rate

HRV – Heart Rate Variability

ICG – Impedance Cardiography

ICT – Information Communication Technology

MAP – Mean Arterial Pressure

MDE – Minimum Detectable Effect (Size)

MH – Mental Health

PEP – Pre-Ejection Period

PIO – Perceived Information Overload

PIOS - Perceived Information Overload Scale

PIU – Problematic Internet Use

PNS – Parasympathetic Nervous System

SAM - Sympathetic-Adreno-Medullary axis

SBDA – Swipe-Based Dating Apps

SBP – Systolic Blood Pressure

SFVC – Short Form Video Content

SM – Social Media

SNS – Social Networking Sites

TPR – Total Peripheral Resistance

TSST - Trier Social Stress Test

1. INTRODUCTION

1.1. Introduction of Social Media

1.1.1. Defining Social Media

Social media (SM) refers to applications, technologies, or software that facilitate the transfer of information or communication across large groups of people (Kaplan & Haenlein, 2010; Kietzmann et al., 2011). Going beyond simple communication, it is characterised by group communication, reputation, and identity maintenance (Kietzmann et al., 2011). It also occupies a wide range of gratifying niches, such as communication, idea sharing, and entertainment (Whiting & Williams, 2013).

The term social media encompasses a wide range of applications/websites. Kaplan and Haenlein (2010) categorised social media platforms based on levels of self-presentation and intensities of social involvement/authenticity (as compared to genuine in-person social communication). "Social Media", therefore, can encompass low-social, low authenticity applications. In these platforms, users are not expressing personal information or doing so in a manner that is remotely analogous to real-life face-to-face communication but are engaging in information transfer, nonetheless. For example, collaborative encyclopaedias (e.g., Wikipedia). Meanwhile, it also encompasses the most high-end presentations and authentic platforms, such as virtual environments (e.g., the Metaverse (Mystakidis, 2022)), which include online personas (high self-presentation) and enable face-to-face interaction. Therefore, this includes platforms such as social networking sites, media-sharing platforms, online gaming, and personal or community blogs (see Figure 1). In this paper, social media will refer to this broader category. Social Networking Sites (SNS) refer to platforms that exhibit high social presence and a moderate level of communication authenticity, such as Facebook or Instagram. Computer-Mediated Communications (CMC) may be used interchangeably with SM in this paper for the sake of simplicity. However, they can also typically refer to any digital technology involved in communication, including one-to-one communication methods such as email or texting. The hierarchical organisation of concepts is as follows: CMC → SM → SNS. Furthermore, many SNSs tend to be Hybrid SNS-shortform video content sharing (SFVC) platforms nowadays. Due to their ubiquity, we will also be examining these under the blanket term of SM.

Figure 1

(From Kaplan & Haenlein, 2010) "Table 1. Classification of social media by social presence/media richness and self-presentation/self-disclosure"

		Social presence/ Media richness		
		Low	Medium	High
Self-presentation/ Self-disclosure	High	Blogs	Social networking sites (e.g., Facebook)	Virtual social worlds (e.g., Second Life)
	Low	Collaborative projects (e.g., Wikipedia)	Content communities (e.g., YouTube)	Virtual game worlds (e.g., World of Warcraft)

These emerging technologies are more than simple technological innovations for entertainment; they present us with newfound social environments that circumvent the usual constraints of in-person interaction. Users of these platforms experience high cognitive demands, such as social comparison, the stress of navigating alien social hierarchies, inundation by excessive quantity of content, a high prevalence of emotionally charged stimuli, and unpredictable and addictive algorithms. Researchers have found these experiences to be associated with psychological distress and harm. In particular, some have raised concerns regarding the risks of SM on mental health (e.g., Huang, 2017; Meier & Reinecke, 2021), particularly how it interferes with one's ability to recover from stress adaptively (e.g., Rus & Tiemensma, 2017; Wolfers & Utz, 2022), a core tenet of psychopathology risk. In coming sections, this paper will explore psychological risks and potential cognitive mechanisms at play.

1.1.2. Social Media and Mental Health

Social media, and more broadly, the advancement of information and communication technologies, are indicative of the modern zeitgeist. Most humans are online (DataReportal et al., 2024), with billions of people spread across various social networking sites (Cunningham et al., 2021). Most people use these sites daily (Pew Research Centre, 2018). However, despite its ubiquity, even some of the original designers are apprehensive about the negative potential of communication technologies on psychological and social well-being (Schwab, 2017).

As the usage of SM has increased, mental illness has also appeared to have become more widespread (Fan et al., 2025). There seems to be a lack of consensus on the relationship between social media and its potential impact on mental health. For example, Cingel et al. (2022) found that social media can potentially raise self-esteem in users, while Huang (2017) simultaneously found that time spent on social media had a weak negative association with psychological well-being (in this case, a combined metric of loneliness, self-esteem, life satisfaction, and depression levels. Public opinion seemingly takes the pessimistic stance that social media is thoroughly harmful (Lee et al., 2024; More in Common, 2025). A long pattern of diverse and often contradictory literature obscures the true nature of SM and mental health. Indeed, decisive evidence to either verify or falsify this conclusion remains elusive. This ambiguity then highlights the need to carefully consider how we define and operationalise mental health and social media concepts, to delineate the true nature of the hitherto inconsistent results more directly.

Furthermore, Fassi et al. (2025) investigated differences in adolescent social media usage behaviours across those with and without mental health conditions. While providing results to suggest that those with mental health conditions generally engage with SM more, they, in fact, also found that SM engagement styles changed depending on the given psychopathological presentation. For example, those with disorders falling under the internalising category (e.g., major depressive disorder, generalised anxiety disorder) spent online time engaging in social comparison. Meanwhile, externalising disorders, such as Attention-deficit hyperactivity disorder, leaned towards having increased app usage without accompanying peer comparison behaviours.

To address the issue of conceptual heterogeneity, Meier and Reinecke (2021) developed a comprehensive theoretical framework using concept mapping. They found that approaches to measuring CMC boiled down to two distinct domains: the Channel-Centred

Approach (Channel-CA) and the Communication-Centred Approach (Communication-CA). Channel-CAs quantified CMC-use by recording the extent to which a user uses or spends time with a given CMC medium or application, regardless of users' differing experiences on the same medium. For example, the minutes a user uses their phone, a given website, or an app's video calling feature per day. Alternatively, Communication-CAs examine individual differences that users may experience in the same channel, in other words, the nature of their online time. For example, two users spending an equal amount of time on the same website may be exposed to wholly different content or stimuli. Depending on desired specificity, these domains can be further divided into subdomains.

These diverse ways of examining SM present an urgent need to consider all conceptual levels when exploring the effect of SM on mental health. For example, say that, using the Channel-CA, it is found that time on Facebook correlates with depression. In a short while, Facebook may drastically alter their algorithm, app design, or application. This makes the previous findings struggle to have a valid practical application to that 'new Facebook'. By employing a communication-centred approach, we can identify what specifically about Facebook, in this example, is causing the depression relationship. Hypothetically, Facebook, in its current form, may contain a high quantity of negative emotional content. We could conclude that negative content may contribute to depression risk, which would be a hugely more future-proof conclusion and could be generalised to any present or future social media. Ultimately, more robust conclusions could be accomplished when considering both approaches.

A benefit of operationalising social media research by examining all its conceptual levels is that it increases the validity and widespread applicability of research, thereby helping to eliminate ethnic bias in this domain, a historical constraint in the literature (Vuorre & Przbylski, 2023). Accordingly, it is fair to assume different cultures may engage with different applications, websites, or online technologies. As such, examining specific websites, devices, or apps (e.g., Facebook) may be completely inapplicable to a culture that does not use said app (e.g., Facebook), but rather a different platform. An example is how the Chinese government restricts access to YouTube, leading Chinese internet users to use alternative sites, such as BilliBilli (Zheng et al., 2023), a relatively underutilised platform in Western countries (Zhang & Scheibe, 2023). Indeed, either examining only the commonly used platforms of one culture and ignoring the others or exhaustively examining each culture's social media platforms one by one, would lack wider generalisability or be incredibly expensive (respectively), and both would be non-resistant to technological progress. In fact, Vuorre & Przbylski (2023) recruited a more representative sample and found that internet engagement has an overall net positive effect on wellbeing, with any negative impacts generally being limited to adolescent and young adult users. Given this effect appeared to manifest in a cross-cultural cohort, it may be fair to consider whether a common qualitative feature of SM/CMC is particularly impactful to this demographic and not to other users, which further emphasises the potential utility of operationalising SM research as including general qualities rather than specific platforms or features, or as phrased by Kaye et al., (2020), "affordances/activities obtained via platforms" in making SM research useful and resistant to future technological change (Orben et al., 2019).

Indeed, in Orben's (2020) article titled "The Sisyphean Cycle of Technology Panics", she details the futility of current dominant academic approaches to addressing societal tech panics. She suggests that any necessary policy changes generated from enhanced understanding are delayed beyond the time for practical implementation. This is due to research regarding these technological 'hot topics' lagging behind further tech innovations, since academic study essentially restarts from scratch with each new piece of technology, software, etc. Instead, they suggest that building on prior technology research prioritising statistical transparency and effects-based (rather than individual technologies) examination would be a far more efficient scientific approach. In fact, new technologies and subsequent culture panics always tend to occur, as described by Finkelhor's (2011) concept of Juvenoia - an established repetitive cycle of anxious fear felt by previous generations towards the culture and technologies of the subsequent. These outrages occurred with the introduction of cultural commonplaces, such as magazines, and they can still be seen today, with some even arguing that the cultural eye of scrutiny has shifted from just SM to the Artificial Intelligence movement (Gilmore et al., 2025). This all supports the idea of investigating social media, not merely as just magnitude but the qualities it exhibits which helps to (1) make flexible and translatable inferences, (2) make and implement rapid policy changes before technologies become too ingrained in common culture to influence meaningfully, and (3) to make any conclusions future-proof and helpful to the investigation of later emergent technologies, which a new moral panic will inevitably accompany. As an aside, Gilmore et al. (2025) suggested that modern culture, particularly as defined by its use of SM, seemingly encourages the incitement of moral panics through the incentives it provides (i.e., audience retention and attention). As such, it could therefore be an interesting thought to consider whether SM, or our wider culture, is itself hindering scientific progress for the reasons discussed. Accordingly, this potentially leads to a more well-founded and valid fear of these technologies but also creates a difficult Catch-22 if that fear then hinders science.

Nevertheless, after identifying and analysing the different conceptualisations underlying the relationship between mental health and SM use, the findings of Meier and Reinecke (2021) yielded complex results. Depending on the level or channel in question, the effect of SM on mental health was either positive, negative, or non-existent. For example, those who use social media 'more intensely' generally perceive their social support network as being stronger (social wellbeing is positively impacted). At the same time, this high intensity of use was also associated with higher level of internalising psychopathology (a mental health conceptualisation that encompasses all disorders or behaviours that involve the direction of negative emotions inwards. I.e., depression, anxiety, or specific phobias (Conway et al., 2019).

Overall, when combining all these domains, they found "a (very) small negative association ($r \approx -.05$ to $-.15$) between MH and SM", the effect being higher for the more specific relationships. This is to say that examining the relationship between MH and SM as a single unified concept does not provide a complete picture; instead, it illustrates the need to consider multiple levels of SM conceptualisation (which is the aim of the present paper). The current paper aims to utilise this standardised approach, as outlined, to inform our study design, ensuring we can achieve the most nuanced and thorough conclusions. Notably, however, the present paper has a limited scope. MRes appropriate designs do not possess the scale required for us to consider every single operationalisation of MH and SM as outlined by

Meier and Reinecke. However, it can be stated that acknowledging the present operationalisation belongs to a larger framework allows us to generate finer-tuned interpretations of results, regardless of the design scope. This then affords us the ability to fulfil our aim of conducting research that can be integrated into the broader literature on this topic.

1.2. Stress

1.2.1. Stress and social media

There is a significant degree of heterogeneity in how studies in the literature have defined and measured 'mental health' as a concept (Greenspoon & Saklofske, 2001; Keyes, 2006), which likely contributes to the high degree of heterogeneity in MH and SM findings (Meier & Reinecke, 2021). As such, we believe it is especially pertinent for us to carefully consider how we operationalise MH, as we did with SM in the above section. An 18-study meta-analysis by Shannon et al (2022) found a significant association between stress and problematic social media use, while work by Wolfers & Utz, 2022 present a functional model displaying how SM is deeply intertwined in multiple aspects of stress and explores a litany of literature supporting stress's connection to MH. However, the causal direction of the relationship between stress and SM is contested (Wolfers & Utz, 2022). Nonetheless, it appears that stress is a largely implicated variable relating to SM use, encompassing all tenets of MH.

Stress has long been considered a fundamental and encompassing risk factor underlying psychopathology (Cirulli et al., 2009). For example, Eisenbarth et al. (2019) found that stress exposure predicted later internalising and externalising pathology, presenting as a fundamental risk factor. Then, from a logical perspective, when considering the definitions of the two conceptual domains of psychological well-being—eudaimonic and hedonic—stress would seemingly be a risk factor axiomatically. To explain, Hedonic wellbeing, i.e. straightforward feelings of pleasure, would undoubtedly be affected by stress (as it does not feel good to be stressed), while Eudaimonic well-being, the state of realising a self whereby you feel confident and comfortable in your life and environment – i.e. achieving one's fullest potential – would also be affected (as stress directly opposes feelings of security in one's self or environment) (Meier & Reinecke., 2021). Backing this up, Khetawat and Steele (2023), in a meta-analysis, found that digital stressors were related to psychosocial distress, a facet of psychological well-being (Eiroa-Orosa, 2020). The Meier and Reinecke paper also stated that stress was a risk factor for both poor psychopathology and reduced psychological well-being, broadly. Together with the overall meta-review finding that global mental health levels were significantly associated with CMC use, the finding that social media also had an, albeit small, positive association with stress risk factor (r = .13) supports the idea that, generally, stress is a decisive and fundamental risk factor for both elements of mental health.

It is no wonder that stress is such a prominent risk factor when considering the wide-reaching consequences of prolonged exposure to stressors. From epigenetic factors on emotional systems in early development (Wang et al., 2021), to oxidative stress and ensuing neurotrophic dysfunction (Salim, 2014). With these and the prior sections in mind, this is why the present paper believes stress is an, if not *the*, critical element for us to research in the context of mental health, being that it fully encompasses all aspects of the dual-continua model of mental health. This is the basis for why we have chosen to investigate stress's connection to social media specifically.

1.2.2. Literature on social media and stress

When examining prior studies that measure the relationship between social media and stress, a distinct lack of consensus appears. By extension, these mixed reports challenge the prevailing notion in the public consciousness that social media use is overwhelmingly negative. An example of the heterogeneity of social media and stress findings is as follows. Rus and Tiemensma (2017) found that using Facebook after an acute social stressor resulted in slower cortisol recovery. This implied that social media use directly following a stressor either halts the recovery process or instead acts as a further social stressor. The latter of which seems unlikely, given the findings of Oppenheimer et al. (2024). Oppenheimer et al. (2024) measured similar physiological markers (heart rate and cortisol) during 20 minutes of social media use or simple online media consumption. They found that this period did not elicit any significant stress responses (at least according to their biomarkers). This shows that social media does not induce stress from short-term use.

However, this study's curation and use of 'non-evocative' content does not provide a naturalistic and ecologically valid social media experience. Indeed, it is likely that due to personalised algorithms that are biased towards videos that are more likely to capture attention (i.e., highly emotional and controversial) (Metzler & Garcia, 2023; Okeke et al., 2023). Accordingly, the extent of stress activation would be different in genuine social media use. Contrastingly, Joseph et al. (2022) found that digitally mediated social interaction elicited momentary increases in cortisol, whereas in-person interaction was associated with a decline in cortisol levels. They found that the valence of emotional experience during these social interactions underpinned the effect on cortisol levels, demonstrating a need to consider this factor.

Regardless of the validity of Oppenheimer et al.'s study, a later study directly contradicts Rus and Tiemensma's study completely. Johnshoy et al. (2020) instead found that a group of individuals instructed to use social media following an acute social stressor showed faster rates of recovery for both cardiovascular (heart rate and blood pressure) and endocrine (inc. cortisol) biomarkers. Additionally, in a subsequent study, Rus and Tiemensma (2018) found that Facebook use before an acute stressor dampened one's psychological and physiological stress responses (heart rate, blood pressure, cortisol), suggesting that social media can elicit positive cognitions and affect that act as a shield against an acute stressor. Likewise, reconciling the apparent contradiction with their earlier study, they propose that a preceding stress event leading to SM use could induce subsequent social media use to be perceived negatively, thereby prolonging the stress response and implying that perception is a key factor at play. However, this study again fails to consider the type of stimuli to which individuals are exposed during their use. If the perception of social media use alters one's stress recovery capacity, then the inherent quality of social media use should undoubtedly be an essential factor to consider.

The studies presented show mixed results regarding the effect of short-term social media use on stress recovery profiles. Clearly, for meaningful research, ecologically valid social media use and consideration of content are critical going forward. Therefore, this present study aimed to consider quality measures of SM content in ecologically valid social media use. Moreover, the studies recruit very reductive cardiovascular indicators of stress, being only heart rate and blood pressure. They also do not consider changes that could be brought about through long-term social media use patterns. The following studies partially address the gaps present in the previous papers.

Primack et al (2018) measured the valence of social media use and found that harmful content predicted depression rates. Similarly, Margousian (2020) investigated whether the perceived valence of social media content (as measured by a 5-point self-report scale), depression, and more sophisticated measures of stress, Including Heart rate variability (discussed in a later section), were linked over one week. While the depression links found in the Primack et al. study was replicated, they also found some links between HRV and SM valence, albeit many of these connections were either barely significant or insignificant. Additionally, Legaspi (2020) found evidence suggesting that higher social media use was associated with worse scores on the same stress metric. However, this study measured social media usage by dividing participants into two groups based on their screen time statistics, categorising individuals as either high or low users. The line drawn between these two is seemingly arbitrary, making it difficult to draw any valid conclusions. This groundless grouping may affect the validity of the study, as it is unlikely that there is a discrete and specific threshold of social media use magnitude beyond which mental health or HRV is affected. Therefore, in the present study, we will utilise a continuous measure of SM-use magnitude when investigating the effect of SM use on stress responses.

Moretta and Buodo (2018) found that individuals with problematic internet use (PIU), characterised by long-term social media usage patterns, exhibited worse resting HRV in all conditions compared to those without PIU, suggesting a diminished autonomic integrity. However, they did not find any difference in skin conductance between the PIU and non-PIU groups, which indicates that there were no differences in sympathetic activity. However, other metrics of stress may be associated with components of the nervous system beyond those mentioned (see Section 1.2.3). This implies that the impact of SM use on stress is not universally applicable to all aspects of the nervous system, reflecting a complex process that warrants further investigation. As such, this present study aims to examine all aspects of the stress response to gain a more nuanced understanding. These authors propose that PIU could be caused by SM usage cues being more deeply encoded into becoming conditioned responses, through the stress itself increasing their salience. This finding aligns with previous demonstrations that hormones released during stress exposure tend to promote habit formation (Schwabe & Wolf, 2009). Consistent with the varied results of the Rus and

Tiemensma (2017; 2018) studies, stress exposure may alter the way SM stimuli are perceived and encoded, causing differences in later stress recovery patterns.

Afifi et al. (2018) found that (non-descript) 'technology use' caused heightened levels of inflammatory markers as well as a sharper increase in cortisol following waking. These results could suggest that the effects of social media could run deeper than immediate superficial impacts, as seen in the two Rus and Tiemensma (2017; 2018) and Oppenheimer et al. (2024) studies, and provide a need to examine longer-term patterns of SM use in the context of social media use, which we will endeavour to do in the present study. Though 'technology use' is measured by frequency of personal devices, not specifically CMC, let alone SM or SNS, so interpreting and extrapolating this study with caution is tantamount. In Meier and Reinecke's (2021) comprehensive meta-review, they found that high SNS use was associated with statistically significantly higher stress levels; the importance of this finding cannot be overstated, given the meta-review's inclusion of 1313 unique publications and 34 meta-analyses. Suggesting that even if stress does not itself elicit momentary stress, it could indeed cause a long-term general increase (i.e. chronic stress) or hinder the effect of stressors from being attenuated over time.

To conclude this section, the multitude of studies discussed demonstrates the general lack of consensus on the effect of social media on stress recovery. There are studies (Afifi et al., 2018; Joseph et al., 2022; Legaspi, 2020; Margousian, 2020; Meier & Reinecke, 2021; Moretta & Buodo, 2018; Rus & Tiemensma, 2017) that present cases where social media can cause lasting negative impacts on the stress response. Numerous studies contradict the notion that social media hinders the stress recovery process (Johnshoy et al., 2020; Oppenheimer, 2024; Rus & Tiemensma, 2018). However, as discussed, these studies possess many methodological constraints that prevent truly valid conclusions from being drawn. These being: they lack measures beyond endocrine, heart rate, and blood pressure metrics of stress response; do not consider stress beyond the momentary timescale; do not consider 'use quality'; and lack ecologically valid social media exposure in their designs. The other papers mentioned that indicate adverse stress outcomes for social media, while inversely possessing designs that more appropriately address the above issues, albeit not entirely. Thus, the conclusions from their papers seem to hold more weight.

Therefore, in our present study, we seek to integrate the strengths of previous studies into a more cohesive and comprehensive design (considering valence, a richer range of stress metrics, and incorporating genuine and long-term social media use) to address all methodological issues outlined above. Due to the robust stress-SM links of Meier and Reinecke's (2021) large meta-review and the stronger methodological designs of pro-stress social media papers, this paper hypothesises that stress attenuates stress recovery. Potential mechanisms and precise hypotheses will be outlined in a later section.

1.2.3. Defining Stress and Metrics

For important context, the nervous system is an expansive whole-body communicative network of cells and organs that liaises with the brain to execute coordinated actions and behaviours necessary for the continued survival of an organism. Fundamentally, the nervous system absorbs, synthesises and processes sensory inputs, to gain an understanding of what actions need to be maintained, performed, or ceased for continued survival (Kandel et al., 2021, p.21; Mobbs et al., 2015). Several biological systems in the body collaborate to maintain homeostasis and respond to stimuli that interfere with this goal. Furthermore, researchers have proposed that repeated effort (or the recruitment of resources) to correct for continuous challenges to homeostasis can lead to cumulative wear and tear on biological systems over time (Day, 2005), contributing to the development of pathological conditions. This concept is known as Allostatic Load (McEwen, 2003). As such, the continued exposure to stressors, or having a reduced ability to recover from them swiftly, could certainly exacerbate or indeed cause MH issues and conditions. As previously discussed, there is a potential link between problematic SM use and stress; therefore, SM could contribute to psychopathology. The following section aims to outline relevant physiological indicators that each may each provide unique insights into the potential link of SM and stress, and how they are useful targets for the present study.

A fundamental aspect of effectively addressing environmental stressors and maintaining homeostasis is increasing the body's availability of glucose and oxygen. This increased supply increases the readiness of musculature to better fight against or 'flight' away from a threat, or the brain to improve attention and vigilance (Chu et al., 2024; Sevil et al., 2019). Overall, bodily increases in blood flow operate to maximise survival chance. The ANS constantly adjusts the level of blood flow and its distribution through intricate adjustments of blood pressure and heart contraction dynamics (i.e., speed or force). In a non-stressed state (parasympathetic), bodily systems function to maintain consistent blood pressure. Despite constant bodily shifts and movements, an innate reflex known as the baroreflex maintains a stable blood pressure (Duschek et al., 2013) through stretch-sensitive baroreceptors in sensitive sections of the aorta and carotid arteries, which project blood pressure information to brainstem structures via the vagus nerve (Critchley & Harrison, 2013). This section of the brainstem (NTS and Nucleus Ambiguus) projects acetylcholinergic inhibitory inputs to the sinoatrial node, slowing its depolarisation rate and subsequent heart contraction (Gordan et al., 2015; Petko & Tadi, 2023). This dynamic adjustment of heart rate, known as heart rate variability (HRV), is an adaptive mechanism for the body in maintaining homeostasis (Ernst, 2017; McCraty & Shaffer, 2015). A high level of HRV reflects healthy function. From this, we can infer that measuring HRV reflects the current dominance of parasympathetic activity (Chu et al., 2024) within the nervous system.

However, during periods of sympathetic activation (stress), this healthy flexibility is inadvertently foregone to prioritise systems that prepare the body for fight-or-flight actions. For example, researchers found limbic brain regions, which respond to stressful stimuli, possess projections to brainstem regions that exert control over the baroreflex (Kim et al., 2018). As such, this demonstrates that stressors directly suppress baroreflex-driven HRV (Ditto & France, 1990). During sympathetic activation in response to stressors, the release of adrenaline triggers an increase in the rate and force of heart contractions through adrenergic receptors in the heart (Harris et al., 1967). The Pre-ejection period (PEP) reflects these changes in contractile dynamics, the speed at which the aortic valve opens for blood flow following electrical contractile signals and is considered a direct measure of sympathetic influence (Johnston et al., 2023).

Cardiac output (CO) is the amount of blood pumped by the heart in each minute (Johnston et al., 2023). CO is an outcome measure of how effectively resources are being mobilised (Asmussen & Nielsen, 1955; King & Lowery, 2023; Wolff, 2008, pp. 169-182).

However, we derive CO from heart rate and stroke volume, the latter of which is only an equation-based estimate when using non-invasive means. Using CO and the average of blood pressure during both the diastolic and systolic phases (known as Mean arterial pressure (MAP)), total peripheral resistance (TPR) can be derived. TPR reflects the overall resistance of the peripheral vasculature to blood flow (Johnston et al., 2023) and can also be a measure of the resultant cardiovascular system's response to input measures, such as HRV or PEP.

As such, TPR is then an outcome measure, reflecting the distribution of blood in the body. As such, the BPS-CT model uses TPR and CO as direct indicators of challenge and threat responses. High TPR and low CO are associated with threat responses. In contrast, high CO and low or stable TPR indicate a challenge response (Johnston et al., 2023), representing two distinct efficiency states of the threat response: poor allocation of resources or adaptive allocation. CO could increase to deliver more oxygen to muscles for an effective response. However, increases in TPR without adequate cardiac output increase (or even a decrease) could impact the appropriate delivery or distribution of the amount of blood passing through the system, due to diverse levels of resistance (vasodilation), which then presents two distinct outcomes. One which is adaptive and one which is maladaptive, or in other words, a challenge state and a threat state (Birenbaum, 2025; Johnston et al., 2023).

As discussed previously, vasodilation can be adaptive in the short term, allowing for the prudent reallocation of blood supply to areas of priority. However, if the system has sustained vasodilation following the removal of a stressor, it may cause vital organ systems to receive inadequate blood. Kline et al. (2003) found evidence consistent with this, as they detected distinct patterns of response to a social stress task. Those whose CO increased, and those whose TPR increased (These groups remained consistent in their responses with another stress task type). Johnston et al. (2023) propose that upward changes in TPR are a result of HPA activation. Previous research has found that HPA activation, concurrent with activation of the SAM axis, is related to threat states and is associated with an organism's failure to adapt effectively to survival threats. Joint SAM and HPA activation being associated with languishing implies that increased TPR may be an indicator of a maladaptive threat response state. At the same time, CO-mediated blood pressure changes are more challenge-based.

Furthermore, TPR-mediated blood pressure increases, in contrast to CO-mediated blood pressure, are associated with numerous adverse health outcomes (Johnston et al., 2023; Birenbaum, 2025). Accordingly, delayed recovery from stress was associated with worsened health outcomes like sustained hypertension (Kline et al., 2003) and the allostatic load concept. Supporting this, myocardial reactivity (high CO responses) often adapts and recovers quickly from stress events. In contrast, vascular responses in vascular responders (TPR-based) tend to take longer to recover, implying that TPR changes reflect a truly unhealthy and concerning type of stress response due to their inability to respond effectively. These cardiovascular responses bear resemblance to distinct challenge and threat responders, as supported by the literature (Johnston et al., 2023). Given the existence of distinct responder types and that one of these groups presents with characteristics with detrimental outcomes, it is vital to examine TPR, on top of all other variables. It allows us to delineate which individual difference variables, perhaps of social media use levels or other moderating variables, could push individuals towards possessing an ill-suited stress recovery system.

Cardiac output and total peripheral resistance, unlike HRV and PEP, provide a measure of the actual outcome of the cardiovascular system in these stress states. HRV and PEP reflect the influence of two distinct stress systems (PNS and SNS). At the same time, the outcome measures provide insight into how efficiently the cardiovascular system mobilises to nervous system cues. For example, these outcome measures can capture any remaining factors that HRV and PEP do not adequately account for, providing us with a deeper range of possible stress response patterns to observe and explore. HRV decrease in response to social media use in the papers discussed in the previous subsection is not necessarily contradictory to those papers that found no impact on heart rate or blood pressure. Circumstances exist where HRV can decrease without affecting heart rate or blood pressure (see: Haker et al., 2000), likely reflecting different stress response profiles of changes in variables not measured by the studies in question (i.e., CO, PEP, TPR). This provides a strong basis for considering a broader range of stress response metrics than previous studies, thereby enhancing the validity of our conclusions.

To conclude, in this study, we have operationalised stress as follows. First, we choose HRV because it reflects parasympathetic vagal control, PEP as it reflects sympathetic influence, and finally CO and TPR as they indicate the actual functional outcome of these nervous system processes and provide an insight into how adaptively a system is operating, and therefore capturing any meaningful differences not captured by the other metrics. Furthermore, there are no studies that examine TPR, CO, and PEP recovery in the context of social media use; this addresses a present research gap and provides further justification for our inclusion of these variables. Due to the practical limitations of the present study, we did not have the resources to collect and analyse endocrine data. Therefore, distinctions between SAM and HPA axis activations were unable to be made. Still, having a design that can differentiate between sympathetic and parasympathetic activity will remain an improvement on the literature, nonetheless. Furthermore, the inclusion of outcome measures (TPR and CO) serves to capture results derived from the influence of HPA/SAM, although they are not directly measured.

1.2.4. The Biopsychosocial Model of Challenge and Threat (BPS-CT)

1.2.4a. Biopsychosocial model

The Biopsychosocial (BPS) approach is a framework that enables researchers and clinicians to conceptualise human health beyond that of the deterministic, purely biological or chemical view. Rather than just considering the actions of the individual when understanding their health condition, for example, why an individual smokes cigarettes, the BPS framework allows for further hierarchical considerations beyond the individual, such as the subcultural context or interpersonal pressures that lead an individual to decide to purchase cigarettes. In essence, this approach encompasses all components that affect an individual, ranging from the most reductionist to the most holistic, and as such, increases clinicians' ability to improve treatment outcomes (1). Fundamentally, higher-level components of the hierarchy can affect lower-level components in a top-down manner.

1.2.4b. BPS-CT

To elaborate, the Biopsychosocial model of challenge and threat (BPS-CT) is a derivative framework developed by Blascovich and Tomaka (1996), as cited in Seery (2013). This framework describes how to objectively assess psychological feelings, a notoriously tricky task, via the recording of objective physiological measures. The BPS-CT operates under the assumption that higher-level psychological states can directly and rapidly alter physiological states. Researchers believe these psychological processes (think: emotional or cognitive thought patterns) to be the core determinants behind the actions one performs. For example, if someone feels afraid, they will engage in fight-or-flight behaviours. Furthermore, the BPS-CT's framework also allows for situational factors to be considered; for example, in the case of the person who is afraid, the context that causes the individual to develop the psychological state of being afraid.

This model is concerned with the two motivational states - 'challenge and threat. Motivational states are unique patterns of biological (and psychological) system activation that drive whether an animal approaches or avoids a stimulus (Blascovich and Tomaka, 1996). A threat state is one in which an individual unconsciously assesses a situation as being too demanding to face with their current resources. Conversely, challenge is a state where an individual deems the resources available to be more than enough and subsequently engages with the situation. (Johnston et al., 2023). Importantly, both states require an unconscious and subjective appraisal of demands versus resources, the *subjective aspect* being fundamental to the concept. The BPS-CT framework describes the specific patterns of physiological activation that correspond to a given state, thus allowing researchers to elucidate the manner of subjective appraisals, which are thought to occur unconsciously (Seery, 2013) and hence were previously unmeasurable by alternative methods (e.g., self-report) (Johnston et al., 2023). Investigating these biomarkers enables researchers to understand the aspects of the environment that contribute to varying stress reactions, particularly those that occur below the threshold of conscious awareness.

Using this approach, by analysing physiological measurements, we could gain an insight of how the varying environment of social media modulates individuals physiological (and therefore implied psychological responses), and help us identify facets of online media which are more likely to trigger unhealthy situational evaluations that lead to chronic stress and contribute to maladaptive pathology, and offer insights into how policymakers and designers can implement changes to mitigate these potential consequences.

1.2.5. Utilising the BPS-CT Approach: Physiological Stress Inducement Measurement via the Trier Social Stress Task (TSST)

Indeed, using the BPS-CT framework would be an effective way to further our current understanding of social media use. However, to obtain a measure of subjective appraisals, we must first measure physiological responses. To account for the confounding factor of natural physiological variability, we intend to induce a change in individuals' physiological state, measure the rate of their recovery back to baseline, and compare this against the extent of recovery in other participants. This way, individual differences do not affect the validity. A commonly accepted method for eliciting a physiological change is to expose individuals to an acute social stressor. The Trier Social Stress Test (TSST) (Johnston et al., 2023) is an accepted and reliable method for accomplishing this.

The TSST is a psychological task that employs social performance scenarios to elicit social stress in individuals (Kirschbaum et al., 1993). In a TSST, participants are first instructed to take five minutes to prepare a speech using a pen and paper to construct a plan for themselves. The content of this often resembles a job interview (Williams et al., 2004). Following this preparatory phase, where researchers intend to elicit a level of anticipatory stress, the presentation plan (that the participant made) is unexpectedly taken away, and the researcher instructs them to start their presentation. Typically, the participant delivers their speech to a 'panel' of intentionally stone-faced confederates/experimenters over a compulsory five-minute period. The last five minutes consist of the mental arithmetic component, a numerical task that, by most people, is considered difficult: counting down from '1,022' and subtracting 13 each time. When the participant makes an error, the panel instructs the participant of their mistake and informs them that they must restart. As a result, the two tasks that the participant performs in front of the panel, due to their performative and challenging nature, create a state of arousal in the participant. In other words, it aims to create an environment where the individual feels as though their performance is being judged socially, which can result in stress. Throughout and after the TSST, researchers record physiological measurements, and from these, experimenters can retroactively determine the level of stress someone experienced, the speed of recovery post-presentation, and whether they entered a challenge or threat state based on the unique physiological patterns. According to the BPSCT model, if an individual feels that their arithmetic or presentation abilities are sufficient, then their resource evaluation would be higher than the appraised demands, and they would enter the challenge state. Conversely, if an individual assesses the situation as being too much for their (subjectively speaking) limited abilities to handle, then they would enter the threat state.

1.3. Potential factors underlying the association of social media with stress responses

As previously outlined, the robust stress-SM links found in Meier and Reinecke's (2021) large meta-review, along with the stronger methodological designs of pro-stress social media papers, this paper hypothesises that stress attenuates stress recovery. To strengthen our basis, this section will explore potential causal mechanisms and variables that supposedly underpin this process. We will discuss reward sensitivity and cognitive overload as two key factors that are highly implicated.

Heponiemi et al. (2004) found that individuals with higher scores on a behavioural activation scale (BAS), a measure of reward sensitivity, showed heightened HR reactivity and parasympathetic withdrawal during demanding tasks, including but not limited to a social stressor-like speech task. Simultaneously, behavioural inhibition scores (Punishment sensitivity) had no impact. Meanwhile, Markarian et al. (2013) found that lower reward sensitivity scores were associated with difficulties in emotional regulation, which encompasses stress. Ironside et al. (2018) found that stress directly blunted reward sensitivity through disturbances in the dopamine system. Specifically, it is believed that during stress exposure, the activity of the left putamen brain region predicts endocrine recovery and is also associated with reward sensitivity. They went on to suggest that reward sensitivity may directly influences the robustness of neurocircuitry that buffers daily stressors. It is clear to see that reward sensitivity is a clear factor in an individual's overall stress response. This is especially pertinent due to the established finding that high social media usage is associated with higher reward sensitivity (Vannucci et al., 2017, as cited in Medrano, 2022; Vannucci et al., 2019, as cited in Medrano, 2022), high problematic SM use being associated with high reward sensitivity (Deng et al., 2021), and that SM users with higher reward sensitivity were more susceptible to feelings of social dissatisfaction and loneliness in line with their usage magnitude, while those with lower reward sensitivity had no such relationship. As for specific stress metrics, Brenner and Beauchaine (2011) found that reduced pre-ejection period (PEP) was associated with an increased tendency towards drug use, while Richter and Gendolla (2009) found PEP reactivity increased in line with a monetary reward, both of which are highly contingent on the reward system. Moreover, Hancock et al. (2025) found that PEP response to stress varied depending on individual reward reactivity. Lastly, HRV reactivity is thought to underlie addictive behaviours and dietary self-control (Maier & Hare, 2017; Oshri et al., 2018). Reward sensitivity appears directly intertwined with both stress response outcomes *and* SM usage, which is why it is one of the core focuses of this paper. Specific mechanisms and operationalisations to measure this will be outlined.

The second variable is cognitive load. It is suggested that excessive stress activation can lead to cognitive overload (Bong et al., 2016). The nature of the information age and the development of instantaneous information access technologies have, understandably, ushered in a period where people are inundated with information, leading to cognitive/information overload in users. Cognitive load theory (CLT) suggests that a stress state further diminishes the already finite resources of the working memory, causing negative impacts on information processing (Plass & Kalyuga, 2019) due to extraneous emotional processing. In line with this, Palmwood and McBride (2017) found that both challenge and threat stress states elicited cognitive depletion in individuals. They suggest that challenge states consume problem solving cognitive resources, while threat states consume emotional coping cognitive resources, with only the latter manifesting a concurrent negative emotional outcome. Overall, stress responses increased cognitive overload. Conversely, some studies have found that increasing cognitive load can lead to increases in galvanic skin response (Conway et al., 2013), a measure of physiological stress (Sharma et al., 2016).

Furthermore, increasing the demands of a cognitive task was found to increase heart rate, consistent with stress response, while also being associated with psychopathological symptoms (Alshanskaia et al., 2024). Overall, it can be surmised that increasing the strain on one's cognitive system through an increased information load can both cause and/or be caused by stress. Fundamentally, stress and cognitive load are linked.

While not explicitly related to SM, Kim et al. (2022) found that individuals with higher 'technostress', a stress response measure resulting from exposure to new technological devices, exhibited increased cognitive load and reduced task performance. Tian et al. (2025) found that information overload derived from SM was associated with many negative emotional symptoms. Moreover, a study by Reinecke et al. (2014) found that an elevated level of cognitive depletion simultaneously positively predicted the amount of media use and the likelihood that users would appraise it negatively. Notably, this latter relationship persisted regardless of the channel in which it was accessed or the way it was used (passive vs. active use). In other words, video games, an active and interactive medium, and television, an inherently passive form of media, are both considered negative by individuals. A key driver of this may be guilt resulting from perceived procrastination when media use is high, as supported by a survey by Panek (2014). This guilt seemingly impairs the ability to engage in these otherwise relaxing activities, which can aid in cognitive recovery. Instead, this guilt could even trigger SM use to drain mental resources. Indeed, Evan et al. (2023)'s study supports this, where the more an individual consumes content perceived as negative, the higher they score on measures of mental ill-being. This paper presents a clear link between the valence of content and MH outcomes. The potential utility of considering aspects of media beyond the channel level – in this case, the subjective valence – is further substantiated by this. Therefore, our study will measure the subjective valence of the media to which media users are exposed. From the papers discussed, a clear link appears to exist between stress, cognitive depletion, and social media use. Specific potential mechanisms will be outlined in subsequent sections.

1.3.1 - Reward Sensitivity Mechanisms at play

Researchers have postulated the existence of two distinct neurological characteristics that underlie and motivate goal-driven behaviour (Carver & White, 1994; Gray, 1981). The behavioural inhibition state (BIS) and the behavioural approach states (BAS), or in other words, reward and punishment sensitivity. Using evidence from lesion and pharmacological experiments, Carver determined that these two states operate entirely separately from one another. The BIS state involves responding to punishment and non-reward by halting the current behaviour and is generally accompanied by feelings of sadness and fear (negative affect). Meanwhile, the BAS system responds to rewarding feedback by encouraging the inciting activity to be continued or repeated. It is associated with feelings of happiness, hope, and other positive emotions (positive affect). In essence, the BAS system refers to one's reactivity to rewarding stimuli. As previous evidence has indicated, reward sensitivity appears to be more closely implicated in stress processing and social media; therefore, we will focus on BAS from here onwards.

If one considers positive valence social media content as rewarding stimuli, and negative valence content as comparatively punishing, the result of being exposed to constant positive stimuli would be a heightened reward sensitivity. This would be a result of the way the reward system operates to promote learning and reinforcement (Richards et al., 2016). Indeed, adolescents (a group that predominately inhabits SM) are found to be particularly sensitive to positive and negative social rewards, which are omnipresent on SM. Furthermore, while not sensitivity per se, Kobayashi et al. (2010) found that the way in which rewards are processed by orbitofrontal cortex neurons is altered when the occurrence of reward is increased. While tenuous, it could suggest that exposure to valent content may have an impact on reward sensitivity or processing, particularly for positive valence social media content. Likewise, an individual possessing a high reward sensitivity would find the effect of positive valent social media content consumption on mood to be amplified, and negative valent content to have an exaggerated opposite effect. At the same time, a higher magnitude of use could feasibly lead to a greater accumulation of reward processing changes or an increased impact of reward feedback on emotional affect, and, therefore, stress processing abilities. Thus, both usage magnitude and usage quality (valence) are crucial to consider.

Similarly, In Orben et al. (2024), it is proposed that habitual checking of social media-based reward cues in adolescent participants (a group particularly neuroplastic) may induce hypersensitivity of the reward system (Maza et al., 2023). Moreover, this is suggested to occur through a process of dysfunctional activation of the dorsolateral prefrontal cortex and the amygdala, which persisted throughout subsequent years. However, it is important to note that while this point followed up on neurological activation measurements, it did not record follow-up SM usage data, meaning that changes in SM usage behaviour over the period were not accounted for. Therefore, this study's validity is somewhat limited, but it remains a noteworthy consideration nonetheless.

As a whole, many facets of modern social media and digital communication technologies appear to be designed to take advantage of our reward pathways directly. To illustrate the basis for our stance that social media use may influence reward sensitivity, two examples of ubiquitous social media features that could impact reward processing are push notifications and short-form video content (SFVC).

Push Notifications are on-screen prompts that display information updates to users, often accompanied by a distinctive audio tone or vibration, serving as a salient conditioning cue (Pielot & Rello, 2015; Shirazi et al., 2014). Push notifications have been found to facilitate feelings of connectedness among users (Devrim, 2023). Although, users often become restless when notifications cease (Pielot & Rello, 2015). Notifications frequently inform users of social rewards or novel content, the exposure to which positively reinforces the act of checking them. During this compulsive checking, notifications are not always present or necessarily pleasurable, which acts as a variable-ratio schedule of reinforcement — a pattern of unreliable reward (or punishment) delivery following a given action. Variable-ratio schedules are one of the strongest, if not *the* strongest, conditioning methods for encouraging future behaviour (Laskowski et al., 2019) in animal models and are remarkably resilient to extinction (Laskowski, 2022). Nasti and Michienzi (2021) found that notifications were linked to addictive use of social media, although not entirely, suggesting that additional variables are at play. As such, we seek to investigate other variables concurrently with reward sensitivity.

These ratio-reward schedules have appearingly influenced the behaviour of users towards compulsive checking of their mobile devices. To demonstrate, figures in literature and market research surveys seem to suggest that users have been found to check their phone over 19 times notifications are actually delivered, with these notifications being ignored most of the time regardless (dscout, Inc., 2016; Pielot et al., 2018; Pradhan et al., 2017; Reviews, 2023). As such, people recognise that they spend too much of their time checking notifications (for example, see: Common Sense Media, 2016), which is an important consideration.

Short-form video content (SFVC) is, as its name implies, relatively short videos on SM platforms – typically around 6 seconds to a minute in length and therefore possess low barriers to entry for people to create their own (Wu et al., 2021). These low barriers and the rapid, explosive commercial success of these forms of videos (Anderson, 2020; Duan et al., 2024; Kaye et al., 2020; Klug et al., 2023; Vandermissen et al., 2014) promoted the ubiquitous adoption of hybrid-SM-SFVC platforms, such as Shorts on YouTube or Reels on Instagram (Duan et al., 2024). As such, most previous SNS platforms now contain SFVC sections. These short-form video platforms possess endless scrolling homepages (Levy, 2025), which begets a state in users where, due to the ease of creation among the public, individuals will be exposed to a large variety of video quality, creating a similar variable ratio schedule of reward, as seen with notifications, that encourages further and unending scrolling in the attempt of finding the next 'good' video (i.e. addictive/compulsive behaviour).

Chung et al. (2023) and Wu et al. (2024) found that SFVC had a negative impact on well-being. The latter found that this effect was partially contingent on the specific content watched, which lends credence to the idea that the valence of content plays a role in the relationship between SM and MH. The former finding was that perceived information overload underpinned this. Zhu et al. (2024) found that addiction to SFVC acted as a chain mediator between SFVC exposure and adolescent depression, suggesting that one's level of addiction (or, in a sense, reward sensitivity) partly drives the link between SFVC and mental illnesses. In Wen et al. (2024), perceived overload of SFVC directly predicted loneliness and mental health (in a sample of older adults). In addition, Liu et al. (2021) show that perceived stress (threat state) was positively associated with SFVC addiction in a cohort of almost 900 college-aged adults. These studies together, therefore, suggest that SFVC addiction may have a direct impact on individual well-being, through altered reward processing (as per the nature of addiction, generally) it causes. However, one must note that these studies tended to use reductive mental illness or wellbeing conceptualisations (such as just measuring depression or loneliness independently), so generalising their results to the broad spectrum of mental wellbeing remains difficult. This limitation in design reinforces the need to consider broader conceptualisations of MH and to use a general risk factor that captures all conceptualisations of MH—physiological stress—in our study design.

Overall, the ubiquity of both notifications and SFVC on SM platforms lends credence to the idea that social media usage magnitude and quality would influence stress recovery. Reward sensitivity itself is thought to be linked and interacts with cognitive overload, which will be explored later.

1.3.2 - Cognitive Overload Mechanisms at play

As previously discussed, cognitive overload appears to be linked to stress and excessive use of social media. The papers explored suggest that cognitively drained individuals may subjectively appraise their social media use as negative and will find their ability to recover from a state of cognitive overload reduced. This tendency towards a negative perception, therefore, emphasises the dangerous phenomenon where time spent on social media makes one overwhelmed due to the overabundance of information, social cues, and notifications to attend to. As a result, impairing one's ability to administer volitional control over their continued use may create a generally negative affective experience.

To measure feelings of overwhelm deriving from the use of information/communication technologies, Misra and Stokols (2012) developed the Perceived Information Overload Scale (PIOS). The paper outlines *perceived information overload* as a term referring to psychological distress resulting from attending to/ attempting to process an excessive amount of information beyond what is possible with one's current mental resources. More specifically, it occurs when someone's environmental demands exceed their own perceived limit, somewhat mirroring the mismatch between demands and resources seen in the threat state of the BPS-CT. The inventory consists of two subscales: one examines overwhelm from technological sources, and the other explores the effect of non-technological environmental stimuli on overwhelm. The idea of including these two inventories was to afford the ability to control for baseline overwhelming stimulation and isolate overload specifically deriving from CMC. As such, we hypothesise that higher daily average screen time will be positively associated with perceived information overload (H2b). For enhanced applicability, we seek to adapt the PIOS to have its items more tailored to SM specifically.

Like reward sensitivity, many aspects of modern social media and ICTs may appear intentionally designed to take advantage of our limited cognitive capacity. To demonstrate how social media contributes to cognitive overload, push notifications and short-form video content (SFVC) are revisited as examples of such features.

A study found that individuals who did not receive notifications during leisure time became stressed due to a fear of falling behind or not being able to meet the societal pressure of responding promptly (Pielot & Rello, 2015). These notifications are often overabundant and include product advertisements or prompts for users to use certain apps, beyond their intended limited role of simply keeping users up to date (Kunkel et al., 2021; Sandeep & Moulya, 2022). Approximately half of all notifications are ignored by users (Pradhan et al., 2017), and it is then expected that users feel overwhelmed when the quantity of notifications increases (Pielot & Rello, 2015). This feasibly contributes to cognitive overload in users. A deficit of cognitive resources can impair the ability to perform cognitive processes, such as emotional processing. For example, a threat state emerges when an individual assesses their available resources as insufficient to meet the necessary demands of the situation. In this example, these resources would be cognitive resources. To use a real-life example, an individual overwhelmed by notifications may believe they no longer possess the necessary focus, concentration, and quick thinking required to give a public speech, and therefore would enter a threat state. Palmwood and McBride (2019) hypothesised that challenge states cause cognitive depletion and a tendency towards problem-solving.

While In contrast, a threat state leads individuals to rely on emotional systems to self-soothe, which can result in emotional exhaustion instead. However, they found that, in conjunction with emotional exhaustion, threat states also led to cognitive depletion. Likewise, as mentioned, SFVC sections on SM apps feature endless scrolling homepages (Levey, 2025). This could feasibly cause a state of overstimulation due to the unending stream of various content (i.e., increased cognitive load). These effects on both reward sensitivity and cognitive load do not occur independently; instead, we suggest that these variables, which have both been demonstrated to have potential detrimental impacts on stress processing, may have been intentionally leveraged to create a bidirectional perpetuating cycle, motivated by the maximisation of consumer profitability.

1.3.3. Dark Patterns: The link between Cognitive Overload and Rewards Processing

Researchers have termed the intentional design decisions whereby applications are constructed in a manner that prompts users to engage in activities they would not otherwise participate in, for the benefit of the designer, as ‘Dark Patterns’ or ‘Damaging Patterns’. (Gomes et al., 2025; Lora et al., 2025; Yaochen & Van Der Blom, 2025; Yin et al., 2025). As discussed in the previous sections, SM use (using both SFVC and push notifications as examples) can cause alterations to reward processing through variable ratio schedules that encourage further unending scrolling and increased cognitive overload due to the unending stream of content. We suggest that these two phenomena together create a maladaptive cycle of encouraging compulsive scrolling, causing more overstimulation, and then a heightened overstimulation, altering the reward system into encouraging more scrolling (and so on). Indeed, this appears to be an intentional, predatory design choice, as it directly promotes further app interaction, which corresponds to increased advertisement revenue for app companies, demonstrating a clear profit (over moral) motive (Molteni, 2022). The existence of this maladaptive cycle is supported, as individuals may not even enjoy the content they are watching, may not intend to enter the short-form section of the app in the first place, or may even feel terrible while using it, yet still find themselves scrolling. These dark patterns of design are apparent in the overabundance of notifications encouraging use, as well as the specific design of the unending scrolling format of SFVC – both seek to maximise the time a user mindlessly spends on their platform (Molteni, 2022; Yin et al., 2025). We will briefly examine how this bidirectional cycle may operate.

Cognitive Load has been proposed to negatively impact the optimal functioning of the reward system (Krigolson et al., 2015). It is possible, in the context of social media, that the process of being overwhelmed by these social media devices creates an environment where individuals are less satisfied with the content they consume or the notifications they receive, and therefore spend more time scrolling or checking to compensate for the reduced sensitivity. This pattern of gradually increased use seems reminiscent of how a drug’s efficacy diminishes over repeated use, causing a maladaptive increase in dose to achieve similar levels of high (Robinson & Berridge, 2003). This strongly suggests the designers of social media may have intentionally designed it to be overwhelming, thereby further encouraging engagement with addictive material and rewarding stimuli. Indeed, this does not seem too far-fetched as supermarket designers have been known to utilise a similar design approach, where shoppers are intentionally made to feel overwhelmed by the number of products on display (ergo: too many decisions), deliberately exacerbated by the layout of the store, to induce a state of decision fatigue where individuals are more likely to purchase products they would not choose to otherwise (Donovan et al., 1994; Gilbride et al., 2015; Yim, 2017). However, Chung et al. (2023)'s study found that the high level of information overload associated with SM use discouraged future use due to 'SM fatigue', which appears to directly oppose this view of the bidirectional cycle. However, it is possible that Chung et al.'s study did not account for differences in reward sensitivity. Perhaps the altered reward sensitivity to SM-rewards buffers the effect of fatigue in some manner, and the cycle still potentially operates, despite Chung et al.'s findings.

Although not specifically in the context of SM, Huang et al. (2021) found that high feelings of cognitive overload regarding job responsibilities increased workplace behaviours driven by the behavioural activation system (BAS), or in essence, heightened reward sensitivity. However, Milyavskaya et al. (2019) found no difference between individuals engaged in a cognitively demanding number task and a control group in their levels of event-related potential activity in response to the presence or absence of rewards, as measured by Electroencephalography. This directly challenges the conclusion of the former paper; however, upon considering the methods and other findings in the latter study, this may not be the case. In Milyavskaya et al. (2019)'s paper, they found that individuals in the boredom group tended to exhibit heightened activity in response to reward feedback and reported higher subjective fatigue. In contrast, self-report fatigue and reward sensitivity were not found to be linked. This suggests that situational alterations to reward sensitivity may occur below the level of conscious awareness. It is possible that an individual's level of subjective overload may be presented differently in those at workplaces in Huang et al.'s sample.

Furthermore, it is possible that the use of a lottery-like game in the latter study removed feelings of autonomous control in users, meanwhile in the former study the decisions an individual would need to be making at work would be highly dependent on them and self-relevant, implying that a link between reward sensitivity and cognitive overload only occurs when individuals have control over the source of rewards, or when the stimulus is highly relevant to the individual, and when individuals genuinely subjectively feel overloaded. Although it is crucial to note that these two studies cannot be used to form wide ranging conclusions, considering them nonetheless is valuable. This presents relevant applications to social media, as, in conjunction with the previous paragraph's evidence, SM creates an environment that presents highly personalised (self-relevant) and (seems) highly controllable by the user.

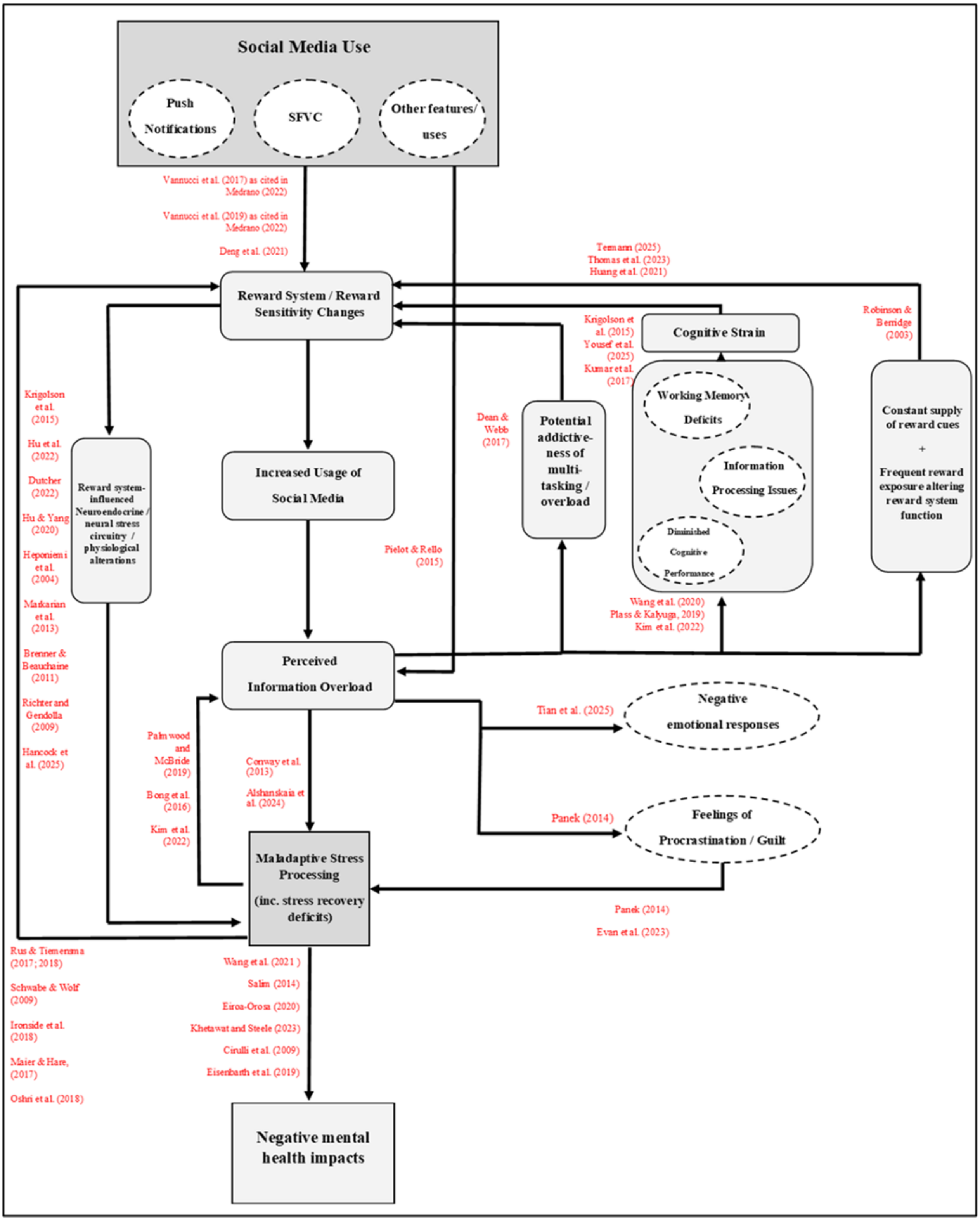
For illustrative purposes, it is important to establish a clear and direct theoretical chain of reasoning, regarding the potential existence of dark patterns in SM design, which the following section will endeavour to provide. To begin, Wang et al (2025) found evidence to suggest that SM-derived information overload impairs cognitive performance by increasing cognitive resource strain. Then, this cognitive strain is thought to dampen the functional ability of the reward processing system, which may directly regulate one's neuroendocrine stress response return to baseline (according to Krigolson et al. (2015)) and neurological structures associated with stress processing (Hu & Yang, 2022; Krigolson et al, 2015). Moreover, Dutcher (2022) surmised that both neuroendocrine and physiological stress were facilitated by reward exposure. Likewise, similar neuroendocrine stress findings were reported in Hu & Yang (2021), who found that reward anticipation buffered both neuroendocrine and physiological stress responses to a TSST, implying a direct role of the reward system in stress responses. These two lend further support to the role of the reward system being involved in the return of one's internal system to homeostasis post-stress.

To compound on the links between cognitive resource depletion, reward, and stress, chronic overstimulation from prolonged SM use is thought to lead to attentional deficits, associated with a maladaptive reward system (Yousef et al., 2025). This is thought to underlie the 2024 neologism: "brain rot" (perceived psycho-emotional deterioration arising from the overconsumption of low-quality digital content) (Yousef et al., 2025; Özbay, 2026), which arose in response to a collective negative experience of modern-SM use, therefore suggesting these effects may be commonplace amongst users. Similar to previous findings, Kumar et al. (2017) examined multiple studies and found that heavy internet use, characterized by high information load, may alter multiple brain areas, including the reward network, through constant, ever-present reward cue stimulation. Going further, some researchers have suggested that multitasking-induced cortisol increases may actually be addictive (Dean & Webb, 2011), which may imply (albeit highly speculatively) that information overload itself may be a reward cue. As a whole, these joint effects have pushed several SNS designers to explicitly suggest that SM information overload and attentional hijacking (leading to information overload) are inherently linked issues (Termann, 2025), as evidenced by co-occurring compulsive behaviours and feelings of subjective overload amongst users of a certain SM platform (Termann, 2025; Thomas et al., 2023).

It is recognised that the theoretical evidence underpinning social media's connection to stress is involved and complex. Indeed, the studies and research discussed are surely not exhaustive. However, we believe together they potentially explain an aspect of the established SM-use to abnormal stress processing / mental illness theoretical chain. As such, Figure 2 presents an illustrative diagram of the connections among each individual difference variable (reward sensitivity and perceived information overload), engagement with social media, abnormal stress processing outcomes, and subsequent potential mental health impacts. This diagram presents the discussed information in a unified and cohesive manner and transparently displays the logic that informs the present study's hypotheses.

Figure 2

Diagram illustrating the relevant theoretical direction of effects between the social media input factor (social media usage and its functionalities/features), and outcome factors (stress processing, MH risk) with associated literature labels.



Note. Literature associated with each directional effect is generally displayed in red to the right side to the relevant arrows, except in cases where this was unfeasible to do so (i.e., horizontal lines and Maladaptive stress processing → Reward system / Reward sensitivity changes)

With all these theoretical and experimental ideas in mind, we then seek to explore these ideas by first examining the relationship between reward sensitivity and subjective information overload, hypothesising that they are positively associated with one another (using the discussed literature as the basis for this), such that lower reward sensitivity corresponds to an individual's higher perceived information overload (H1c). Once the present study establishes a link (or lack thereof), we then seek to investigate the nature of the individual effects of the reward sensitivity pathway (H3a, H3b) and the perceived information overload pathway (H3c, H3d) on the rate of stress recovery to a stressor. And then, to examine whether a model including both overload and variance more strongly explains variance than any model with either mechanism on its own (H4). The following section will outline specific hypotheses comprehensively.

It is essential to acknowledge that there are likely other factors at play in the relationship between social media and mental health. However, these do not fall within the parsimonious scope of a master's degree research project. Nevertheless, that is not to say that we do not believe the chosen factors are insufficient. It will still provide valuable insights and further contribute to an ever-growing body of literature.

1.4. The present study

1.4.1. Rationale and Aims

It appears that social media use, particularly the presence of notifications and exposure to short-form content, can lead to states of skewed reward processing (and therefore addictive behaviours) and a high cognitive load. However, it is unclear whether these effects persist once a user 'logs off' or have long-term, detrimental effects. This study aims to investigate the long-term effects of different patterns of consistent social media use on stress reactivity and recovery by examining differences in feelings of overwhelm and altered reward/punishment sensitivities. We have chosen to include a broad variety of stress metrics to fill gaps left by the present literature and to ensure the most robust and valid interpretations can be reached. To address this, we have adopted directional hypotheses driven by theory but approached with caution, given the tentative and divisive state of the literature, and thus will remain open to being falsified and interpreted within the broader context. The goal of this research, then, is to provide a greater insight into how the ubiquitous nature of social media affects our long-term stress processing ability, which has direct implications for the broader concept of mental health. The results of this study, combined with the growing literature in this area, will hopefully inform the decisions of application designers and potentially even policymakers regarding digital communication technology regulation, to shape digital communication into its most healthy form possible.

While it seems as though examining both stress reactivity and stress recovery rates is instrumental to providing the most comprehensive picture of SM's impact on stress, the scope of this project does not allow us to examine both. To elaborate, Linden et al (1997) demonstrated that both recovery and reactivity have independent roles in stress processing. They found that stress recovery was an often-underutilised design approach that yields new effects not found in stress reactivity studies. Indeed, evidence seems to point to the fact that they are separate, non-associated components (De Calheiros Velozo et al., 2023). Which, in the case of SM-relevant literature, seems to be supported. As Rus and Tiemensma (2017) found that using Facebook after an acute social stressor resulted in slower stress (endocrine, in this case) recovery, while their study a year later found that SM use prior to an acute stressor reduced participants' stress reactivity (Rus & Tiemensma, 2018). Instead of being two contradictory papers, they could instead reflect distinct aspects. Indeed, an individual possessing dramatic stress reactions with a rapid ability to recover from stress would fundamentally differ from someone whose stress persists for a long time. Indeed, long-lasting stress reactions (i.e., chronic stress) are most strongly associated with the aetiology of mental illness (Hassamal, 2023). As such, we choose to focus our limited resources on stress recovery for this project.

1.4.2. Hypotheses

Although there have been many findings with mixed or contradictory results, the present study chooses to recruit directional hypotheses informed by evidence-based mechanisms and the findings of robust meta-reviews (e.g., Meier & Reinecke, 2021). It aims to thoroughly examine the link between stress and SM use beyond the levels previously achieved in the literature. The complete hypotheses for this study are:

Initial Correlation Hypotheses:

(These hypotheses seek to explore links across key variables before further testing.)

- H1a. High reward sensitivity will be associated with a longer average daily screen time.
- H1b. Higher screen time will be associated with higher levels of subjective overload.
- H1c. Lower reward sensitivity will be associated with higher levels of subjective information overload.
- H1d - Reward sensitivity will be positively associated with more positive valence social media content.
- H1e - Lower valence will be associated with higher levels of subjective overload.

Primary Stress Response Hypotheses:

H2 - Social media use will predict physiological stress recovery capacity.

- H2a. More negative valence social media content exposure will be associated with poorer stress recovery capacity.
- H2b. Greater screen time will be associated with a reduced stress recovery ability.

Moderation Hypotheses

- H3a. The relationship between social media valence and physiological stress recovery will be moderated by reward sensitivity.
- H3b. The relationship between social media valence and physiological stress recovery will be moderated by reward sensitivity.
- H3c. The relationship between screen time and physiological stress recovery will be moderated by reward sensitivity.
- H3d. The relationship between screen time and physiological stress recovery will be moderated by subjective information overload.

Combined Model (Exploratory):

- H4 - A model including both subjective information overload and reward sensitivity will explain more variance in stress recovery than either predictor alone, while accounting for baseline differences.

2. METHODS

2.1. Data collection

This dataset was collected as a smaller part of a larger study exploring the effect of solitude and social interaction on stress processing conducted by Dr Thuy-Vy Nguyen and Dr Jonathan McPhetres at the University of Durham Psychology Department's Solitude and Physio Labs, known as 'The Cottage Study'. This broader study context has informed or resulted in some of the methodological decisions or limitations; these are outlined in the following sections as they arise.

2.2. Participants

2.2.1 Sample Size Justification

The present study operated within a larger study context. As such, a priori power analyses to determine minimum sample size targets were not possible because of pre-specified sample size targets for the larger 'Cottage Study' (approx. 40-50 participants) that were not practically feasible to deviate from, if power analyses indicated doing so. For reasons outlined in a following section, only about half of these participants were able to be included in the present study's purposes. Nonetheless, the sample size was limited to this value due to the expensive time and financial costs associated with administering each session, and time restraints. These costs include the high compensation per participant due to the day-long study period, the large amount of equipment required, and the time and labour required to run and organise the study (including the lead experimenter and confederates). While time restraints derived from an agreed set duration for laboratory space occupation/use, which, due to long study days, only enabled a limited number of sessions. Likewise, the recruitment rate may have been a determining factor in the sample size, as the study's long duration may have led to relatively few volunteers willing to participate.

While the present study is generally speculative and exploratory based on theoretical underpinnings, consistent with prior literature examining physiological stress, social media, and mental health, a theoretically significant effect size we would expect to detect would be small-to moderate effect sizes (e.g. approx. $\eta^2 = .048$ (4.8% of variance explained) in Rus & Tiemensma (2018); and $r = .13$ (1.69% of variance explained) in Meier & Reinecke's (2021) large scale review). As such, it appears as though effect sizes in this literature are typically relatively small. As such, a large sample size would likely be required to detect these effects reliably. Implications of our sample size limitations are discussed in later sections.

2.2.2 Participant Recruitment

After being granted ethical approval by the University of Durham Psychology Department's ethics committee (Project ID 5434), recruitment was initiated through word-ofmouth advertisement or from the University participant pool 'SONA'.

According to the conditions of ethical approval and the specific stipulations required for the wider study context, participants were excluded from participation if they did not meet all the conditions of a compliance checklist. The compliance items indicating eligibility were as follows: No food or drink within the last hour, no teeth brushing in the previous hour, not a regular smoker or vaper, no exercise within 24 hours, no alcohol consumption within 24 hours, not taking regular medication, not on contraception, not currently pregnant/breastfeeding, no chronic health issues, and must have been awake for at least two hours before the commencement of the study.

Following the exclusions, 44 participants ultimately participated in the study. As alluded, the wider study (within which this present study was conducted) had participants split into two conditions after stress exposure: social isolation and social interaction. To maintain control of the post-stress environment in our study, for the sake of validity and because we are only interested in stress recovery as a function of social media usage, we have chosen to include only participants in social-isolation conditions in our analysis. This left us with a remaining sample of 24 participants.

2.2.3 Participant Demographics

Twenty-four participants were ultimately included in our analysis. The demographic breakdown of the sample is as follows. To note, due to a technical error, gender and ethnicity data were not available for one participant. This participant's gender and demographic data are labelled as undefined in the breakdown.

The mean age of the participants was 21.48 years (SD = 2.86). In terms of self-reported gender identity, 15 (62.5%) were female, 8 (33.3%) were male, and 1 (4.2%) was undefined. Regarding reported ethnicity, 12 (50%) of participants were white, 9 (37.5%) of participants were Asian, 2 (8.3%) of participants were 'mixed two or more ethnic groups', and 1 (4.2%) participant was undefined.

2.3. Study Design

For the present study, a mixed design was utilised, as both within-subject repeated measures of physiological stress metrics and cross-sectional between-subject variables of self-reported individual differences were also recorded.

Four physiological stress indices (HRV, PEP, CO, and TPR) were used and assessed at 3 time points: baseline, during a trier social stress test (TSST) (Stress phase), and 5 hours post-stress task (the latest point available of the broader study context) (post-stress phase).

Stress recovery for each physiological index was operationalised as a 'recovery index', reflecting the proportional extent to which physiological stress measures returned to baseline levels, relative to the extent of stress reaction from baseline to stress (scores equalling 1 indicate a 100% return to baseline levels, scores of 0 - 1 indicate that stress levels persisted above the baseline levels, scores below 0 represent stress levels that have worsened *after* the stress phase ended, and scores above 1 reflect that scores that rebounded or overcompensated to a level better than the initial baseline phases).

Individual difference measures were assessed through self-report measures and individual mobile phone usage statistics. These variables were reward sensitivity (BAS), perceived information overload from social media (PIO), perceived valence of recent social media content, and daily average screen time over the previous complete week.

2.4. Materials

2.4.1. Materials

Perceived information overload from SM (PIO), reward sensitivity, and social media valence data were collected using an online survey created and administered via Qualtrics. Communication between the experimenter and participant was facilitated using Microsoft Teams. AcqKnowledge Version 5.0.0.0 (Almond, 2017) was used to record, store, and process participants' physiological data. Microsoft Excel was used for the processing and formatting of data. IBM SPSS Statistics Version 29.0.0.0 was used to analyse and visualise data for hypothesis testing.

2.4.2 Apparatus

The TSST equipment included a pen and a sheet of A5 Paper (for the participant to plan), as well as a mobile phone and a desktop miniature tripod to record the participant's speech and arithmetic task during the TSST. An iPad was also provided to the participant for post-stress activities.

Three disposable Ag/AgCl electrodes were fitted to participants in a '3-electrode system' configuration (two below each clavicle and one on the front-left side of the torso, just below the vertebral rib) to measure ECG. Likewise, four Double Ag/AgCl electrodes were attached bilaterally to participants on the sides of the neck and torso, just below the vertebral ribs. The distances between the neck and torso sensors were approximately equidistant on both sides of the participant, and the left and right electrodes were placed at approximately the same level (ICG 8-spot electrode configuration). A '*BioNomadix Wireless Cardiac Output Amplifier*' (for ICG) and a '*BioNomadix Wireless RSP with ECG Amplifier*' (for ECG) were threaded through a hook-and-loop fastener waistband. Both the ECG signal and impedance (Z0 and its derivative dZ/dt) were collected at the standard sampling rate of 1000 Hz. ECG was integrated with an MP150 system (Biopac Systems Inc.) and a two-channel ICG amplifier module (NICO100C), respectively. The data was recorded and written using AcqKnowledge Version 5.0.0.0 (Almond, 2017). Participants were fitted with an '*Omron Evolv Upper Arm Blood Pressure Monitor (HEM-7600T-E)*', which experimenters manually activated and noted results on the digital display.

2.4.3. Measures

Daily average Screen time - An objective daily mean screen time figure over the previous complete week was recorded from the participants' mobile phones' in-built screentime analytic applications. Approximately a week prior to data collection in the baseline and demographics questionnaire, participants were instructed to enable the screen time monitoring feature of their mobile device.

Perceived social media valence - The valence of social media content was recorded using a two-item Likert scale developed for this study. This scale was adapted from the single item five-point Likert scale used in Margousian (2020)'s study ("*Subjects recorded and rated their exposure to the social media content from (a) very negative, (b) negative, (c) neutral, (d) positive, or (e) very positive*"), and added a second item to improve reliability and specific statements for understandability. Our adapted valence scale consisted of the following statements: 'Over the last week, would you generally consider the content you have seen on social media apps/sites to be emotionally…', and 'Generally, would you consider the content on the social media app/sites you use to be…'. Participants then responded on a scale from 1 being 'very negative' to 5 being 'very positive' with three being neutral (etc). A mean score is taken of the two items to provide the valence score. Due to the technological and practical limitations of the broader study context, this was merely a subjective measure. Furthermore, due to this metric only having two items, a reliability test was unable to be performed. However, as an alternative, a Pearson's correlation was conducted across the two items of this scale to provide an insight into inter-item consistency.

Perceived information overload (PIO) from social media - To measure feelings of overwhelm deriving from the use of information/communication technologies, we intend to use an adapted version of Misra and Stokols' (2012) Perceived Information Overload Scale (PIOS), altered to only include the questions involving technological sources, and said questions are changed to refer to specifically SM concepts, not just CMC or general technology. The complete set of six questions can be found in the Appendices (Appendix A). Still, an example of one item is: 'In the last month, how often have you felt overwhelmed by video or images online?', for which the participant submits a response on a 5-point frequency Likert scale of Never to Very often. The mean of all six responses is taken to construct the single subjective information overload figure for the participant. Cronbach's alpha reliability testing was performed on the results of this metric to investigate the consistency across its items.

Reward sensitivity - To measure reward sensitivity, the Behavioural Activation Scale (BAS), a component of the comprehensive Behavioural Activation and Behavioural Inhibition Scales (BAI) (Carver & White, 1994), was employed. The BAI questions that measured BAS were all items excluding items 1, 6, 10, 13, 15, 18, and 20. These items were statements on a 4-point Likert scale, indicating the extent of agreement with one being 'strongly disagree' and four being 'strongly agree'. For example, item five is 'When I get something I want, I feel excited and energised.' See the Appendices (Appendix B) for the complete list of items. None of these items were reverse scored, so a mean score of all five items were taken as the single BAS/reward sensitivity score. Despite being a preestablished measure of reward sensitivity, a Cronbach's alpha reliability test was performed on the results of this metric to investigate its consistency across items in our sample.

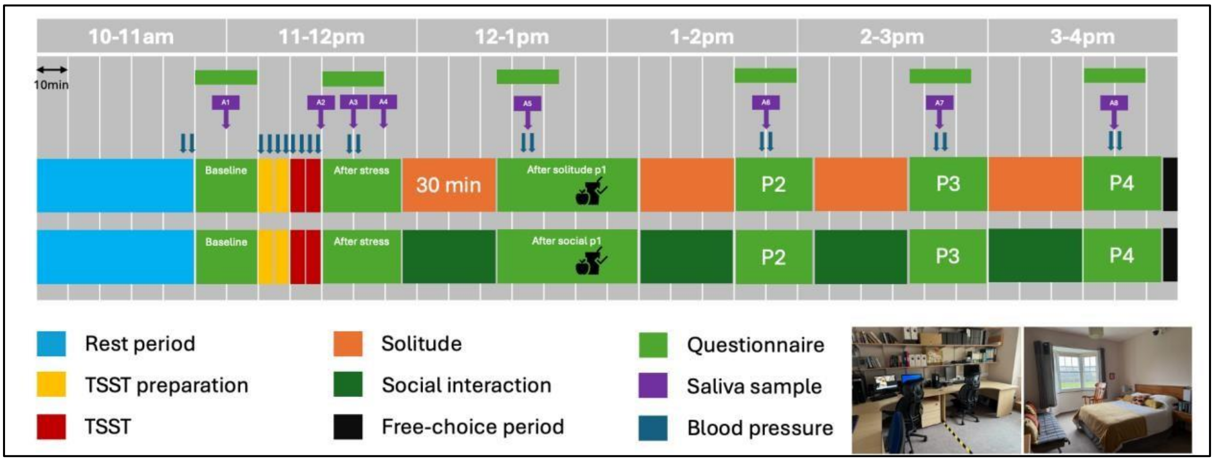
2.5. Procedure

Informed consent to participate in the study was first gained. Then, approximately one week before the participant attended the lab in person for the core part of the study, participants completed a demographic and baseline survey. This included the majority of within-subjects and demographic variables: (1) an inventory measuring recent perceived information overload, in regards to social media use, (2) A two-item inventory measuring the valence of how participants perceive the content they have seen online recently, (3) the behavioural activation scale (from the Behavioural activation inventory), to measure reward sensitivity, and (4) demographic information (age, gender, ethnicity).

As per the study timeline as seen in Figure 3, each participant, upon commencing the in-person study, was guided through an (approximately) 6-hour study period and was again required to provide consent to participate. The structure of activities and tasks was consistent across all participants, as follows. All Participants arrived at approximately 10:00 pm, and the consent and exclusion criteria checklists were then completed. Before storing personal belongings (including all electronic devices), participants' daily mean mobile phone screentime (over the last full week) was recorded.

Figure 3

The Study timeline (of the wider study context)



Note. Many aspects of the study timeline are extraneous components of the broader study context (i.e. saliva sample, free choice period, and social interaction) and are therefore irrelevant to the present study. “P4” represents the post-stress period, approximately 5 hours following the commencement of the TSST (stress phase). Lunch breaks were provided (indicated by the food and drink icon) at approximately 12:40 pm-1:10 pm for all participants. The bottom bar represents the timeline for the present study’s socially isolated sample.

Next, participants were fitted with the ECG electrodes, ICG electrodes and the *Omron Evolv Upper Arm Blood Pressure Monitor (HEM-7600T-E)* blood pressure arm cuff (electric sphygmomanometer) on their non-dominant arm. These were intended to measure Electrocardiography (ECG) signals, Impedance-Cardiography (ICG) signals continuously, as well as intermittent blood pressure measurements at regular intervals. Once connections to AcqKnowledge software were established, continuous recordings of raw ECG and ICG signals were initiated, along with regular blood pressure measurements. These were later segmented into discrete phases. The first of which was the baseline phase, which measured ‘typical’ physiological profiles of each participant.

Following this began the stress phase. Participants were guided through the TSST task (Kirschbaum et al., 1993). Specifically, participants were informed that they were to give a speech about their dream job after an eight-minute preparation period (five minutes to write out a plan; three minutes to review their notes) had ended. Participants were provided with a pen and paper to plan their speech. The pen was taken away after 5 minutes. After preparation, participants were led to a separate room where an ‘evaluator’ confederate was present and ready to record their speech on a mobile phone, positioned on a tripod. Additionally, the paper plan that the participants had prepared was unexpectedly taken away from the participant, to elicit further stress.

The speech was to last five minutes, was performed to the unenthused and strict ‘evaluator’, and was followed by a difficult (and unexpected) five-minute mental arithmetic task (counting backwards from a large number in steps of a difficult amount, for example: 1022 in backwards steps of 13 or counting backwards from 2043 in steps of 17 (Narvaez Linares et al., 2020)). Two sets of blood pressure data points were recorded during each phase of the TSST (preparation, review, speech, and arithmetic phases). Furthermore, the continuous ECG and ICG data were later segmented into a stress phase and were averaged accordingly. Once these tasks were completed, it was thought that an adequate stress response had been elicited, and they were led back to their separate participant room.

The participants continued to have their blood pressure and physiological signals measured throughout the remainder of the study period. Participants engaged in a variety of socially isolated tasks and activities for the rest of the study period. Although the nature of these activities is not particularly relevant to the present study, for transparency, an outline of potential activities will be provided. Activities were approx. 30-40 minutes of passive social media or internet use, 30-40 minutes of playing a computer game against a 'robot' opponent, 30-40 minutes of playing a board game alone, and 30-40 minutes of free-choice (non-sleep or social interaction) activities (including reading a book the participant brought from home, reading the scientific books in the participant's room, using colouring books, playing with toys, light exercise, resting on the bed, or any of the activities as mentioned earlier). Fundamentally, all participants did not experience significant social interaction following the stress phase. After 5 hours of engaging in activities and participating in non-relevant surveys (part of the broader study context), the final approx. 30-40 minutes (final activity) of continuous physiological data were segmented into a 'post-stress phase'. Measures of blood pressure were also taken at this point.

Once the study period concluded, participants were disconnected from the physiological measurement apparatuses and subsequently debriefed, being informed that the TSST was intentionally designed to induce stress and were debriefed accordingly. Participants subsequently received financial compensation for their participation.

2.6. Data Analysis Plan

Data processing was conducted using AcqKnowledge Version 5.0.0.0 (Almond, 2017), MindWare HRV analysis and IMP analysis (*Software - MindWare Technologies*, n.d.), and Microsoft Excel. Analyses were conducted using IBM SPSS Statistics Version 29.0.0.0.

2.6.1. Data Processing

The first step of processing physiological data was the conversion of physiological data files using BIOPAC AcqKnowledge Version 5.0.0.0 (Almond, 2017) to a file format compatible with the MindWare HRV analysis software (ECG data) and MindWare IMP analysis software (ICG data) (AcqKnowledge 3 file), both included in the MindWare Application Suite for physiological processing. For both ECG and ICG data, each peak was manually inspected to verify the accuracy of the automatic peak assignment, identifying any errors, noisy data, or missing values. In the case of erroneous peak assignment, false peaks were removed, and for ECG data alone, a new midbeat estimation was created between the prior and subsequent correct peaks. For ICG data specifically, the ensemble was checked for normal values and was adjusted accordingly in the event of irregular values. Furthermore, peaks assigned to out-of-range signals were removed.

Following the cleaning of the data, the two MindWare software programs calculated the mean heart rate variability, pre-ejection period, and cardiac output for each segment. Relevant to this study, the segments included baseline, stress preparation, stress review, stress speech, stress arithmetic, and six segments of the post-stress phase. The Baseline segment, Stress-phase segments, and post-stress segments for HRV, PEP, and CO were recorded onto Microsoft Excel. All stress and post-stress segments were averaged into mean stress phase indices and mean post-stress phase indices. The mean of systolic and diastolic blood pressure for each segment was calculated and combined, if necessary. Using the formulas outlined in Johnston et al. (2023), each participant's mean arterial pressure (MAP) was calculated from the systolic (SBP) and diastolic blood pressure (DBP) **[MAP = 0.3 x ((2 x DBP) + SBP)]**.

From this, total peripheral resistance was calculated as per Johnston et al. (2023)'s formula: **TPR = 80 x (MAP/CO*)***. Therefore, at the baseline, stress, and post-stress time points, mean measures of HRV, PEP, CO, and TPR were generated.

As mentioned previously, Stress recovery for each physiological index was operationalised as a 'recovery index', reflecting the proportional extent to which physiological stress measures returned to baseline levels, relative to the extent of stress reaction from baseline to stress. This was calculated through the following formula: [**Recovery Index = (Stress – Post-stress)/(Stress – Baseline)** for those variables that generally increase in stress (CO, TPR) and **Recovery Index = (Post-stress – Stress)/(Baseline – Stress)** for those variables that generally decrease during stress (HRV, PEP)]. Therefore, Scores equalling 1 indicate a 100% return to baseline levels, scores of 0 - 1 suggest that stress levels have persisted at a level worse than baseline levels, scores below 0 represent stress levels that have worsened after the stress phase ended, and scores above 1 reflect that scores have rebounded or compensated to a level better than the baseline. At this point, stress recovery indices for HRV, PEP, CO, and TPR were generated.

For within-subject individual difference variables measured using self-report instruments, all individual item scores on the inventories used were averaged together to create a single mean value for each measure (the precise process is described in Section 2.4.3. "*Measures*"). For screen time data, weekly totals of screen time in minutes were added into Excel and divided by 7 to get a daily average.

2.6.2. Data analysis

The present study aimed to investigate social media usage patterns (in terms of magnitude/quality) in relation to stress recovery dynamics. We also sought to examine whether individual differences in reward sensitivity and perceived information overload from social media moderate these relationships. Prior to hypothesis testing, we checked for and removed extreme outliers and tested whether the data set adequately meets assumptions for the use of the intended parametric tests. If not met, non-parametric alternatives were to be utilised. For each hypothesis involving physiological stress recovery, all four stress indices will be tested under the broad blanket term of ‘stress recovery’ in each hypothesis.

Outliers were inspected to identify and remove influential cases that reflect errors in data collection technologies, software calculation errors, or survey input mistakes. They were carefully examined to differentiate between erroneous outliers and true extreme values. We sought to identify univariate outliers by first determining the normality of each variable using Shapiro-Wilk testing, and then using boxplot screening and standardised z-score screening (Z-score > 3.29 indicating outliers (Mowbray et al., 2018)) if the data was normally distributed, or just the boxplot screening (if the data was found to be non-normal).

Notably, the limited resources available for this project restricted this study to being exploratory only (which will be elaborated on later). As such, p-values for each test are planned to be provided in their original form, without correction for multiple comparisons. Holm-Bonferroni and Bonferroni corrections were considered (and therefore calculated using Aslaksen (2016)’s custom SPSS syntax) for each test/test family as a conservative indicator of significance. Still, uncorrected values will be used to describe potential patterns found in our data that act as preliminary bases for further examination.

The following details each of the hypotheses and the intended parametric tests:

H1 Correlation Hypotheses:

For the following hypotheses: **H1a.** *“High reward sensitivity will be associated with a longer average daily screen time”*, **H1b.** *“Higher screen time will be associated with higher levels of subjective overload”*, **H1c**. *Lower reward sensitivity will be associated with higher levels of subjective information overload”*, **H1d.** “*Reward sensitivity will be positively associated with a more positive valence social media content*”, and **H1e. “***Lower valence will be associated with higher levels of subjective overload*” Pearson's correlation tests were intended to be used.

The H2 Regression hypotheses:

- **H2a.** *"Greater screen time will be associated with a reduced stress recovery ability"* will be tested using a simple linear regression test, with screen time as the independent variable and the stress recovery index as the dependent variable.
- **H2b.** "*More negative valence social media content exposure will be associated with poorer stress recovery capacity*" will be tested using simple linear regression, with social media valence as the independent variable and stress recovery capacity as the dependent variable.

Regressions were to be conducted regardless of normality, due to established normality violation robustness of linear regression analyses.

H3 Moderation Hypotheses:

All the following hypotheses required the use of a moderation analysis. To conduct this test, the PROCESS macro (Hayes, 2013) SPSS add-on was installed onto SPSS.

- **H3a.** "*The relationship between screen time and physiological stress recovery will be moderated by subjective information overload.*" -
  - A moderation analysis was to be conducted: Screen time predicting physiological stress recovery, moderated by subjective information overload.
- **H3b**. "*The relationship between social media valence and physiological stress recovery will be moderated by reward sensitivity.*" -
  - A moderation analysis was to be conducted: Social media valence predicting physiological stress recovery, moderated by reward sensitivity.

H4 Combined Model Hypotheses

- **H4.** "*A model including both subjective information overload and reward sensitivity will explain more variance in stress recovery than either predictor alone*" -
  - Hierarchical Multiple regression tests were to be conducted. Using stress recovery index metrics as the dependent variable. Perceived information overload and reward sensitivity are introduced in steps as primary and secondary predictors. This will test whether there is a significant change in R^2 from adding a second predictor. This will then be repeated in the reverse step order.

3. RESULTS

3.1. Outlier detection and normality testing

Univariate outliers were inspected to identify and remove influential cases that reflect errors in data collection technologies, software calculation errors, or survey input mistakes. They were carefully examined to differentiate between erroneous outliers and true extreme values. We sought to identify univariate outliers by first determining the normality of each variable using Shapiro-Wilk testing, and then using boxplot screening and standardised z score screening (Z-score > 3.29 indicating outliers (Mowbray et al., 2018)) if the data was normally distributed, or just the boxplot screening (if the variable was found to be nonnormally distributed).

Shapiro-Wilk tests were conducted on all variables. PEP recovery index and HRV recovery index were the only variables that yielded significant Shapiro-Wilk test results, suggesting non-normality. As such, outlier screening was only performed using box plot screening for these two variables. For the remaining variables, outliers were screened using both box plots and standardised z-score screening methods. Physio variables in which extreme outliers were detected and subsequently removed: HRV recovery index had one, TPR recovery index had one, CO recovery index had two, and PEP recovery index had four. This totalled to eight removed outlier cases. Mild outliers were kept under the assumption that they represented valid population variance (true outliers) and for the sake of the already limited sample size. Following the removal of outliers (besides those that reflected true variance), additional Shapiro-Wilk tests were performed on all variables. Results indicated that most variables were normally distributed. Following a single HRV outlier removal, HRV recovery index remained non-normal ($W(21) = .897$, $p = .031$). Upon further investigation, HRV recovery index possessed non-substantial levels of skew ($\gamma_1 = .886$, SE = .501) and kurtosis ($\kappa = 2.213$, SE = .972). According to Orcan's (2020) approach of defining significant skew and kurtosis at 1.95 x SE, these results indicate non-significant levels of skew and a substantial level of kurtosis (heavy leptokurtic distribution). Likewise, using Hatem et al. (2022)'s boundaries for levels of kurtosis and spread, skew is moderate, and kurtosis is large.

Therefore, for the linear regression analyses involving HRV recovery index (H2), bias-corrected bootstrapping with 5,000 resamples (Davison & Hinkley, 1997) will be employed to generate standard errors and 95% confidence intervals, thereby mitigating the biased effects of non-normality (Hayes, 2022).

Indeed, researchers suggest bootstrapping in all cases, even if parametric assumptions are met (Hayes, 2022, p. 123; Field, 2018), when samples are particularly small (as is the case in the present study). Given this recommendation, the fact that the SPSS PROCESS Macro defaults to 5000 resample bootstrapping, and the need to do so for non-normal HRV, bootstrapping was performed for the non-normal HRV for H2a and H2b.

3.1.2. Missing cases

All missing cases of the different stress indices would be due to any of the following: failure of measurement instruments, unusable data due to noise/artefacts, or an insurmountable error in MindWare HRV or IMP analysis software. To clarify, the HRV recovery index had two missing cases, the PEP recovery index had four missing cases, the CO recovery index had four missing cases, and the TPR recovery index had five missing cases. Due to the nature of these missing values generally being random circumstantial errors in data collection or processing, we could assume these datapoints are missing at random (MAR). Likewise, some of the self-report metrics are missing (one missing for the valence scale, one missing for the information overload scale, and one for the BAS scale; all from the same participant), which reflects a glitch or failure in the software. This also indicates MAR. For screen time, screen time was attained from the participants' phone's screen time analytic app, of which users were instructed to enable approximately one week prior to the study. Several users had forgotten or failed to enable this feature; other participants' mobile phones were of an unfamiliar operating system (OS) that did not include this screen time feature, insufficient training of research assistants in data storage protocols, and one data point was missed due to a data recording error (this totalled to 14 missing cases). It was thought that those who owned certain phones or forgot to enable this feature would predictably cause missing values, and therefore, we would assume these missing cases to occur not at random (MNAR). However, following a Little's MCAR test of relevant variables (screen time, valence, PIO, reward sensitivity, HRV, PEP, CO, and TPR recovery indices), there was no statistically significant evidence for any variable's missing data not being completely random ($\chi^2(68) = 67.831$, $p = .483$). Implications of this on our findings will be discussed.

3.1.3. Measure reliability testing

McDonald's Omega could not be estimated for PIOS due to several near-zero and negative item intervariances, suggesting poor multidimensionality. Indeed, Principal Axis Factoring analysis revealed three significant factors contained within the scale, if using the Kaiser > 1 rule (i.e., eigenvalues > 1) (2.235, 1.666, and 1.071, respectively). Despite appearing to violate the assumption of unidimensionality, a Cronbach's alpha test was conducted on the six items and suggested our perceived information overload scale adapted to social media possessed a moderate to low level of reliability ($\alpha = .614$). However, due to assumption violations, definitive reliability judgments that can be made from this are limited.

Despite the BAS scale being taken directly from an established scale, we chose to examine its reliability for our given sample, and because we took the mean of the subscales to calculate an overall BAS. Again, McDonald's Omega could not be estimated for the 13-item BAS scale due to several near-zero and negative item intervariances, suggesting poor multidimensionality, which was partly supported by a principal axis factoring analysis that suggested that the BAS scale, in our sample, measures five latent factors (eigenvalues = 4.125, 1.839, 1.439, 1.353, and 1.184, respectively). However, the sharp initial drop found in the scree plot (elbow test; see: Zhu & Ghodsi, 2006) and the predominantly large initial factor eigenvalue indicate that there is one dominant factor in the model, suggesting an extent of unidimensionality. Indeed, since the BAS scale was taken from a preexisting scale where BAS had four different types of BAS under the same umbrella, it would suggest that reward sensitivity is measured as a whole (unidimensional), with slight multidimensionality in that it measures distinct BAS types. Regardless, we then estimated Cronbach's alpha for the 13-item BAS scale and found moderate-to-good levels of reliability ($\alpha = .761$).

Valence of social media scale item scores were not normally distributed (item 1 =

$W(23) = .818$, $p = <.001$; item 2 = $W(23) = .801$, $p = <.001$) and therefore a one-tailed nonparametric Spearman's correlation test was performed. A significant weak-to-moderate correlation was found ($r_s(21) = .378$, $p = .038$) between the two items. Implications of these results will be discussed in the following chapter.

3.2. Descriptive Statistics

Table 1 outlines the descriptive statistics for the present study.

Table 1

Descriptive statistics for all participants (N = 24) following outlier removal

	N	Minimum	Maximum	Mean	Std. Deviation
Perceived Valence of SM	23	2	4.5	2.93	0.7
Daily Mean Screen Time (Minutes)	10	126.86	722	386.39	212.9
Perceived Information Overload from SM	23	1.5	3.83	2.49	0.63
Reward Sensitivity (BAS)	23	2.08	3.54	2.91	0.34
HRV Recovery Index	21	-2.9	7.1	0.97	0.5
PEP Recovery Index	16	-4.68	0.76	-0.56	1.28
CO Recovery Index	18	-2.71	2.83	0.27	1.39
TPR Recovery Index	18	-4.26	6.83	0.1	2.32

Note. All variables, except HRV recovery index, were normally distributed.

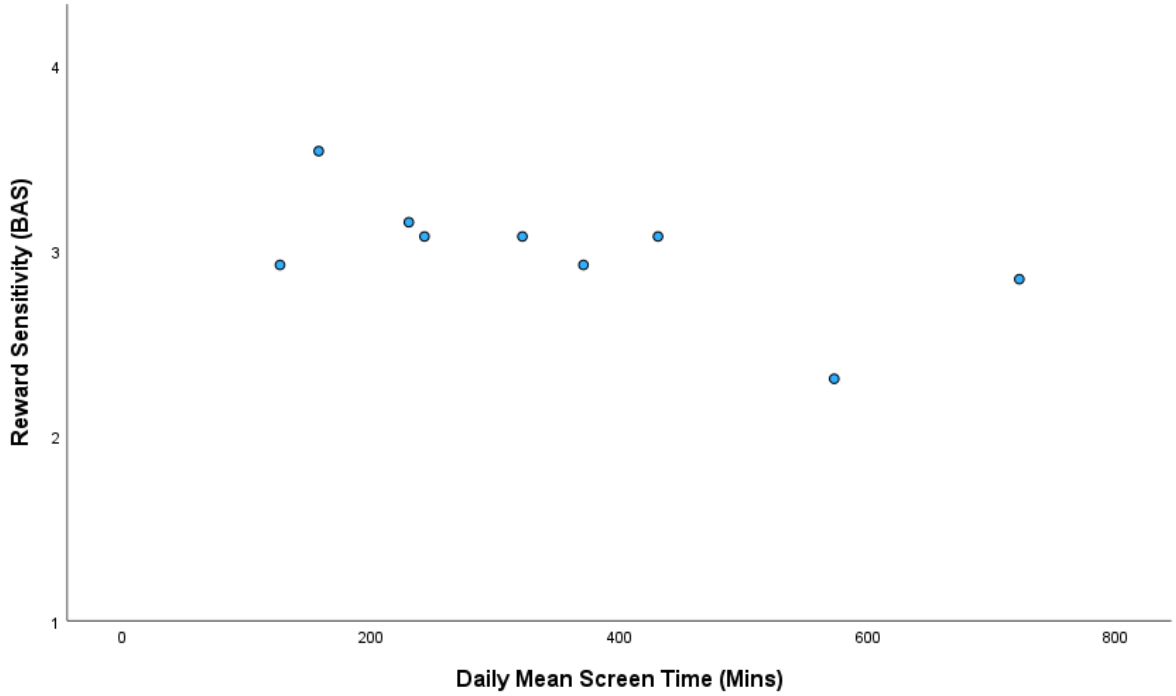
3.3. Hypothesis Testing

3.3.1. Correlation Hypotheses (H1)

For hypothesis 1A (High reward sensitivity will be associated with a higher average daily screen time), sample limitations (N = 9) did not allow us to perform inferential analysis. Instead, a preliminary descriptive plot of the relationship between reward sensitivity and screen time is examined and is shown in Figure 4. The apparent trend seems to suggest a slight negative relationship, which would be contrary to our hypothesis; however, as this is a descriptive observation, any confirmation of null results cannot be definitively drawn.

Figure 4

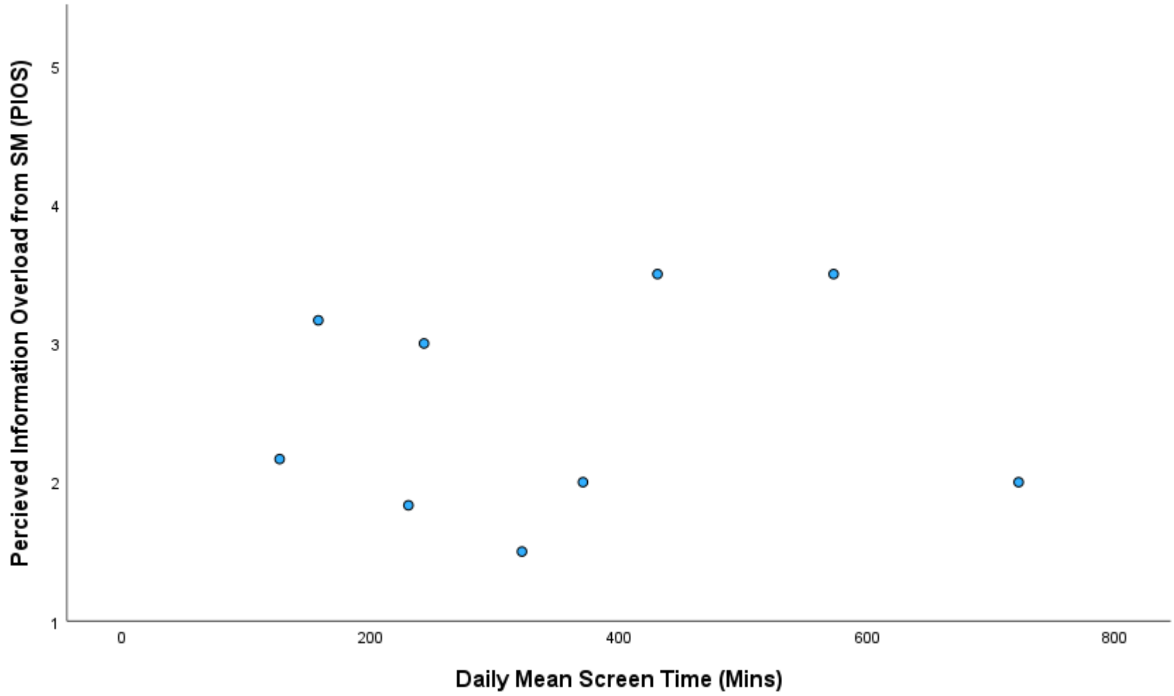
Scatterplot of reward sensitivity and daily mean screen time



Likewise, the sample for Hypothesis 1B (higher screen time will be associated with higher levels of subjective overload) similarly suffered from restricted sample size (N = 9) and could not be tested inferentially. Instead, a preliminary descriptive plot of the relationship between reward sensitivity and screen time is examined and is shown in Figure 5. There appears to be no consistent discernible trend seen in these data points, which would be contrary to the hypothesis. Again, this is not sufficient for null results to be confirmed.

Figure 5

Scatterplot of perceived information overload and daily mean screen time



For hypothesis 1C, it was hypothesised that high perceived information overload would be associated with greater reward sensitivity. Following confirmation of the necessary test assumptions, a one-tailed Pearson's correlation test was conducted (N = 23). The results indicated that the two variables were not significantly correlated ($r(21) = .042$, $p = .424$), thereby failing to reject the null hypothesis.

For Hypothesis 1D, we hypothesised that Reward sensitivity would be positively associated with more positive valence social media content. Following the confirmation of necessary test assumptions, a Pearson's correlation test was conducted (N = 23), and it was found that reward sensitivity scores were significantly positively associated with perceived SM valence ($r(21) = .463$, $p = .013$).

Finally, for hypothesis 1E, it was hypothesised that lower social media valence would be associated with higher levels of subjective overload. Following the confirmation of necessary test assumptions, a Pearson's correlation test was conducted (N = 23), and it was found that levels of perceived information overload were not significantly associated with perceived valence of social media content (r(21) = -.010, p = .482), failing to reject the null hypothesis.

A sensitivity analysis conducted in G*Power 3.1 (α = .05, power = .80) indicated that with a sample size of N = 23, the Pearson correlation analyses in this section only possessed sufficient power to detect moderate to large effects (minimum detectable r = .494). Smaller effects could therefore not be reliably detected. To note, Hypothesis 1D yielded a significant effect (r = .463) with an effect size below this calculated reliable detection threshold (r = .482), suggesting that the present study would fail to reliably replicate this effect at least 80% of the time (potential dubious reliability), suggesting this result should be interpreted with increased scepticism. This will be discussed in a later section.

3.3.2. Hypothesis 2

Following linear regression testing to investigate whether SM Valence predicted HRV recovery index scores (H2Ai) (N = 20), the test results indicated there was no significant predictive relationship detected in the present sample. Both the overall regression model and the prediction test did not reach the significance threshold (R^2 = .010; Adjusted R^2 = -.045; F (1, 18) = .185; *p* = .672; SE = .578) and (β = -.101, p = .672), respectively. For transparency and posterity, an additional linear regression analyses was performed for this hypothesis but with previously removed spurious outlier(s) included (N = 21) to examine the impact of outlier removal, which similarly did not detect any results beyond the significance threshold ((R^2= .039, Adjusted R^2 = -.011; F(1, 19) = .778, *p* = .389; SE = .930) & (β = -.190, p = .389)), suggesting that outlier removal did not significantly alter results in this case.

A sensitivity analysis conducted in G*Power 3.1 (α = .05, power = .80) indicated that with a sample size of N = 20, linear regression tests only possessed sufficient power to detect very large effects (approximate minimum detectable effect size of $f^2 \approx .439$), which translated to an approximate $R^2 \approx .305$. Smaller effects could therefore not be reliably detected. This minimum detectable effect would also further increase in the samples with fewer than 20 participants, which further demonstrates limited power.

Other physiological stress recovery indices (PEP, CO, TPR) lacked sufficient sample size to be examined using parametric testing and were instead tested using non-parametric Spearman's rank correlation tests. While, unfortunately, lacking the capacity to test predictive relationships, it was thought that examining correlational relationships may still reveal useful information. None of the tests were significant; the results of these tests are found in Table 2.

Table 2

Spearman's Rank Correlation analysis results for H2Aii – iv following the removal of spurious outliers.

	Metric	*N*	*df*	*r*	*p*
Valence → Stress recovery (H2a).	PEP	15	13	-.457	.087
	CO	17	15	.044	.866
	TPR	17	15	.386	.126

Despite examination of outliers suggesting they reflect genuine measurement errors rather than true population variation, a sensitivity analysis was conducted for the purposes of transparency and posterity. This involved rerunning the prior Spearman's rank correlation analyses with outliers removed to examine whether outlier removal drastically alters the results. The results of this outlier sensitivity analysis are shown in Table 3.

Table 3

Spearman's Rank Correlation analysis results for H2Aii – iv, with spurious outliers included in the analysis for outlier removal sensitivity testing.

	Metric	N	df	r	p
Valence → Stress recovery (H2a).	PEP	19	17	-.215	.378
	CO	19	17	-.171	.483
	TPR	18	16	.321	.193

For Hypotheses H2Bi – H2Biv, due to a combination of data collection errors and study limitations, the present sample was severely restricted beyond a suitable level for inferential testing (N = 8-9), including non-parametric alternatives. As such, only descriptive examinations of relationships between stress recovery metrics and screen time were able to be explored, possessing no confirmatory bases. As such, the patterns observed cannot be taken as a valid or reliable indicator of effect or null effect. As a potential preliminary area of interest for more aptly powered studies, descriptive patterns are as follows. In the present sample, mean daily screen time and HRV recovery index appeared to have a moderate to strong positive relationship (N = 9; r(7) = .383). PEP recovery index and mean daily screen time presented with a very low negative association (N = 8; r(6) = -.048). CO recovery index and Daily mean screen time seemed to have a strong negative association (N = 9; r(7) = -.700). Finally, TPR recovery index and daily mean screen time's relationship appeared to be weakly negatively correlated (N = 8; r(6) = -.286). Figures 6-9 display visualisations of these relationships.

Figure 6

Scatterplot of the relationship between HRV Recovery Index and Daily mean screen time.

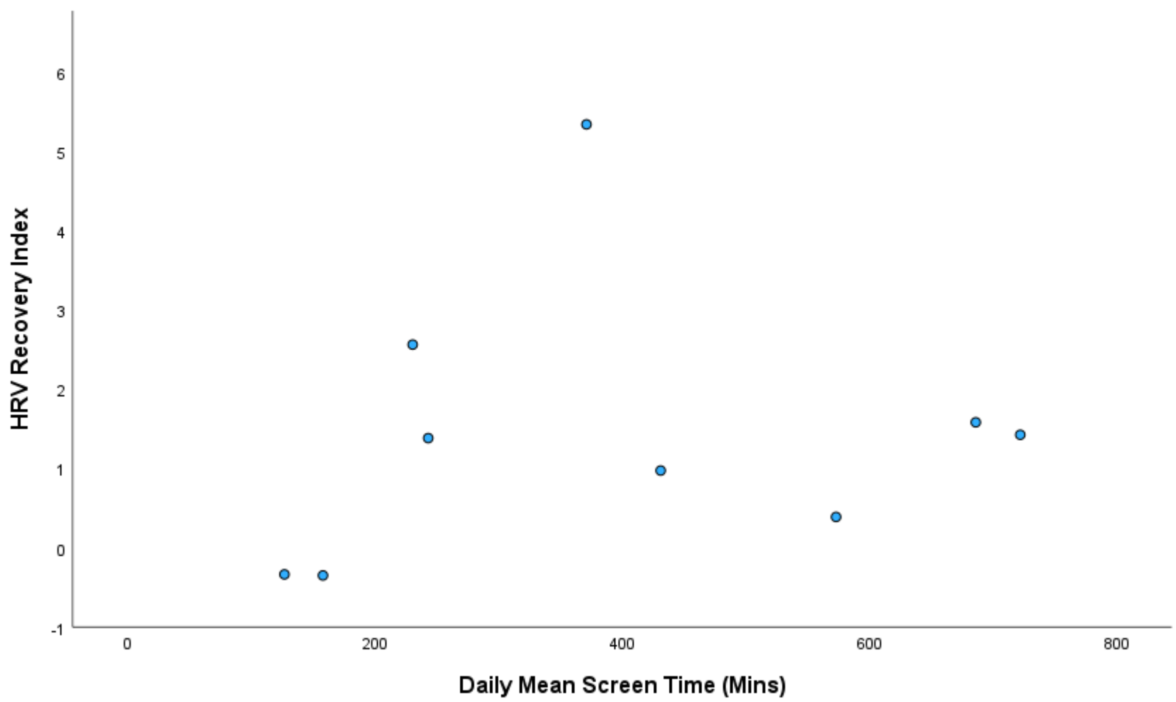


Figure 7

Scatterplot of the relationship between PEP Recovery Index and Daily mean screen time.

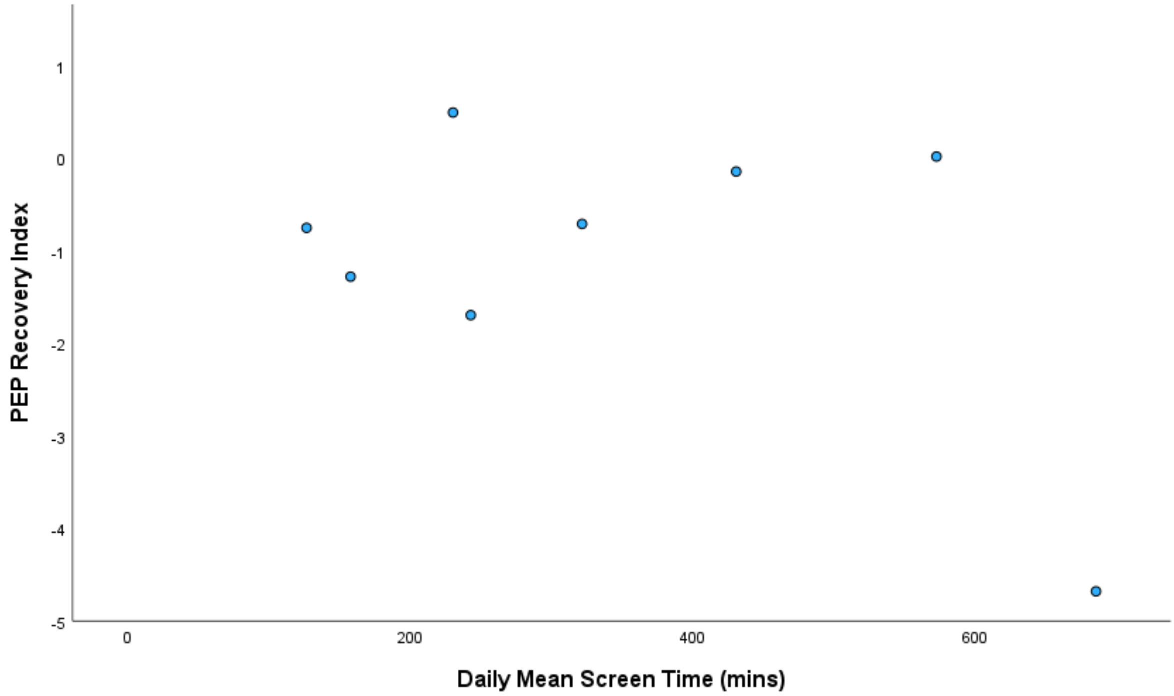


Figure 8

Scatterplot of the relationship between the CO Recovery Index and Daily mean screen time.

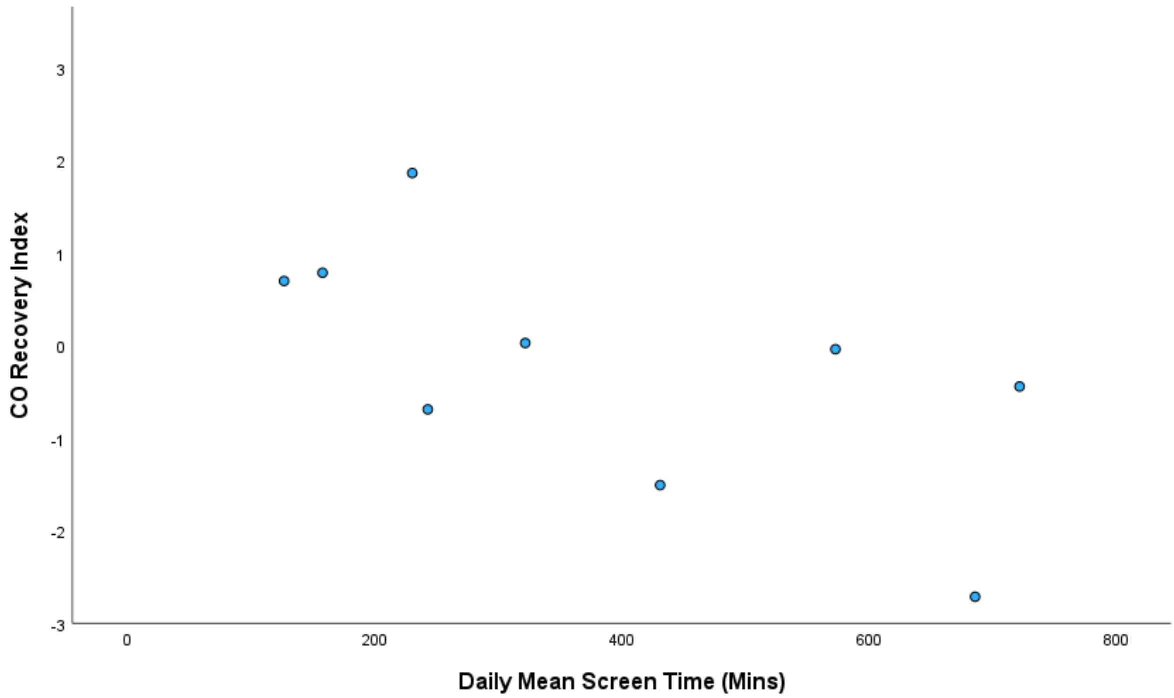
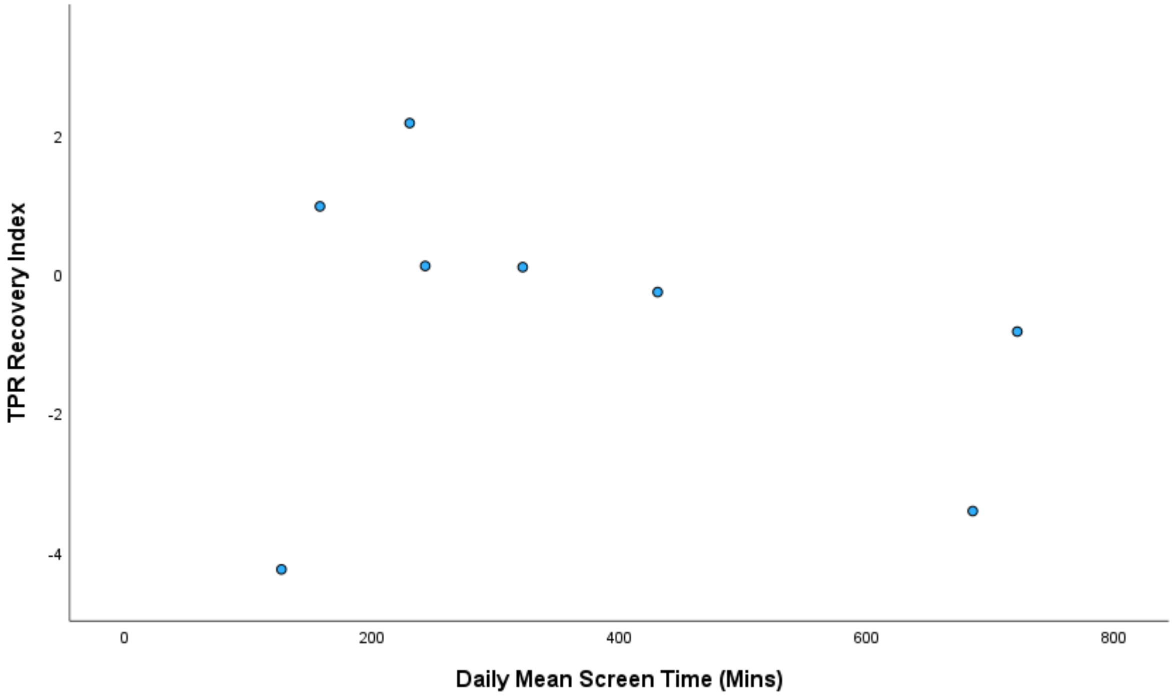


Figure 9

Scatterplot of the relationship between TPR Recovery Index and Daily mean screen time.



3.3.3. Hypothesis 3

The third hypothesis of this paper was that the predictive relationship between social media use (valence/screen time) will be moderated by either reward sensitivity or perceived information overload. Physiological stress recovery was measured by four different metrics (HRV, PEP, CO, and TPR) and was therefore tested individually. As HRV Recovery Index and Daily Mean screen time were the only tests with a sample size remotely sufficient for a regression analysis (N=20), it was similarly the only tests able to undergo an inferential moderation analysis, with either reward sensitivity or information overload as moderators. The remaining metrics were examined descriptively.

Hypothesis 3A

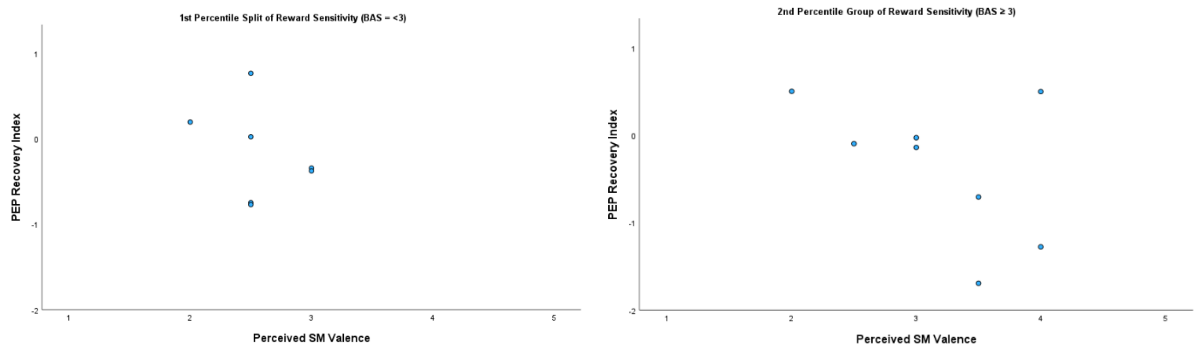
Firstly, SPSS PROCESS Macro (Hayes, 2013) was used to examine whether reward sensitivity moderated the relationship between perceived SM valence and HRV Recovery index (H3Ai) (N = 20). The test indicated that the overall model was not significant (R^2 = 0.138, F(3, 16) = .856, p = .484). Importantly, interactions between valence and reward sensitivity were not significant (B = .916, SE = 2.383, t = .384, p = .706), indicating that reward sensitivity did not moderate this relationship. The same analysis was performed with the removed spurious outlier included to examine the sensitivity of the results to its removal. This version (N = 21) similarly presented with a non-significant overall model (R^2 = .114; F(3, 17) = .732; p = .547) and no significant moderation (B = 1.63; SE = 3.06; t = .533; p = .60). These results suggest that the removal of the outlier had little impact on the results.

A post hoc sensitivity analysis conducted in G*Power 3.1 (α = .05, power = .80) indicated that with a sample size of *N* = 20, the moderation analysis only possessed sufficient power to detect fairly large effects (minimum detectable effect size of $f^2 \approx .441$), which corresponded to an $\Delta R^2 \approx .38$, according to the full model variance (R^2 = .138). Smaller effects could therefore not be reliably detected.

When examining visualised descriptive relationships between PEP recovery index and SM Valence at differing levels of reward sensitivity (H3Aii) (Group below median and group above median), there does not appear to be any difference between high and low reward sensitivity groups, as such not suggesting a moderative impact of reward sensitivity for the PEP-Valence relationship, however it is important to note that this null result is not confirmatory and further inferential testing must be conducted to verify this preliminary observation. Figure 10 provides a visualisation of this.

Figure 10

Scatterplots of the relationship between PEP Recovery index and Perceived SM Valence at low and high levels of reward sensitivity

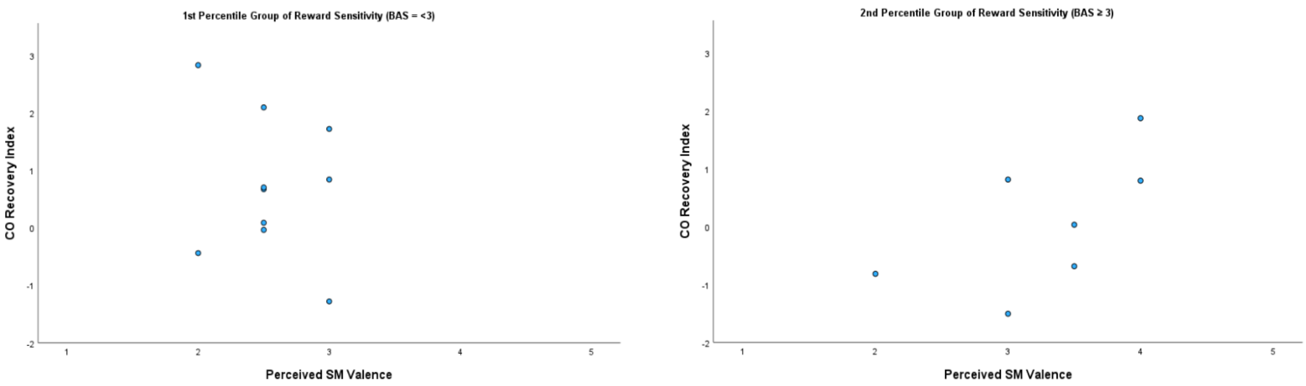


Secondly, when examining visualised descriptive relationships between CO recovery index and SM Valence at differing levels of reward sensitivity (H3Aiii) (In either a group below the

median or a group above the median), it appears that high levels of reward sensitivity entail a fairly strong positive association. In contrast, lower reward sensitivity manifests as either a potential negative association or no discernible association. This preliminary observation may suggest a potential moderating effect of reward sensitivity on the CO-Valence relationship; however, this is not confirmatory, and further inferential testing is needed to verify it. Figure 11 provides a visualisation of this.

Figure 11

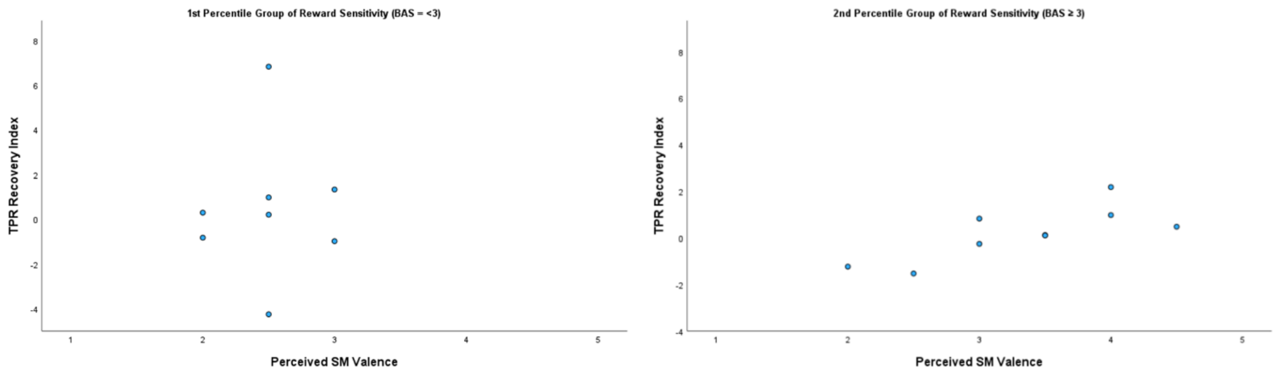
Scatterplots of the relationship between CO Recovery index and Perceived SM Valence at low and high levels of reward sensitivity



Finally, when examining visualised descriptive relationships between TPR recovery index and SM Valence at differing levels of reward sensitivity (H3Aiv), it appears that high levels of reward sensitivity show a weak positive association between TPR recovery index and SM Valence, while at a lower reward sensitivity, no discernible association is seen. This preliminary observation may suggest a potential moderating effect of reward sensitivity on the TPR-Valence relationship; however, this is not confirmatory, and further inferential testing is needed to verify it. Figure 12 provides a visualisation of this pattern.

Figure 12

Scatterplots of the relationship between TPR Recovery index and Perceived SM Valence at low and high levels of reward sensitivity



Hypothesis 3B

Secondly, SPSS PROCESS Macro (Hayes, 2013) was used to examine whether perceived information overload moderated the relationship between perceived SM valence and HRV Recovery index (H3Bi) ($N = 20$). The test indicated that the overall model was not significant ($R^2 = 0.41$, $F(3, 16) = .228$, $p = .875$). Furthermore, interactions between valence and reward sensitivity were not significant ($B = -.331$, $SE = 1.64$, $t = -.201$, $p = .843$), indicating that reward sensitivity did not moderate this relationship. The same analysis was performed with the removed spurious outlier included to examine the sensitivity of the results to its removal. This version ($N = 21$) similarly presented with a non-significant overall model ($R^2 = .174$; $F(3, 17) = 1.2$; $p = .341$) and no significant moderation ($B = 1.2$; $SE = 1.83$; $t = .655$; $p = .521$). These results suggest that removing the outlier had little impact on the results, except for shifting the direction of the interaction coefficient, though not to any substantial degree.

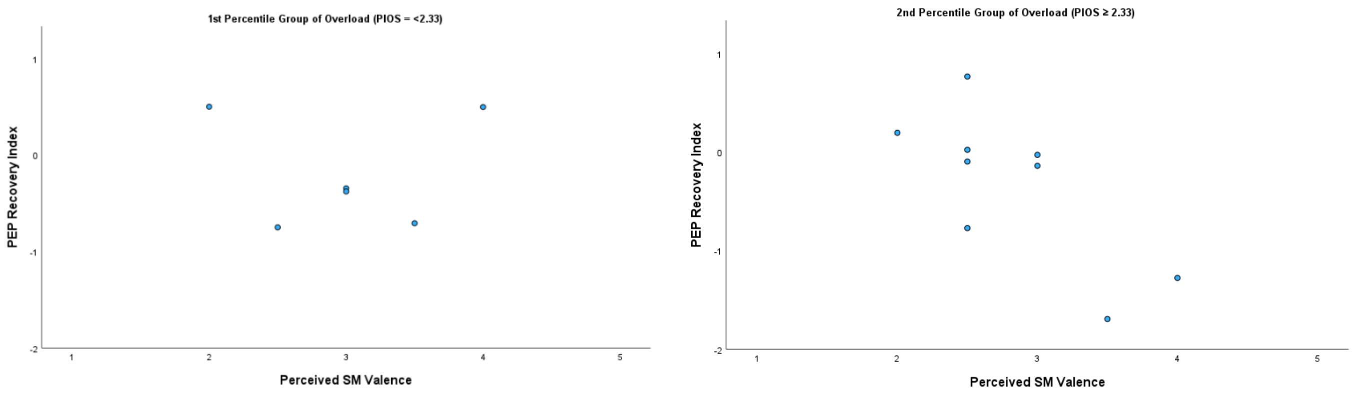
A post-hoc sensitivity analysis conducted in G*Power 3.1 ($\alpha = .05$, power = .80) indicated that with a sample size of $N = 20$, the moderation analysis only possessed sufficient power to detect fairly large effects (minimum detectable effect size of $f^2 \approx .441$), which corresponded to a $\Delta R^2 \approx .424$, according to the full model variance ($R^2 = .041$). Smaller effects could therefore not be reliably detected.

Remaining stress recovery metrics (PEP, CO, TPR) lacked sufficient sample sizes for inferential testing, a nd therefore only descriptive exploration of these hypotheses was possible under the current design/study.

When examining visualised descriptive relationships between PEP recovery index and SM Valence at differing levels of information overload (H3Bii) (Group below median and group above median), it appears that high levels of information overload show a moderately strong negative association between PEP recovery index and SM Valence. In contrast, at lower levels of information overload, no discernible association is observed. This preliminary observation may suggest a potential moderating effect of reward sensitivity on the PEP-Valence relationship; however, this is not confirmatory, and further inferential testing is needed to verify it. Figure 13 provides a visualisation of this.

Figure 13

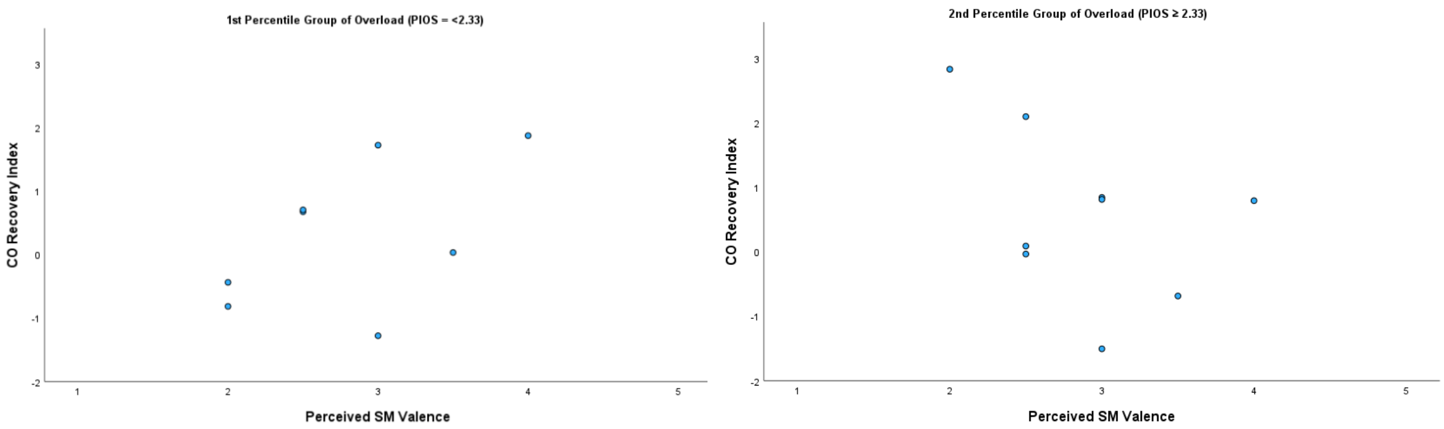
Scatterplots of the relationship between PEP Recovery index and Perceived SM Valence at low and high levels of information overload



Next, when examining visualised descriptive relationships between CO recovery index and SM Valence at differing levels of information overload (H3Biii) (Group below median and group above median), it appears that high levels of information overload show a moderately strong negative association between PEP recovery index and SM Valence. In contrast, at lower levels of information overload, a positive association trend seems to appear. This preliminary observation may suggest a potential moderation effect of Information overload on the CO-Valence relationship, which elicits a reversal in trend direction; however, this is not confirmatory, and further inferential testing is needed to verify this preliminary observation. Figure 14 provides a visualisation of this.

Figure 14

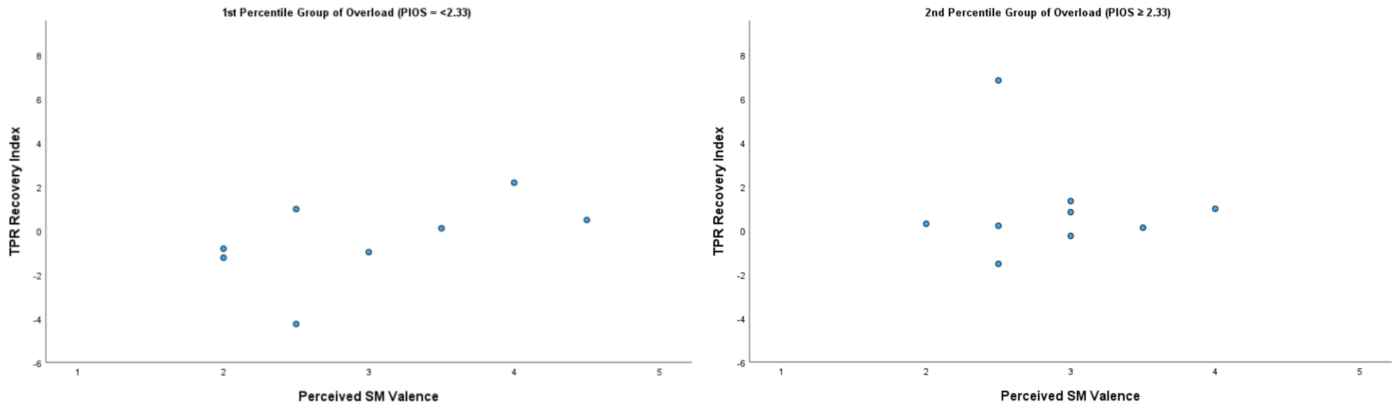
Scatterplots of the relationship between the CO Recovery index and Perceived SM Valence at low and high levels of information overload



Finally, when examining visualised descriptive relationships between TPR recovery index and SM Valence at differing levels of information overload (H3Biv) (Group below median and group above median), no discernible difference in trend is observable between high and low levels of information overload. This preliminary observation may indicate a lack of moderating effects of information overload on the TPR-Valence relationship, which elicits a reversal of trend direction; however, this is not confirmatory, and further inferential testing must be conducted to verify this preliminary observation. Figure 15 provides a visualisation of this.

Figure 15

Scatterplots of the relationship between TPR Recovery index and Perceived SM Valence at low and high levels of information overload



H3C & H3D were not inferentially tested (as planned) or descriptively examined due to the considerable sample size limitations of the screen time data ($N < 10$), rendering these tests or comparisons non-useful/unfeasible. This was partially due to the process of splitting datasets into two groups for this type of analysis. Ultimately, data would be too noisy to examine even descriptive trends earnestly.

3.3.4. Hypothesis 4 (/Exploratory Analysis)

Hierarchical multiple regression analyses were conducted to examine whether perceived information overload and reward sensitivity (BAS) together predicted physiological recovery better than either predictor individually. As with other hypotheses, physiological stress recovery was measured using four stress metrics.

Firstly, to examine the prediction of HRV Recovery index by information overload and reward sensitivity (H4a) ($N = 20$), a hierarchical regression was employed. When Information overload was entered at Step 1, it explained 2.6% of the variance in HRV recovery index. Adding reward sensitivity at Step 2 accounted for an additional 6.5% of variance, which did not meet the significance threshold ($\Delta R^2 = .065$; $p = .286$). In the reverse model, reward sensitivity entered at Step 1 explained 7.1% of the variance, with information overload contributing an additional 2% at Step 2, which did not meet the significance threshold ($\Delta R^2 = .02$; $p = .550$).

For transparency, outlier sensitivity was assessed in a subsequent test that included a previously removed outlier ($N = 21$). These results indicated that information overload entered at Step 1 explained 11.5% of the variance in HRV recovery index. Adding reward sensitivity at Step 2 accounted for an additional 1.4% of variance, which did not meet the significance threshold ($\Delta R^2 = .014$; $p = .599$). In the reverse model, reward sensitivity entered at Step 1 explained 1.7% of the variance, with information overload contributing an additional 11.2% at Step 2, which did not meet the significance threshold ($\Delta R^2 = .112$; $p = .145$). Overall, the inclusion of this outlier had no substantial bearing on the test results, aside from slight variations in some percentages; therefore, the conclusions remain the same.

A post-hoc sensitivity analysis was conducted in G*Power 3.1 ($\alpha = .05$, power = .80) indicated that with a sample size of N = 20, the hierarchical regression only possessed sufficient power to detect fairly large incremental effects (minimum detectable effect size of $f^2 \approx .441$), which corresponded to an $\Delta R^2 \approx 0.4$, according to the full model variance ($R^2 = .091$). Smaller effects could therefore not be reliably detected.

The remaining stress metrics did not have sufficient sample sizes for inferential testing. However, descriptive hierarchical regression results are detailed, presenting potential preliminary patterns (while lacking confirmatory bases). These results are seen in Table 4.

Table 4

Descriptive hierarchical multiple regression effect size estimates of individual difference variables (perceived information overload and reward sensitivity) and each physiological stress recovery index

	DV	Step Order	N	ΔR^2
PEP (H4B)	PEP Recovery	Overload → BAS	15	.073
	PEP Recovery	BAS → Overload	15	.003
CO (H4C)	CO Recovery	Overload → BAS	17	.083
	CO Recovery	BAS → Overload	17	.008
TPR (H4D)	TPR Recovery	Overload → BAS	17	.036
	TPR Recovery	BAS → Overload	17	.244

4. Discussion

4.1. Summary of Results

4.1.1. Summary for Hypothesis 1

Due to unforeseen methodological shortcomings, certain tests' samples were insufficient to perform inferential testing (those tests involving screen time), and therefore, not all tests had confirmatory bases. In terms of tests with a confirmatory basis, we hypothesised that reward sensitivity would be positively associated with exposure to more positive-valence social media content (H1d). Following a one-tailed Pearson's correlation test, we found a significant, moderately strong correlation between reward sensitivity and SM valence. This result indicates a pattern in line with our alternate hypothesis. Moving forward, we hypothesised that high levels of perceived information overload would be associated with a higher reward sensitivity (H1c), but following a Pearson's correlation analysis, no significant relationship between variables was detected. Similarly, it was hypothesised that lower social media valence would be associated with higher levels of subjective overload (H1e); however, no significant relationships were detected after inferential testing.

The study also hypothesised that reward sensitivity and daily average screen time would be positively associated (H1a). The present sample was insufficient to test this hypothesis inferentially. Accordingly, descriptive observation of the trend seemed to suggest a slight negative association, which would directly contradict our hypotheses. Though this is not confirmatory evidence and therefore should be viewed with intense caution, which is not to say it would not still be a useful direction for further experimental scrutiny. Moreover, we hypothesised that high levels of perceived information overload would be associated with longer average daily screen time (H1b). Although we could not inferentially test this relationship, descriptive examination did not reveal any discernible association in our sample.

Our results, showing a significant and moderately strong correlation between reward sensitivity and SM valence, align with previous research. As discussed in the introductory section, Richards et al. (2016) suggest that constant exposure to positive stimuli (presumably positively valenced) encourages increases in reactivity to reward. Indeed, this effect may be compounded in groups, most commonly on SM platforms (Statista, 2024), and particularly among adolescents, who are particularly receptive to the positive and negative social rewards found there. This effect is further substantiated by Kobayashi et al. (2010), who found that increased reward frequency alters the reward circuitry (specifically the orbitofrontal cortex) toward increased sensitivity to rewarding consequences. In fact, the orbitofrontal cortex is considered one of the last brain regions to mature and, as such, is thought to be highly susceptible to environmental influences (Ruge et al., 2025). Indeed, the implication gleaned from Richard et al. (2016)'s findings (that adolescents would be particularly susceptible to SM social cues) is reflected by the fact that our present sample mainly consisted of Undergraduate-aged University students, having a mean age of 21.48 years. It is a highly contested issue, but many researchers have suggested that the developmental span of adolescence can extend to 24 years (Sawyer et al., 2018), meaning our sample could reflect a population particularly sensitive to the positive social cues (i.e., rewards) encountered during their SM use. It appears unclear what the purpose of this function is. However, some have speculated that it arises from all social stimuli – regardless of valence – acting as more salient stimuli for those still undergoing social neurocircuitry development (Foulkes & Blakemore, 2016). For this reason, this suggests that the prevalence of positive valence stimuli on SM platforms may be a fundamental driver of user behaviour, as increasing reward sensitivity would likely help reinforce rewarding behaviours.

However, these behaviours may also not be adaptive. Indeed, adolescents with higher reward sensitivity tend to engage in riskier decision-making, such as drinking, drug use, speeding, etc. (Scott-Parker & Weston, 2017). Certainly, risky online behaviours could feasibly be encouraged (online gambling, unhealthy dependency on internet use, cyberbullying, meeting dangerous strangers, or disclosing private information (Brevers et al., 2019; Gámez-Guadix et al., 2016; Sasson & Mesch, 2016) or addiction-like dependence that causes discomfort on use cessation (Wadsley & Ihssen, 2025). However, the present study did not measure the social extent of the content rated, meaning the valenced stimuli measured in our study were not limited to social stimuli, so these ideas should be received with scepticism.

To further demonstrate the idea that our sample may capture a portion of the population, particularly susceptible to valenced social content. Our sample had a disproportionately high number of those who self-identified as female. This again suggests our sample may be particularly susceptible to the effect we are examining, as males and females were found to differ in their fundamental motivations towards risky online behaviour (Sasson & Mesch, 2016), and that female participants tended to experience heightened reactivity to 'kind' social interaction, which could present as analogous to positive valence SM social content, with this effect levelling off as female participants aged (Altikulaç et al., 2019). Additionally, in Proverbio et al. (2008), female participants showed distinct brain activation to social stimuli, suggesting they may be predisposed to find social stimuli more salient. However, it is essential to note that definitive conclusions cannot be drawn unless a further study is conducted with a larger sample, encompassing a broader range of ages and sufficient representation of all gender identities, to include these variables as control covariates in the analysis. As a whole, though, our findings in this case may have important implications beyond our present focus of stress recovery and should be carefully examined in future, more robust studies.

While not having confirmatory power, the unexpected negative associative trend between reward sensitivity and daily average screen time (as observed descriptively) appears to contradict the discussed ideas informed by previous research if verified by future inferential testing (Kobayashi et al., 2010; Richards et al., 2016; Ruge et al., 2025). If constant exposure to positive social stimuli encourages increases in reactivity to rewards (Richards et al., 2016), then it would be reasonable to assume that higher quantities of SM use would correspond to higher reward sensitivity. However, the opposite appeared to be observed. When examining the reasons this preliminary pattern may have been observed, a study by Efraim et al. (2020) found that children with high screen time and a sedentary lifestyle showed reduced reward network activation compared with typical responses to images of high-calorie food (salient reward). This implies that higher screen time generally indicates a user is more sedentary, as the time they would otherwise spend moving/exercising is spent online instead. Having a low activity level may disrupt the usual adaptive process of responding to rewarding stimuli, thereby increasing sensitivity for learning purposes.

Kouvonen et al. (2006) appearingly found that sedentary lifestyles became more prevalent when there were mismatches between effort and received reward. Similarly, studies have found that reduced reward sensitivity (albeit a more specific aspect, reward satiety) was linked to lower fitness behaviours (Kiive et al., 2025). An individual with reduced ability to feel satisfaction in response to a reward would require more reward to achieve satiation, corresponding to an increased effort requirement. Therefore, activities that produce easier and more frequent rewards as a function of the effort invested would be preferred, which explains why low reward-sensitive individuals would prefer sedentary activities and low-fitness behaviours, as they are far less effort-expensive. Overall, sedentary / lower fitness behaviours may act as a third-variable influence, obscuring the true nature of the association between screen time and reward sensitivity. This therefore suggests that activity level should be measured and controlled for as a covariate in future studies to determine the statistical basis of this idea. However, until future inferential tests are performed, it will remain unclear whether our observed trend is evidence of a third-variable effect or merely random noise detected in an extremely limited population.

Moving on, screen time not showing a trend consistent with higher levels of subjective information overload seems unexpected given expectations from the literature (e.g., Kim et al., 2022). However, the non-confirmatory nature of these observations makes them non-definitive. Indeed, the lower relative power of the screen time analyses, given that only nine participants were available for this analysis, suggests it may instead reflect random noise. It is, therefore, entirely possible for a faint existent (in a wider population) effect to have gone undetected (type 2 error) or, in the case that this lack of discernible trend truly represents the broader population's lack of association (when confirmed in actual inferential tests), that quantity of screen time does not influence one's susceptibility to experiencing PIO. Indeed, it is possible that mental resources are being consumed when users are not actively attending to content on their screen. Accordingly, Smit et al. (2004) found that vigilance task performance was not affected when more stimuli were added or complexity increased, but only when performance was actively sustained in a demanding condition (presumably where commitment is higher). This suggests that higher information loads (i.e., screen times) do not inherently deplete mental resources, but only when they are actively being processed. This idea could be supported by the fact that the working memory typically onboards task-relevant stimuli (Byyny, 2016). However, if this were the case, one would assume that extreme valence (either positive or negative) would be salient enough stimuli to be attended to and would thus increase cognitive load, but this was not found in our study. However, it is possible that this relationship is not linear; perhaps both valence extremes capture attention more than moderate or neutral levels. Yiend's (2010) review of the attention literature supports this, finding that emotional stimuli directly modulate attention compared to neutral stimuli. A further study by Rieger et al. (2017) found that valenced media exposure had a positive effect on post-task-based exertion recovery. Additional inferential research is required to investigate and verify trends/effects in more detail.

Finally, the remaining insignificant hypothesis result was that reward sensitivity was not associated with perceived information overload. This directly contradicts the idea suggested by Krigolson et al. (2015) that cognitive load impacts the optimal functioning of the reward processing system. Although it is not surprising that this test did not yield significant results, given that this connection is relatively underexplored in the literature and is highly speculative.

4.1.2. Summary for Hypothesis 2

The second hypothesis of this paper was that social media usage patterns (indicated by either social media valence (H2A) or daily average screen time (H2B)) will predict the extent of one's physiological stress recovery, as operationalised by the four-stress metrics of HRV, PEP, CO, and TPR. Unfortunately, due to sample size restrictions and unforeseen methodological circumstances, as well as spurious outlier removal, the majority of the planned regression analyses could not be conducted, except for SM Valence predicting the HRV Recovery index (H2Ai). In cases where sample size only slightly fell short of reasonable parametric requirements, non-parametric alternatives were employed, unfortunately, meaning cause-and-effect relationships were unable to be explored but merely the extent of association (which we thought may still be valuable to explore in light of unfortunate restrictions). As such, the hypotheses surmising that SM Valence would predict the stress indices of PEP (H2Aii), CO (H2Aiii), and TPR (H2Aiv) were instead explored using non-parametric Spearman's rank correlation analyses, and said hypotheses are thereby revised as being associative. Furthermore, hypotheses with severely restricted sample sizes – those involving screen time as the predictor – were decided to be explored only through descriptive observation and therefore lacked any confirmatory basis. The present paper will nonetheless describe these descriptive trends, for transparency and as potential preliminary bases for further study.

Firstly, for Hypothesis 2A, Linear Regression analysis was conducted between SM Valence and HRV stress recovery index, yielding no significant result. This suggests that the valence of SM content exposed to does not cause predictable changes in HRV recovery capacity; therefore, we fail to reject the null hypothesis in this case. Likewise, with the revised Spearman's correlation analyses of H2Aii-iv, no significant results were detected, meaning we also fail to reject these null hypotheses. When observing descriptive trends of Hypothesis 2B, since all failed to meet inferential testing requirements, no inferential evaluations could be drawn. HRV, PEP, and TPR do not appear to have a discernible associative trend with daily mean screen time. However, CO did appear to have a slight negative relationship with daily mean screen time. However, it is important to reiterate that these are only descriptive observations and non-confirmatory of any effects or lack thereof.

Despite its lack of a confirmatory basis, CO appearing to be negatively associated with daily mean screen time may be a worthwhile target for further experimentation. Indeed, if this trend is replicated inferentially in a larger sample, it would be consistent with previous studies on stress recovery, which have found significant effects on heart rate (e.g., Johnshoy et al., 2020; Rus & Tiemensma, 2018), since cardiac output is closely associated with heart rate (Tulumen et al., 2011). As discussed in the introductory chapter, high cardiac output is related to adaptive and healthy challenge stress responses, while low values are associated with maladaptive threat responses. As such, this observed descriptive trend may suggest that having a higher screen time predicts a longer time spent in threat-states following acute social stressors, or (in other words) slower or completely stunted physiological recovery. Though it is difficult to claim this with any certainty, as inverse levels of TPR typically accompany CO levels in challenge/threat states. Nevertheless, observation of trends in our data did not indicate an association between TPR and social media usage metrics, though, again, there is little confirmatory basis for this null effect (except H2Aiv). Regardless, the preliminary observation showing that Blunted CO reactivity appears associated with higher screen time levels possibly aligns with previous research and the results of prior hypotheses. As discussed, Ironside et al. (2018) found that stress directly blunted reward sensitivity through disturbances in the dopamine system, while reward sensitivity differences were thought to underlie general emotional processing deficiencies, including stress (Markarian et al., 2013).

Acknowledging these, while also considering our significant inferential and observed non-confirmatory trend indicating that reward sensitivity appeared associated with both social media usage conceptualisations (significantly with valence and an observed non-confirmatory trend with screen time), a claim could be made that reward sensitivity may feasibly underlie the near-significant predictive relationship of daily average screen time negatively on cardiac output recovery index. However, since reward sensitivity was seemingly associated with screen time and definitely with valence, it does not make sense why valence (with its larger sample size, no less) was also not significant or at least approaching a significant association with CO, like screen time appears to. However, this is all contingent on the tenuous observations of the low sample size screen time, so this should be considered with caution and taken as preliminary conjecture. This further demonstrates the limited inferential power of the present study.

4.1.3. Summary for Hypothesis 3

The next family of hypotheses in this paper was that we hypothesised the predictive relationship between valence and physiological stress recovery would be moderated by either reward sensitivity (H3a) or perceived information overload (H3b). Similarly, we hypothesised that the predictive relationship between daily average screen time and physiological stress recovery would be moderated by reward sensitivity (H3c) or perceived information overload (H3d). In line with our running operationalisation of stress metrics, physiological stress recovery was measured using four different metrics (HRV, PEP, CO, and TPR). The latter two hypotheses lacked sufficient sample size for inferential or even descriptive testing and therefore could not be formally tested in this sample. Likewise, non-HRV stress metrics had a slightly insufficient sample size for parametric testing, and since no available non-parametric test was possible, we decided it was prudent to instead observe these stress metrics and their potential moderations descriptively (H3Aii, H3Aiii, H3Aiv, H3Bii, H3Biii, and H3Biv).

For H3Ai and H3Bi, potential moderations of the predictive relationship between HRV recovery index and valence by both conceptualisations of SM usage (Reward Sensitivity and Overload, respectively) were tested using moderation analysis. Neither usage conceptualisations were found to significantly moderate the predictive relationship, which causes us to fail to reject these null hypotheses. When examining descriptive trends of the other stress metrics in the models of valence, differing levels of reward sensitivity seemed to elicit different associations between CO/TPR and valence, suggesting patterns consistent with moderation in these given metrics. Similarly, when examining descriptive trends of the other stress metrics in the models of valence, differing levels of information overload seemed to elicit different associations between PEP/CO and valence, suggesting patterns consistent with moderation in those cases. At the same time, other stress metrics did not possess any observable differences in trend. However, these cases are non-confirmatory and therefore are not definitive evaluations of any effect or lack thereof. Accordingly, potential cases of moderation should be examined inferentially in future studies to provide a confirmation for these preliminary indications.

As a potential area of note, when examining the potential moderation of the relationship between Valence and PEP recovery index by information overload, it appears as though, at lower levels of information overload, no association is discernible. Meanwhile, high levels of information overload seem to moderate the relationship into an apparent negative association. If confirmed in later inferential testing, this would imply that higher levels of information overload induce a state where stress recovery capacity becomes sensitive to valent content, particularly positive content, leading to worsened stress recovery, while lower levels of PIO did not elicit such an effect. In a similar vein, the predictive relationship of valence on the CO recovery index appears positively associated in low overload conditions, but not in high overload conditions. This suggests a phenomenon where having a low level of information overload facilitates faster CO recovery when exposed to more subjectively appraised positively valent content, while higher levels of PIO appear to cause positive valence content exposure to, again, cause attenuated stress recovery, in this case, CO recovery.

Preliminary non-confirmational evidence may suggest that perceived information overload alters how the perceived valence of social media content relates to two distinct physiological recovery indices. For PEP recovery, which reflects sympathetic influence, medium to high levels of perceived information overload modulate the effect that valence has on it. Specifically, as PIO increases, the negative association between valence and PEP/CO recovery becomes intensified. This implies a potential threshold beyond which PIO begins to have an impact on this association. Accordingly, it suggests that a certain level of cognitive load can eliminate and even reverse the positive effect of content positivity. While being non-confirmational in our analysis, it highlights an interesting potential line of inquiry.

This may align with previous findings. Exposure to positive stimuli has been found to facilitate faster recovery following stress exposure (Brown et al., 2013). Alternatively, exposure to either polarity of valence has been found to improve cognitive exertion recovery compared to no exposure (Rieger et al., 2017). Conjunctively, the study by Reinecke et al. (2014) found that a high level of cognitive depletion altered the valence evaluation of media content. It is fair to suggest that positive valence content acts as a soothing stimulus to those in threat states, perhaps mitigating pessimistic assessment of available resources, as threat states rely heavily on emotional systems to self-soothe rather than engage in proactive problem-solving strategies (Palmwood & McBride, 2019). However, when overload is high, valence perceptions of otherwise positive content are thought to be inverted through guilt cognitions, from perceived procrastination when media use is high (Panek, 2014). This would support the inversion of valence impact on CO recovery impact at differing levels of PIO. This is a highly speculative exploration of non-inferential results. For established reasons, definitive conclusions cannot be drawn until future inferential tests are performed. Indeed, this study suffers from low power, so the possibility of spurious relationships, sample-specific effects, random noise, or unconsidered third-variable effects remains a strong possibility.

In conclusion, inferential tests revealed no significant evidence of SM usage conceptualisations moderating the relationship between HRV stress recovery. Descriptively, we did observe preliminary patterns in our data suggesting PIO may have a moderating effect on two stress indices, which is a novel pattern, but cannot be verified definitively within the capabilities of the present study. As such, we emphasise those preliminary emergent patterns as pertinent avenues for targeting in more powerful and aptly designed studies.

4.1.4. Summary for Hypothesis 4

Finally, the final hypothesis of this paper hypothesised that perceived information overload and reward sensitivity (BAS) together predicted physiological stress recovery better than either predictor individually (H4). This was intended as an exploratory hypothesis to provide a basis for future studies on the maladaptive reward sensitivity and information overload cycle concept presented in the dark pattern literature. Stepwise hierarchical regression analyses were performed. Since HRV was the only metric with a sufficient sample size, this metric was the only stepwise hierarchical regression that could be interpreted inferentially, while the other metrics were explored as descriptive effect size estimations. Following testing, HRV was found not to be significant, preventing the null hypothesis from being rejected in this case. Most of the descriptive effect size estimates for each stress metric were fairly low or seemingly absent, aside from when TPR was the metric chosen. In this case, when perceived information overload was entered as the first step and reward sensitivity as the second, the addition of reward sensitivity did not significantly enhance the model's strength. However, when reward sensitivity was entered as the first step and perceived information overload as the second, the addition of overload significantly increased the predictive strength of the model. This thereby is preliminary evidence to suggest that the level of recovery predicted by reward sensitivity may not yield any more explanatory strength than overload.

In contrast, overload appeared to demonstrate more unique predictive power beyond reward sensitivity. This suggests that overload may be a stronger predictor than reward sensitivity, thereby implying that cognitive overload is the dominant predictor of this stress recovery metric, providing grounds for future investigation. For all other tests/metrics, no significant effects were detected. To reiterate, as in previous cases, we cannot make definite inferences from these results but rather acknowledge patterns in the underpowered study as potential targets for a more powerful examination.

4.2. Overall Interpretation

The two distinct interpretations of our results are either that there are at most minimal effects, if any, between social media and stress processing or, on the other hand, that our study is underpowered and instead has illuminated potential links between social media and stress processing that the present study has not adequately captured using its resources.

Based on a combination of our confirmatory inferential results and descriptive observations, it would appear as though reward sensitivity may represent a core factor that drives social media engagement, while cognitive overload instead may be a key driver behind SM-derived attenuated stress recovery. Furthermore, it may be possible that reward sensitivity and cognitive overload do not function on the same operational level, suggesting our conceptualisation of a hypothetical bidirectional cycle may be flawed. To support this idea, note that reward sensitivity may directly influence one's likelihood of using social media more frequently or for more extended periods, explaining its observed significant correlation with valence and observed potential relationship to screen time (descriptive). Meanwhile, there were preliminary observed patterns that suggest that information overload may moderate the relationship between other factors and stress recovery but was not immediately linked to or predictive of screen time/valence. This may suggest that cognitive overload is more of an upstream cognitive influence on the system (a higher-level factor). At the same time, reward sensitivity may act as a more downstream and immediate influence on social media usage decisions. Foremost, then, a future study should be conducted to amend the issues of the present study, preventing inferential evaluations, upon which these potential changes to our theoretical conceptualisation are partially based. Secondly, a study should be conducted to investigate this conceptualisation specifically. Even the use of a more appropriate design for measuring the feedback loop, such as structural equation modelling (a method of examinations the present project did not have the ample resources to pursue), would be a highly valuable path forward.

Overall, we have observed inferential and exploratory patterns that suggest both reward sensitivity and information overload are related to conceptualisations of social media use, with varying levels of effect. Since some of these patterns are non-confirmatory, further research is imperative to confirm or falsify the preliminary patterns found in our study, in order to provide valid bases for the ideas explored. In the event that these patterns are repeated in more powerful studies, it would have numerous implications for both app design and policymakers. Firstly, it may supply evidence for the existence of ‘dark pattern’ app designs that intentionally take advantage of inherent cognitive vulnerabilities, such as reward sensitivity and cognitive overload. While such findings could not discern whether these are deliberately predatory, they would provide a strong basis for increased regulation of application design regardless. As previously outlined, push notifications and SFVC are both prominent examples of SM design features that may have direct impacts on, or directly take advantage of, the reward system and limited cognitive capacity. For example, variable-ratio reward schedules are found in the designs of endless scrolling SFVC homepages, and to an extent, the scrolling pages of generic social update content. Alternatively, another example, endless scrolling video designs or countless notifications are vectors of information overload. Though the lack of any discernible descriptive association between screen time and overload in our data set (which could potentially be reflective of a true population lack of association), and our proposed explanation that perceived overload may not be driven by the magnitude of stimuli, but the number of stimuli being actively attended to, seems to challenge the latter point. Nonetheless, there are several apps that utilise some of these suggestions currently. For example, Instagram for a time had the ‘nudges’ feature that involved a ‘time for a break?’ prompt to appear during late-night or lengthy scrolling sessions (Bojkov, 2018), which would seek to influence the continued use. However, this does not seem to be dictated by regulatory bodies and therefore could be removed randomly, without warning, and at the discretion of tech companies. Indeed, some online discussions have suggested these features may have been removed. Because of the proprietary nature of app designs, truly knowing the extent and nature of the allocation of these features remains obscured and unverifiable, which demonstrates the need for regulation and feature clarity.

As a whole, the preliminary results of the present study can inform further research to investigate the validity of our speculative interpretation of results (that the state (level of overload) you are in while using SM seems to be more important than the content specifically consumed). This seems to be contrary to the reductive public stance that SM is inherently negative. Instead, being in an optimal mental state when using SM does not seem to have any substantial ramifications. Meanwhile, being already drained could have negative effects, regardless of superficial content positivity/negativity. If later inferential testing is consistent with some of the present studies' inferential results and observed non-confirmatory patterns, it may suggest that for optimal stress recovery outcomes, careful considerations of one's own mental state prior to SM may be crucial. Furthermore, actions to prevent PIO from SM may be advisable. For example, reducing notification settings, establishing scrolling limits, or practicing mindful use. Overall, the negative public consensus towards SM appears to be a misconception, due to its simplicity. Indeed, it would be unwise to comprehensively deem something as inherently negative without considering the underlying contextual factors present when people use it. It could be argued that social media is merely a digitised reflection of modern society (Ohiagu & Okorie, 2014), and seeing SM as negative could instead be telling of the state of culture, fundamentally (or at least the pessimistic or juvenoic (cf. Finkelhor, 2011) outlooks people generally possess). Moreover, as discussed in Orben (2020), continuing to thoughtlessly invest scientific resources in response to new public technological panics is not ultimately valuable and is not an effective way of understanding technology, which ultimately acts as a caution against lending credence to exaggerated public opinions towards SM.

4.3. Study Evaluations

4.3.1 Study Limitations

While this study provided initial insights into whether social media use influences stress recovery capacity and the processes that may underlie this relationship, the conclusions that can be drawn from these insights are limited; they should be approached with caution due to the multiple methodological and statistical limitations. Due to the broader study context within which the present study operated, our possible methodologies were limited, thereby limiting the design's confirmatory power. Limitations will now be outlined.

Firstly, the low-quality sample has reduced the study's statistical power and overall validity. As discussed in the study demographics, 44 participants participated in the wider study design, which was informed by general recruitment limitations and a power analysis that estimated a target sample size for the hypotheses tested for the wider ‘Cottage Study’. Due to the dichotomous social-interaction and social-isolation conditions that participants were divided into for the wider study context, 24 participants from the social-isolation group were ultimately included in our analysis to ensure consistency in the post-stress condition.

Furthermore, outlier removal and errors in data collection further reduced this limited number. Of these 24, eight variable-wise exclusions were made in the stress recovery index metrics (from a total of 96 figures) due to the removal of extreme outliers. These outliers were thought to occur due to poor physiological setup or errors in the recording software and reflected values massively exceeding typical expected values. Furthermore, due to a glitch in Qualtrics’s data storage, one participant had no values for reward sensitivity, perceived information overload, or social media valence scales. Finally, for screen time, as discussed previously, data were obtained from the participants’ phones’ screen time monitoring feature, which was instructed to be enabled one week prior to the study. Several users had forgotten or failed to enable this feature, despite the prompting. Other participants’ mobile phones had Chinese or custom operating systems that did not have this screen time feature, which was not accounted for in the data collection plan. Moreover, three outliers were missing due to data not being uploaded by an experimenter, and one data point was missing due to a data recording error. These meant that screen time had 14 missing cases. Moreover, as a whole, there were only five participants who were valid listwise. This is a detrimentally small number of participants given the number of participants that ran, and this means our study severely lacked the intended power, as evidenced by our post-hoc minimum detectable effect size (MDE) sensitivity analysis for hypothesis 1. Indeed, the detected effect size was actually smaller than the MDE at .80 power, implying we were underpowered compared to the general standard for experimental power and that our results were potentially unreliably replicable. Furthermore, it could be stated that the limited sample left our sample ungeneralisable to the wider population. It fundamentally hindered our ability to conduct inferential analysis on screen time, which directly went against our aim of equally considering both aspects of the multi-channel approach to social media mental health study operationalisation.

The issues faced by our sample size limitations are reflected in our range of valence scores, which suffer from a restricted range problem, as the valence scores of our sample only ranged between 2 and 4.5 (the whole scale was 1-5). BAS scores also exhibited a restricted range problem, with a sample range of 2.08 to 3.54, out of a possible range of 1 to 4. Perceived information overload from SM was less restricted, possessing a range of 1.5 to 3.83 (on a 1-4 scale). Therefore, this places limits on the overall generalisability and validity of the present sample.

Furthermore, the present study predominantly consisted of White and Asian university students, with little to no representation of other ethnic groups, which further limits the generalisability of our study to the wider population. Due to highly personalised social media algorithms, the way in which content is shown to people would certainly differ between different ethnic groups. Furthermore, due to the wide range of experiences, ethnicities are likely to vary in their valence perception, a phenomenon partially established in the literature (e.g., Lorette & Dewaele, 2024). Additionally, ethnicities would likely differ in prior stressor exposure, which would inform their current stress response. As a whole, our sample likely does not reflect a complete range of possible social media experiences or baseline stress characteristics found in the true population.

Additionally, the sizeable proportion of Asian international student participants in the sample may partially underlie the substantial number of missing cases, as Chinese operating systems often lacked screen time functionalities. Since a huge proportion of Chinese mobile phone users use Huawei devices (Du & Rojniruttikul, 2025), which utilise an Android-based (a Google-owned operating system) user interface known as Emotion UI (Nazir et al., 2025) but have their Google-based functionalities limited in China because of restrictions enforced by both the US and China (Moon, 2019). These restrictions prevent the use of Android-native Google applications, such as 'Digital Wellbeing', which is the app that measures screen time. It appears that Huawei's screen time statistics may need to be manually enabled or downloaded, explaining why a large proportion of participants lacked this mobile phone functionality. This presents a possible issue of bias as they feasibly reflect a group with different baseline stress characteristics, which were consequently excluded from analysis (reducing validity). For example, it was found that Android and Apple mobile phone users differed, albeit slightly, in a variety of personality factors (Götz et al., 2017). However, a Little's MCAR test revealed no significant evidence to suggest cases were not completely random, but careful consideration of this should be made, nonetheless. Larger samples with a heightened diversity should be recruited in the following studies to mitigate this issue, with a heightened standard of scrupulosity when ensuring participants possess compatible devices for the given study design.

There were also design limitations present that stemmed from the scope limitations imposed on MRes projects. Using self-reported valence alongside the objective measure of screen time in a design intended to consider both aspects on equal footing (multi-channel approach) may not have been a robust decision. Indeed, memories of emotional stimuli often are biased (e.g., Lacreuse et al., 2013; Loftus & Palmer, 1979), which may suggest that memories of previous social media emotionality could be inaccurately remembered and reported. Utilising a design where an objective design of social media valence was not possible in the current study's resources. Future research should seek to measure objective valence. For example, utilising a screen scanning application, which conducts semantic analyses on all the text content a user is exposed to in a given period. Furthermore, if the study allows it, using eye-tracking could provide insights into the valence of the content actually attended to by users. This would result in more robust and valid data.

Also, on the topic of design, this design is cross-sectional and does not directly manipulate social media use across individuals. The wider study context did not permit direct exposure to SM content, let alone the manipulation of the content that was exposed. As such, we had to use a simple measure. Likewise, we were limited to using general screen time as an indicator of social media use, which is fundamentally unreliable due to the enormous variety of non-social media activities a user could be spending this screen time on. This makes it difficult to generate any valid cause-and-effect inferences about the effect of social media on stress recovery. Manipulating social media within the study period, like in Rus and Tiemensma's (2017; 2018) studies, would be the way forward for future research.

Additionally, while saliva samples for endocrine analysis were collected as a part of the wider Cottage Study, logistical and training constraints prevented the inclusion of these metrics in the present study. Having endocrine data would have provided invaluable insights into an aspect of the stress system not covered by our physiological metrics – distinctions between the SAM and HPA axes.

Moreover, the wider Cottage Study context required participants to be guided through a variety of tasks and activities not relevant to the present study, which could act as uncontrolled extraneous variables, limiting validity. Additionally, as many other projects operated under this wider study context, the lead experimenter varied day-to-day. This may have unintentionally exposed the participant to extraneous social interaction, which varied depending on the disposition of the several different research assistants. This is prudent, as an experimenter with a happy and friendly disposition would likely elicit different stress profiles compared to a cold, neutral experimenter. Indeed, evidence for such experimenter effects was demonstrated by Siegwarth et al. (2012), where participants led by 'warm experimenters' had greater task performance and lower physiological and subjective stress reactions than those led by 'cold experimenters'. This potentially affected our validity through an uncontrolled experimental environment, which is likely compounded over time during our relatively lengthy six-hour total study length.

Following the study, when assessing the reliability between items of our self-report scales, we found that perceived information overload from the social media scales used had limited reliability between its items, with no predominant factor. Conversely, while the reward sensitivity (BAS) scale also had moderate reliability between measures and several detected latent factors, it exhibited stronger reliability in its items due to one of the latent variables seeming to predominate over the weaker ones. Again, correlations between the two valence items were found to be significant but at a weak to moderate level of association. Overall, the measures utilised in this study suffered from limited inter-item reliability throughout. This likely means our study, as a whole, demonstrated limited reliability, diminishing the strength of our conclusions. Going forward, enhanced consideration of measurement instrument reliability should be considered prior to data collection.

4.3.2 Study Strengths

In light of these limitations, it is important not to understate the various strengths and utility the present study may possess. As it stands, the present study employs a unique approach to investigate potential links between social media and stress processing. This current study aimed to examine many variables to create comprehensive conceptualisations of social media, using an experimental design informed by the multi-channel approach framework, to ensure our findings regarding social media are the most valid and applicable to genuine social media platforms and daily use. We believe we have partially achieved this through our considerations of both valence and screen time, or (in other words) quality and magnitude, through careful application of Meier and Reinecke's (2021) multi-channel approach to SM - mental health research. Moreover, we have constructed a proof-of-concept for future research to refine and perfect. Although screen time tests suffered from a low sample size due to many missing cases and could be examined only descriptively for some hypotheses, we believe their inclusion demonstrates a thorough experimental approach and should continue to be included in improved research designs.

Furthermore, this study was the first (or among the first) to investigate specific stress metrics related to SM use (PEP, CO, TPR). Indeed, utilising four different stress metrics was a rigorous and thorough approach to the research question at hand. The utilisation of the BPS-CT's framework for the collection of objective physiological stress metrics facilitated this. Likewise, our calculation of the recovery index was not commonly reported in the literature. However, it allowed us to operationalise stress recovery in a transparent and accessible manner, given its straightforward scale (1 = recovery, >1 = rebound, <1 = not fully recovered, <0 = worsened). It is of great pertinence for one to present research in a digestible manner, as the keystone of science depends on collaboration. This is to prevent unnecessary barriers to entry, which are ultimately detrimental to the research process. Again, our use of reward sensitivity and perceived information overload is an underexplored area in SM-stress literature; therefore, our paper contributes, albeit not to any confirmatory degree, to the currently lacking literature. Notably, we seem to be the first to aim to experimentally explore the 'dark pattern' bidirectional link between reward hijacking and cognitive overload in the social media design context. Our study lacks the necessary power, specific SM-manipulations, and longitudinality to perform precise inferential tests on this and/or make causal judgments of these maladaptive spiral ideas. However, it can, again, be said that this provides a proof-of-concept basis for future studies investigating this topic, using tailor-made designs. As a whole, while the study is currently underpowered, it presents a potential key stepping stone for those with more available resources to operate under similar frameworks using more robust designs, thereby creating more nuanced and tailored research.

Additionally, our study possesses robust data analysis considerations and transparency. Our reliability testing of the scales used and the clearly described revision of hypothesis tests in response to sample insufficiencies enabled us to conduct a fair preliminary exploration of the variables observed without overstating inferential conclusions or making unfounded claims. This demonstrates transparency and further underscores its utility as a pilot study for future research on this vital topic.

Another strength was the time-resistant utility of the present study's approach to operationalisation. Indeed, an example of this strength in action is the previously discussed, even more recent (than SM) moral panic about Artificial Intelligence (AI) (Gilmore et al., 2025). Using previous experimental approaches would require significant time and resources to reexamine the links between this new AI technology and MH or stress reactivity (etc.), like SM before it. Instead, an approach similar to the present study could allow conclusions to be drawn from the qualities and affordances comprising the new technologies. For example, if our findings were inferentially confirmed, evaluations regarding information overload or reward-altering components could be applied to models of artificial intelligence if these features are indeed established to exist within AI. Henceforth, one could assume that the accessibility and low cost of AI content creation tools (as compared to human labour)

(Prakash & Sabharwal, 2024) may facilitate a far faster turnover of content (quantity over quality), which seemingly could contribute to perpetuating “brain rot” (Yousef et al., 2025; Özbay, 2026) and may feasibly elicit PIO due to high exposure to information, which, as discussed at length, may dynamically link to other stress-inducing factors. Overall, this further establishes the present study’s usefulness as a pilot demonstration of an improved experimental approach, despite its inferential limitations.

Overall, the present study, although methodologically and statistically limited, was an ambitious and comprehensive examination of social media and stress at a level of specificity not previously seen in the literature. There were both confirmatory and non-confirmational observed patterns that our uniquely thorough design appeared to demonstrate, which highlight a variety of valuable next steps and methodological developments to achieve better inferential confirmation of these patterns and associated theoretical accounts. Therefore, it has significant utility for the broader literature and research community and serves as a strong preliminary study for future research.

4.4. Future directions

We have comprehensively discussed the limitations and strengths of the present study. This subsection outlines how researchers should consider conducting further investigations on this topic to mitigate the issues faced, while also continuing to demonstrate the strengths of our design approach. This would ensure that a comprehensive approach to investigating SM platforms is employed, while showing sufficient experimental power to make confirmatory inferences. We have explored potential explanations and limitations of our results and briefly touched upon how these possibilities could be tested. This section will provide more detail.

If the observed preliminary patterns in our data were intended to be retested in a more robust study, it is imperative that power analyses be performed prior to recruitment, using previously observed effect sizes as a guide, regardless of their significance. The present study, due to the wider cottage study context, did not have this option or the resources to recruit a larger sample (even if we had been afforded the capability to perform power analyses prior to recruitment), and therefore suffered from a meagre sample size. However, many of the observed effects were not previously demonstrated or found in the literature, so the feasibility of ever doing so prior to our study seems uncertain. Nonetheless, this illustrates the present paper’s utility as a potential pilot study of sorts for further examination.

Furthermore, the present study’s sample characteristics were certainly biased towards university-aged young adults. Further study should ideally be conducted with a larger sample, encompassing a broader range of ages and sufficient representation of all gender identities, to include these variables as control covariates in their analyses because of potential age and gender specific effects. These together would ensure a study design where the implied patterns detected by the present study can be tested in a confirmatory manner.

Our descriptive exploration of the observed patterns of H1A, which suggests that daily average screen time negatively correlated with reward sensitivity, may indicate the presence of a spurious third variable. Indeed, we speculate that sedentary / lower fitness behaviours may act as a third-variable influence on screen time. We admit the possibility that lower reward sensitivity would provide an incentive for low effort activities to be prioritised, such as mobile phone use. As such, this may obscure the true nature of the association between screen time and reward sensitivity. Accordingly, in a future design to explore this, activity level should be measured and controlled for as a covariate in future studies to determine the statistical basis of this idea. In line with this, a study by Erbaş and Gümüş (2020) found that physical activity motivation significantly correlated with scores on a social media addiction scale. The aforementioned study utilised the 'Motivation Scale for Participation in Physical Activity' (MSPPA) by Demir and Cicioğlu (2018). As such, the use of such a scale, or the recently adapted version of the original to English (Amal et al., 2024), could be useful in future experimentation. Indeed, Amal et al.'s updated version is demonstrably robust and thorough. The scale measures several underlying subconstructs, with each being highly reliable (Cronbach's alpha scores all were above .8) and possessing considerable levels of discriminant and convergent validity. Researchers certainly should consider the integration of this scale, or those similar, to parse the potential confounding effect of activity level on reward sensitivity and stress.

To expand on the possibility of third-variable effects, a concept that frequently arose in the literature is sleep quality or sleep deprivation rates. Theoretically, manifesting in increased screen time due to SM addiction (Meyerson et al., 2023; Sümen & Evgin, 2021), or pre-sleep information overload deleteriously impacting sleep quality (Li et al., 2023; Xie & Wang, 2025). It is feasible that variable energy levels associated with sleep disturbances would stifle the already limited cognitive capacity (e.g., Benkirane et al., 2022) or interfere with baseline reward processing (Mullin et al., 2013). In fact, papers arose that provided evidence to suggest that sleep patterns interact with the level of physical activity/likelihood towards sedentary activity and social media usage profiles (Zhou et al., 2023). Essentially, sleep levels could interact with every factor we observed, which is unsurprising given how fundamental sleep is to the human experience. Since the demographics of our sample reflect a demographic of university-aged adults, who commonly present with (Hershner & Chervin, 2014) and are particularly vulnerable to sleep deprivation (Phillip et al., 2004), it could mean our sample may not appropriately capture the wide ranges of sleep on our factors for generalisable interpretations to be made.

Overall, SM-related sleep disturbances should undoubtedly be a consideration in future study design. The choice whether to use subjective sleep quality scales (like those discussed in Fabbri et al. (2021)) or more objective sleep pattern monitoring methods (such as polysomnography or actigraphy (Krystal & Edinger, 2008)) would be up to the discretion afforded by the available resources of the individual researcher. Of course, using objective measures (e.g., the BPS-CT approach to stress measurement) can yield a level of validity beyond self-report, but sleep studies are generally resource-intensive (Rodway & Sanders, 2003), so a careful cost-benefit analysis should be considered if aiming to investigate this going forward.

On the topic of the present study's potentially biased sample, in a prior section, we discussed that the detected pattern of strong correlation between reward sensitivity and SM valence could be driven by the heightened reactivity of adolescents and young adults to valenced social stimuli. However, the valence scale used did not differentiate between social and non-social stimuli, meaning that this explanation should be viewed with substantial scepticism until future testing is performed. Further experimentation could be conducted to capture this nuanced aspect of the content. Indeed, this would further benefit the multichannel operationalisation, as measuring valence alone is highly reductive when examining the communication-centred elements of social media consumption (see Meier & Reinecke's (2021) hierarchical conceptualisations). After all, reducing stimuli to either good or bad is likely not practical, and, as discussed, the act of comparing objectively measured BPS-CT physiological stress indices to subjectively measured content valence rests on precarious logic. Accordingly, utilising a screen scanning application in conjunction with eye tracking apparatuses could help address these methodological gaps, through the conduction of semantic analyses on all attended text during SM use, providing an objective measure of valence, and even possible categorisation of stimuli into social categories. Indeed, machine learning algorithms have progressed to a point where semantic and 'social-ness' image analysis could also be feasible (Chen et al., 2023).

As discussed in the interpretation of the preliminary observed differing relationships between Valence and stress metrics found across high and low levels of PIO (H3Bii-iv), we suggest a potential soothing effect of positive-valence content on stress, facilitating improved recovery, which is sensitive to effect reversal depending on the level of cognitive resource depletion. It was suggested these effects may arise through the active exposure to other SM stimuli or behavioural-emotional responses, such as procrastination, which induces guilt, and therefore prolongs stress response (Palmwood & McBride, 2019; Panek, 2014). This should be explored in further studies. Taking measurements of attitudes towards social media use could help investigate this. However, there is no widely used, standardised self-report instrument to measure SM attitude. Many studies investigating topics related to this created original inventories (e.g., Goel & Singh, 2016) and the few that do measure this are highly specific to a given cohort, such as student attitudes to SM or have not been adapted for multiple languages, such as in Otrar and Argin (2015) or Argin (2013) as cited in Alican and Saban (2013). While the latter inventory did demonstrate high inter-item reliability (Cronbach's alpha > 0.85), a standardised and more generalised metric should be developed and validated before investigations into this can occur and yield true validity for the wider population. Therefore, the development and validation of such an instrument is a crucial next step for future researchers.

Moving on, when considering all the theoretical evidence explored in this paper regarding dark or predatory patterns, investigating specific types of social media platforms could be pertinent to uncovering which aspects are most damaging. As such, dating apps, as a specific sub-domain of social media platforms, should also be examined in the same context and operationalisation as in the present study. Online dating or dating apps are digital environments where individuals foster romantic connections through performative social advertisement. More specifically, Swipe-Based Dating Applications (SBDAs) are SM-adjacent mobile phone applications that possess similar endless swiping/scrolling features like SFVC applications (Holtzhausen et al., 2020; Toma, 2015). If reward sensitivity is in fact affected by the salience of reward stimuli and the variable-reward ratio schedules, then dating apps present an even more addictive environment due to the increased perceived value of potential rewards while possessing the same variable-reward ratio schedule, endless scroll designs to SFVC. They operate under the same frameworks as traditional social media but seem to additionally function to take advantage of inherent psychosocial insecurities (Blake et al., 2022; Huang et al., 2025). Given the direct targeting of emotional needs and vulnerabilities, dating apps may directly affect emotional processing (Holtzhausen et al., 2020), such as stress processing (Potarca & Sauter, 2023), and perhaps even more strongly than generic-SM. Then it would be fair to suggest these may have even more worrying consequences on mental health. As such, this could be an enlightening branch for further exploration and research. If examining screen time, future studies should record daily average screen time measures and perhaps even perceived (or objective, as previously suggested) valence for each application used (potentially including SBDAs).

As a whole, the present study's design integrated both the BPS-CT and the multichannel approaches. This integrated approach has potential for the thorough and valid conclusions to be ascertained, beyond the unintegrated approaches found in previous literature. Furthermore, this section has discussed several ways in which this approach could be approached going forward, for the directive of improving both experimental power and validity, which provides ample rationale for further research into this topic. However, we acknowledge that the feasibility of conducting research with the suggested improvements depends on individual researcher capacity and resources.

4.5. Conclusions

To conclude, the present study aimed to investigate the relationship between stress recovery and different social media usage conceptualisations, based on their joint relationship to two distinct potential factors. These factors were reward sensitivity and perceived information overload and were chosen based on a deep exploration of prior trends found in the literature. This aim was presupposed by the ubiquitous use of social media today and its contentious impact on stress processing, which was identified as a core risk factor for wider mental illness.

The study utilised a social-stress-inducing paradigm, aligned with the BPS-CT framework, to elicit and measure physiological stress recovery. This data was then analysed in relation to subjective self-report variables (valence, perceived information overload, and reward sensitivity) and measures of screen time. Unfortunately, the present study suffered from a restricted sample size and consequential low power, meaning not all hypotheses could be tested inferentially. When exploring both the implications of the few inferential results and the other descriptive emergent patterns through the lens of preliminary bases for future study, we observed some notable patterns. Through inferential testing, it was observed that reward sensitivity was positively correlated with perceived social media valence. Meanwhile, descriptive observations suggested reward sensitivity was negatively correlated with screen time (though lacking confirmatory power). Simultaneously, we detected no significant correlation between valence and perceived information overload following inferential testing or any descriptive trends to suggest screen time was correlated with perceived information overload (though, not concrete proof of a null effect). Likewise, following inferential testing, no significant correlation between information overload and reward sensitivity was detected in our sample. Regression testing revealed that social media valence did not significantly predict HRV recovery index. Non-parametric revised correlation analyses between valence and all non-HRV recovery indices similarly did not detect any significant result. Finally, the revised correlation analyses of daily mean screen time and stress recovery metrics were only observed descriptively with estimated effect sizes, due to their severely limited sample size. There were preliminary patterns that potentially suggest that screen time may be moderately positively associated with HRV recovery index and strongly negatively associated with CO recovery index. However, these results are non-confirmatory, and inferential evaluations cannot be made. This means it remains unclear whether the magnitude of social media exposure did not influence one's capacity to recover from stress. Our inferential testing appears to suggest that valence has no bearing on any stress recovery outcome.

Later inferential moderation analyses with HRV outcomes and descriptive exploration of trends of high/low individual difference variable levels yielded no significant inferential results (regarding PIO or reward sensitivity moderating the relationship between valence and HRV). Instead, descriptive exploration showed patterns that suggest that Information overload may moderate the predictive relationship of social media valence on both the PEP recovery index and the CO recovery index, while reward sensitivity presented patterns suggesting it moderated associations between CO and TPR with valence. While certainly not concrete and confirmatory, these, interestingly, appear to suggest that social media use may influence stress recovery but only as a function of individual difference variables (reward sensitivity / PIO), and in two out of four different stress metrics. However, these must be viewed with great caution, and it must be continually reiterated that these preliminary patterns are presented as guides to future inferential verification only. Finally, descriptive hierarchical regression effect estimations seemed to suggest that cognitive overload may explain additional variance in the TPR stress recovery index over reward sensitivity, hinting at the existence of two different functional levels of these two factors, which should be targeted in a later study for verification.

While not confirmatory patterns, the implications of these results suggest a potential route to improved understanding. This study utilised a uniquely thorough experimental approach to investigate social media and stress recovery. However, through a process of innate methodological limitations and unfortunate circumstances, this approach did not achieve sufficient power to utilise this approach to draw definitive inferential conclusions for every intended hypothesis test. Nonetheless, exploration of emergent statistical patterns suggests existent phenomena that partially provide support for a more sophisticated model of SM-based stress, based on the integration of prior literature and research. Furthermore, some of our preconceived notions were challenged by the detected patterns, suggesting future avenues for further study, and more comprehensive theoretical models at a complexity beyond our current simple account.

In conclusion, the present study shows preliminary evidence for complex relationships between social media usage, stress recovery, information overload, and reward sensitivity; as such, further research is crucial in confirming these patterns, which could have sizable and significant implications on the connection between social media and mental health. Furthermore, the present study challenges the reductive notion that many possess, that social media use is an inherently negative force. Instead, it suggests that the mental state we possess with which we interact with social media may be massively important in determining the nature of its impact, beyond the simple emotionality or magnitude of SM use. It suggests a far more complex picture than the public consensus would lead the uninformed masses to believe. This exact nature remains elusive, but a commitment to continued investigation shall continually add more clarity until a comprehensive understanding is finally reached.

REFERENCES

Afifi, T., Zamanzadeh, N., Harrison, K., & Callejas, A. (2018). WIRED: The impact of media and technology use on stress (cortisol) and inflammation (interleukin IL-6) in fast paced families *. *Computers in Human Behavior*, *81*, 265–273. https://doi.org/10.1016/j.chb.2017.12.010

Alican, C., & Saban, A. (2013). Ortaokul Ve Lise De Öğrenim Gören Öğrencilerin Sosyal Medya Kullanımına İlişkin Tutumları: Ürgüp Örneği. *Erciyes Üniversitesi Sosyal Bilimler Enstitüsü Dergisi*, *1*(35), 1–14.

Almond, A. (2017). Acqknowledge (Software). In *The International Encyclopedia of Communication Research Methods* (pp. 1–2). John Wiley & Sons, Ltd. https://doi.org/10.1002/9781118901731.iecrm0001

Alshanskaia, E. I., Zhozhikashvili, N. A., Polikanova, I. S., & Martynova, O. V. (2024). Heart rate response to cognitive load as a marker of depression and increased anxiety. *Frontiers in Psychiatry*, *15*. https://doi.org/10.3389/fpsyt.2024.1355846

Altikulaç, S., Bos, M. G. N., Foulkes, L., Crone, E. A., & van Hoorn, J. (2019). Age and Gender Effects in Sensitivity to Social Rewards in Adolescents and Young Adults. *Frontiers in Behavioral Neuroscience*, *13*. https://doi.org/10.3389/fnbeh.2019.00171

Amal, C., Bipin, G., & Tekkurşun Demir, G. (2024). Adapting the Motivation Scale for Participation in Physical Activity. *Physical Education Theory and Methodology*, *24*, 396–403. https://doi.org/10.17309/tmfv.2024.3.07

Anderson, A. S. and M. (2018, March 1). Social Media Use in 2018. *Pew Research Center*. https://www.pewresearch.org/internet/2018/03/01/social-media-use-in-2018/

Anderson, K. E. (2020). Getting acquainted with social networks and apps: It is time to talk about TikTok. *Library Hi Tech News*, *37*(4), 7–12. https://doi.org/10.1108/LHTN-01-2020-0001

Aslaksen, P. (2016). *SPSS syntax for Holm-Bonferroni and Bonferroni correction.* https://doi.org/10.13140/RG.2.2.22235.98087

Asmussen, E., & Nielsen, M. (1955). Cardiac Output During Muscular Work and Its Regulation. *Physiological Reviews*, *35*(4), 778–800. https://doi.org/10.1152/physrev.1955.35.4.778

Benkirane, O., Delwiche, B., Mairesse, O., & Peigneux, P. (2022). Impact of Sleep Fragmentation on Cognition and Fatigue. *International Journal of Environmental Research and Public Health*, *19*(23), 15485. https://doi.org/10.3390/ijerph192315485

Birenbaum, J. R. (2025). *The Intersection of Race and Sex in Cardiovascular Health Disparities: Examining Differences in the Relationship Between Heart Rate Variability and Cardiovascular Measures in African American Men and Women* [M.A., University of California, Irvine]. https://www.proquest.com/docview/3195963003/abstract/691C613431794742PQ/1

Blake, K., Portingale, J., Giles, S., Griffiths, S., & Krug, I. (2022). Dating app usage and motivations for dating app usage are associated with increased disordered eating. *Journal of Eating Disorders*, *10*(1), 186. https://doi.org/10.1186/s40337-022-00693-9

Blascovich, J., & Tomaka, J. (1996). The Biopsychosocial Model of Arousal Regulation. In M. P. Zanna (Ed.), *Advances in Experimental Social Psychology* (Vol. 28, pp. 1–51). Academic Press. https://doi.org/10.1016/S0065-2601(08)60235-X

Bojkov, N. (2018, December 25). Top New Instagram Updates and Features in 2021. *EmbedSocial*. https://embedsocial.com/blog/new-instagram-features/

Bong, C. L., Fraser, K., & Oriot, D. (2016). Cognitive Load and Stress in Simulation. In V. J. Grant & A. Cheng (Eds), *Comprehensive Healthcare Simulation: Pediatrics* (pp. 3–17). Springer International Publishing. https://doi.org/10.1007/978-3-319-24187-6_1

Brenner, S. L., & Beauchaine, T. P. (2011). Pre-ejection period reactivity and psychiatric comorbidity prospectively predict substance use initiation among middle-schoolers: A pilot study. *Psychophysiology*, *48*(11), 1588–1596. https://doi.org/10.1111/j.1469-8986.2011.01230.x

Brevers, D., Sescousse, G., Maurage, P., & Billieux, J. (2019). Examining Neural Reactivity to Gambling Cues in the Age of Online Betting. *Current Behavioral Neuroscience Reports*, *6*(3), 59–71. https://doi.org/10.1007/s40473-019-00177-2

Brown, D. K., Barton, J. L., & Gladwell, V. F. (2013). Viewing Nature Scenes Positively Affects Recovery of Autonomic Function Following Acute-Mental Stress. *Environmental Science & Technology*, *47*(11), 5562–5569. https://doi.org/10.1021/es305019p

Byyny, R. L. (2016). Information and cognitive overload: How much is too much? *The Pharos of Alpha Omega Alpha-Honor Medical Society. Alpha Omega Alpha*, *79*(4), 2–7.

Carver, C., & White, T. (1994). Behavioral Inhibition, Behavioral Activation, and Affective Responses to Impending Reward and Punishment: The BIS/BAS Scales. *Journal of Personality and Social Psychology*, *67*, 319–333. https://doi.org/10.1037/0022-3514.67.2.319

Chen, Y., Sherren, K., Smit, M., & Lee, K. Y. (2023). Using social media images as data in social science research. *New Media & Society*, *25*(4), 849–871. https://doi.org/10.1177/14614448211038761

Chu, B., Marwaha, K., Sanvictores, T., Awosika, A. O., & Ayers, D. (2024). Physiology, Stress Reaction. In *StatPearls*. StatPearls Publishing. http://www.ncbi.nlm.nih.gov/books/NBK541120/

Chung, D., Chen, Y., & Meng, Y. (2023). Perceived Information Overload and Intention to Discontinue Use of Short-Form Video: The Mediating Roles of Cognitive and Psychological Factors. *Behavioral Sciences*, *13*(1), 50. https://doi.org/10.3390/bs13010050

Cingel, D. P., Carter, M. C., & Krause, H.-V. (2022). Social media and self-esteem. *Current Opinion in Psychology*, *45*, 101304. https://doi.org/10.1016/j.copsyc.2022.101304

Cirulli, F., Francia, N., Berry, A., Aloe, L., Alleva, E., & Suomi, S. J. (2009). Early life stress as a risk factor for mental health: Role of neurotrophins from rodents to non-human primates. *Neuroscience & Biobehavioral Reviews*, *33*(4), 573–585. https://doi.org/10.1016/j.neubiorev.2008.09.001

Common Sense Media. (2016). *Technology Addiction: Concern, Controversy, and Finding Balance*. https://www.commonsensemedia.org/sites/default/files/research/report/csm_2016_technology_addiction_research_brief_0.pdf

Comparing Climate Change Content and Comments across Instagram Reels, TikTok, and YouTube Shorts and Long Videos—Duan—2024—Proceedings of the Association for Information Science and Technology—Wiley Online Library. (n.d.). Retrieved 25 September 2025, from https://asistdl.onlinelibrary.wiley.com/doi/abs/10.1002/pra2.1012?casa_token=3M3Nj-Ydp-EAAAAA%3AQP6YGXYnPZAJkq6xo0mmIgSAck2k_F595N3H9kTT8QcCLchnISiXwJrfpsdK0tgcmRqPxYTCFdyS0oEfCg

Conway, C. C., Li, Y. I., & Starr, L. R. (2019). Trait anhedonia is a transdiagnostic correlate of internalizing problems during adolescence. *Journal of Research in Personality*, *81*, 56–63. https://doi.org/10.1016/j.jrp.2019.05.004

Conway, D., Dick, I., Li, Z., Wang, Y., & Chen, F. (2013). The Effect of Stress on Cognitive Load Measurement. In P. Kotzé, G. Marsden, G. Lindgaard, J. Wesson, & M. Winckler (Eds), *Human-Computer Interaction – INTERACT 2013* (pp. 659–666). Springer. https://doi.org/10.1007/978-3-642-40498-6_58

Critchley, H. D., & Harrison, N. A. (2013). Visceral Influences on Brain and Behavior. *Neuron*, *77*(4), 624–638. https://doi.org/10.1016/j.neuron.2013.02.008

Cunningham, S., Hudson, C. C., & Harkness, K. (2021). Social Media and Depression Symptoms: A Meta-Analysis. *Research on Child and Adolescent Psychopathology*, *49*(2), 241–253. https://doi.org/10.1007/s10802-020-00715-7

Davison, A., & Hinkley, D. (1997). Bootstrap Methods and Their Application. *Journal of the American Statistical Association*, *94*. https://doi.org/10.2307/1271471

Day, T. A. (2005). Defining stress as a prelude to mapping its neurocircuitry: No help from allostasis. *Progress in Neuro-Psychopharmacology and Biological Psychiatry*, *29*(8), 1195–1200. https://doi.org/10.1016/j.pnpbp.2005.08.005

De Calheiros Velozo, J., Vaessen, T., Lafit, G., Claes, S., & Myin-Germeys, I. (2023). Is daily-life stress reactivity a measure of stress recovery? An investigation of laboratory and daily-life stress. *Stress and Health*, *39*(3), 638–650. https://doi.org/10.1002/smi.3213

Dean, D., & Webb, C. (2011). Recovering from information overload. *Mckinsey Quarterly*, *1*(1), 80–88.

Demir, G. T., & Cicioğlu, H. İ. (2018). *Motivation Scale For Participation In Physical Activity (MSPPA): A study of*. https://journals.indexcopernicus.com/search/article?articleId=2231421

Deng, X., Gao, Q., Hu, L., Zhang, L., Li, Y., & Bu, X. (2021). Differences in Reward

Sensitivity between High and Low Problematic Smartphone Use Adolescents: An ERP Study. *International Journal of Environmental Research and Public Health*, *18*(18), 9603. https://doi.org/10.3390/ijerph18189603

DEVRİM, N. (2023). You Have 1 Notification: User Experiences on Notifications on Smartphones. ISCT-PhD PROCEEDINGS BOOK, 14, 63.

Digital 2024: Global Overview Report. (2024, January 31). DataReportal – Global Digital Insights. https://datareportal.com/reports/digital-2024-global-overview-report

Ditto, B., & France, C. (1990). Carotid baroreflex sensitivity at rest and during psychological stress in offspring of hypertensives and non-twin sibling pairs. *Biopsychosocial Science and Medicine*, *52*(6), 610.

Du, M., & Rojniruttikul, N. (2025). *Business Case Study: Antecedents of User Satisfaction with Huawei Mobile Phones*.

Dutcher, J. M. (2022). Brain Reward Circuits Promote Stress Resilience and Health: Implications for Reward-Based Interventions. *Current Directions in Psychological Science*, *32*(1), 65–72. https://doi.org/10.1177/09637214221121770

Duschek, S., Werner, N. S., & Reyes del Paso, G. A. (2013). The behavioral impact of baroreflex function: A review. *Psychophysiology*, *50*(12), 1183–1193. https://doi.org/10.1111/psyp.12136

Efraim, M., Kirwan, C. B., Muncy, N. M., Tucker, L. A., Kwon, S., & Bailey, B. W. (2021). Acute after-school screen time in children decreases impulse control and activation toward high-calorie food stimuli in brain regions related to reward and attention. *Brain Imaging and Behavior*, *15*(1), 177–189. https://doi.org/10.1007/s11682-019-00244-y

Eiroa-Orosa, F. J. (2020). Understanding Psychosocial Wellbeing in the Context of Complex and Multidimensional Problems. *International Journal of Environmental Research and Public Health*, *17*(16), 5937. https://doi.org/10.3390/ijerph17165937

Eisenbarth, H., Godinez, D., du Pont, A., Corley, R. P., Stallings, M. C., & Rhee, S. H. (2019). The influence of stressful life events, psychopathy, and their interaction on internalizing and externalizing psychopathology. *Psychiatry Research*, *272*, 438–446. https://doi.org/10.1016/j.psychres.2018.12.145

Erbaş, Ü., & Gümüş, H. (2020). Participation in Physical Activity and Social Media Addiction in Students. *International Journal of Psychology and Educational Studies*, *7*(4), 52–60.

Ernst, G. (2017). Heart-Rate Variability—More than Heart Beats? *Frontiers in Public Health*, *5*. https://doi.org/10.3389/fpubh.2017.00240

Evans, O., Hardacre, S., Rubin, M., & Tran, M. (2023). Content appraisal and age moderate the relationship between passive social media use and mental ill-being. *Frontiers in Psychology*, *14*, 1181233. https://doi.org/10.3389/fpsyg.2023.1181233

Fabbri, M., Beracci, A., Martoni, M., Meneo, D., Tonetti, L., & Natale, V. (2021). Measuring Subjective Sleep Quality: A Review. *International Journal of Environmental Research and Public Health*, *18*(3), 1082. https://doi.org/10.3390/ijerph18031082

Fan, L., Zhang, Z., & Li, X. (2025). The influence of after-school tutoring on the mental health of middle school students: A mediating effect test based on sleep deprivation and academic performance. *PLOS ONE*, *20*(4), e0321048. https://doi.org/10.1371/journal.pone.0321048

Fassi, L., Ferguson, A. M., Przybylski, A. K., Ford, T. J., & Orben, A. (2025). Social media use in adolescents with and without mental health conditions. Nature Human Behaviour, 9(6), 1283–1299. https://doi.org/10.1038/s41562-025-02134-4

Field, A. P. (2018). *Field, A.P. (2018) Discovering Statistics Using IBM SPSS Statistics. 5th Edition, Sage, Newbury Park. - References—Scientific Research Publishing*. https://www.scirp.org/reference/referencespapers?referenceid=3504991

Finkelhor, D. (2011). The Internet, Youth Safety and the Problem of "Juvenoia".

Foulkes, L., & Blakemore, S.-J. (2016). Is there heightened sensitivity to social reward in adolescence? *Current Opinion in Neurobiology*, *40*, 81–85. https://doi.org/10.1016/j.conb.2016.06.016

Frontiers | The Mixed Effect of Role Overload on Extra-Role Performance: The Mediation Role of Behavioral Inhibition System/Behavioral Activation System Responses. (n.d.). Retrieved 25 September 2025, from https://www.frontiersin.org/journals/psychology/articles/10.3389/fpsyg.2021.748732/full

Full article: Perceived Overload on Short Video Platforms and Its Influence on Mental

Health Among the Elderly: A Moderated Mediation Model. (n.d.). Retrieved 25 September 2025, from https://www.tandfonline.com/doi/full/10.2147/PRBM.S459426

Gámez-Guadix, M., Borrajo, E., & Almendros, C. (2016). *Risky online behaviors among adolescents: Longitudinal relations among problematic Internet use, cyberbullying perpetration, and meeting strangers online*. https://doi.org/10.1556/2006.5.2016.013

Gilbride, T. J., Inman, J. J., & Stilley, K. M. (2015). *The Role of Within-Trip Dynamics in Unplanned versus Planned Purchase Behavior—Timothy J. Gilbride, J. Jeffrey Inman, Karen Melville Stilley, 2015*. https://journals.sagepub.com/doi/10.1509/jm.13.0286?icid=int.sj-full-text.citingarticles.456

Gilmore, J. N., Whims, T., Blair, B. W., Katarzynski, B., & Steffen, L. (2025). Technology acceptance, moral panic, and perceived ease of use: Negotiating ChatGPT at research one universities. *Convergence*, *31*(4), 1251–1266. https://doi.org/10.1177/13548565251337576

Global internet users age distribution 2024. (2024). Statista. https://www.statista.com/statistics/272365/age-distribution-of-internet-users-worldwide/

Goel, D., & Singh, M. (2016). *IMPACT OF STUDENTS ATTITUDES TOWARDS SOCIAL MEDIA USE IN EDUCATION ON THEIR ACADEMIC PERFORMANCE*. *10*(2).

Gomes, T., Correia, A., de Souza, J., & Schneider. (2025). *Unveiling the Expanding Landscape of Attention-Capture Damaging Patterns*.

Gordan, R., Gwathmey, J. K., & Xie, L.-H. (2015). Autonomic and endocrine control of cardiovascular function. *World Journal of Cardiology*, *7*(4), 204–214. https://doi.org/10.4330/wjc.v7.i4.204

Götz, F. M., Stieger, S., & Reips, U.-D. (2017). Users of the main smartphone operating systems (iOS, Android) differ only little in personality. *PLOS ONE*, *12*(5), e0176921. https://doi.org/10.1371/journal.pone.0176921

Gray, J. A. (1981). A Critique of Eysenck's Theory of Personality. In H. J. Eysenck (Ed.), *A Model for Personality* (pp. 246–276). Springer. https://doi.org/10.1007/978-3-642-67783-0_8

Greenspoon, P. J., & Saklofske, D. H. (2001). Toward an Integration of Subjective WellBeing and Psychopathology. *Social Indicators Research*, *54*(1), 81–108. https://doi.org/10.1023/A:1007219227883

Haker, E., Egekvist, H., & Bjerring, P. (2000). Effect of sensory stimulation (acupuncture) on sympathetic and parasympathetic activities in healthy subjects. *Journal of the Autonomic Nervous System*, *79*(1), 52–59. https://doi.org/10.1016/s0165-1838(99)00090-9

Hancock, K., Chen, F., & Daigle, L. (2025). Pre-ejection period (PEP) in reward task and recurring victimization: A pilot study. *Journal of Experimental Criminology*. https://doi.org/10.1007/s11292-025-09665-w

Harris, W. S., Schoenfeld, C. D., & Weissler, A. M. (1967). Effects of Adrenergic Receptor Activation and Blockade on the Systolic Preejection Period, Heart Rate, and Arterial Pressure in Man. *The Journal of Clinical Investigation*, *46*(11), 1704–1714. https://doi.org/10.1172/JCI105661

Hassamal, S. (2023). Chronic stress, neuroinflammation, and depression: An overview of pathophysiological mechanisms and emerging anti-inflammatories. *Frontiers in Psychiatry*, *14*. https://doi.org/10.3389/fpsyt.2023.1130989

Hatem, G., Zeidan, J., Goossens, M., & Moreira, C. (2022). NORMALITY TESTING METHODS AND THE IMPORTANCE OF SKEWNESS AND KURTOSIS IN STATISTICAL ANALYSIS. *BAU Journal - Science and Technology*, *3*(2). https://doi.org/10.54729/KTPE9512

Hayes, A. F. (2013). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach* (pp. xvii, 507). The Guilford Press.

Heponiemi, T., Keltikangas-Järvinen, L., Kettunen, J., Puttonen, S., & Ravaja, N. (2004). BIS-BAS sensitivity and cardiac autonomic stress profiles. *Psychophysiology*, *41*(1), 37–45. https://doi.org/10.1111/1469-8986.00118

Hershner, S. D., & Chervin, R. D. (2014). Causes and consequences of sleepiness among college students. *Nature and Science of Sleep*, *6*, 73–84. https://doi.org/10.2147/NSS.S62907

Holtzhausen, N., Fitzgerald, K., Thakur, I., Ashley, J., Rolfe, M., & Pit, S. W. (2020). Swipebased dating applications use and its association with mental health outcomes: A crosssectional study. *BMC Psychology*, *8*(1), 22. https://doi.org/10.1186/s40359-020-0373-1

Hu, W., & Yang, J. (2021). Reward anticipation buffers neuroendocrine and cardiovascular responses to acute psychosocial stress in healthy young adults. *Stress*, *24*(6), 805–813. https://doi.org/10.1080/10253890.2021.1923690

Huang, C. (2017). Time Spent on Social Network Sites and Psychological Well-Being: A Meta-Analysis. *Cyberpsychology, Behavior and Social Networking*, *20*(6), 346–354. https://doi.org/10.1089/cyber.2016.0758

Huang, Y.-T., & Gong, A.-D. (2025). Too vulnerable to resist: Problematic use of dating apps associated with social appearance anxiety, social interaction anxiety, and rejection sensitivity. *Computers in Human Behavior*, *165*, 108566. https://doi.org/10.1016/j.chb.2025.108566

Impacts of reward schedules and a dopamine agonist on dopamine receptor expression in an animal model of gambling addiction. (n.d.). Retrieved 25 September 2025, from https://opus.uleth.ca/items/a6ff7385-9774-4475-bdbf-8d64d258d230

Ironside, M., Kumar, P., Kang, M.-S., & Pizzagalli, D. A. (2018). Brain mechanisms mediating effects of stress on reward sensitivity. *Current Opinion in Behavioral Sciences*, *22*, 106–113. https://doi.org/10.1016/j.cobeha.2018.01.016

Johnshoy, Q., Moroze, E., Kaser, I., Tanabe, A., Adkisson, C., Hutzley, S., Cole, C., Garces, S., Stewart, K., & Campisi, J. (2020). Social media use following exposure to an acute stressor facilitates recovery from the stress response. *Physiology & Behavior*, *223*, 113012. https://doi.org/10.1016/j.physbeh.2020.113012

Johnston, P. R., Volkov, A. E., Ryan, W. S., & Lee, S. W. S. (2023). Planning, conducting, and analyzing a psychophysiological experiment on challenge and threat: A comprehensive tutorial. *Behavior Research Methods*, *55*(3), 1193–1225. https://doi.org/10.3758/s13428-022-01817-4

Joseph, N. T., Santos, T. de los, & Amaro, L. (2022). Naturalistic social cognitive and emotional reactions to technology-mediated social exposures and cortisol in daily life. *Biological Psychology*, *173*, 1–6. https://doi.org/10.1016/j.biopsycho.2022.108402

K, S. T., & B, M. (2022). Influence of App Notifications and Push Messages of Most Popular Food Delivering Applications Among the Users in Mysuru. *ECS Transactions*, *107*(1), 10563. https://doi.org/10.1149/10701.10563ecst

Kaye, L. K., Orben, A., Ellis, D. A., Hunter, S. C., Houghton, S., Kaye L. K., Orben, A., Ellis, D. A., Hunter, S. C., & Houghton, S. (2020). The Conceptual and Methodological Mayhem of "Screen Time". *International Journal of Environmental Research and Public Health*, *17*(10). https://doi.org/10.3390/ijerph17103661

Kandel, E. R., Koester, J., Mack, S., & Siegelbaum, S. (2021). *Principles of neural science* (Sixth edition.). McGraw Hill.

Kaplan, A. M., & Haenlein, M. (2010). Users of the world, unite! The challenges and opportunities of Social Media. *Business Horizons*, *53*(1), 59–68. https://doi.org/10.1016/j.bushor.2009.09.003

Keyes, C. L. M. (2006). Subjective Well-Being in Mental Health and Human Development Research Worldwide: An Introduction. *Social Indicators Research*, *77*(1), 1–10. https://doi.org/10.1007/s11205-005-5550-3

Khetawat, D., & Steele, R. G. (2023). Examining the Association Between Digital Stress Components and Psychological Wellbeing: A Meta-Analysis. *Clinical Child and Family Psychology Review*, *26*(4), 957–974. https://doi.org/10.1007/s10567-023-00440-9

Kietzmann, J. H., Hermkens, K., McCarthy, I. P., & Silvestre, B. S. (2011). Social media? Get serious! Understanding the functional building blocks of social media. *Business Horizons*, *54*(3), 241–251. https://doi.org/10.1016/j.bushor.2011.01.005

Kiive, E., Katus, U., Eensoo, D., Villa, I., Mäestu, J., Veidebaum, T., & Harro, J. (2025). Parsing reward sensitivity reveals distinct relationships with energy intake, metabolic markers, physical activity and fitness. *Acta Neuropsychiatrica*, *37*, e8. https://doi.org/10.1017/neu.2024.63

Kim, H.-G., Cheon, E.-J., Bai, D.-S., Lee, Y. H., & Koo, B.-H. (2018). Stress and Heart Rate Variability: A Meta-Analysis and Review of the Literature. *Psychiatry Investigation*, *15*(3), 235–245. https://doi.org/10.30773/pi.2017.08.17

Kim, S. Y., Park, H., Kim, H., Kim, J., & Seo, K. (2022). Technostress causes cognitive overload in high-stress people: Eye tracking analysis in a virtual kiosk test. *Information Processing & Management*, *59*(6), 103093. https://doi.org/10.1016/j.ipm.2022.103093

King, J., & Lowery, D. R. (2023). Physiology, Cardiac Output. In *StatPearls*. StatPearls Publishing. http://www.ncbi.nlm.nih.gov/books/NBK470455/

Kirschbaum, C., Pirke, K.-M., & Hellhammer, D. H. (1993). The ‘Trier Social Stress Test’: A tool for investigating psychobiological stress responses in a laboratory setting. *Neuropsychobiology*, *28*(1–2), 76–81. https://doi.org/10.1159/000119004

Kline, K. A., Saab, P. G., Llabre, M. M., Spitzer, S. B., Evans, J. D., McDonald, P. A. G., & Schneiderman, N. (2003). Hemodynamic response patterns: Responder type differences in reactivity and recovery. *Psychophysiology*, *39*(6), 739–746. https://doi.org/10.1111/1469-8986.3960739

Klug, D., Evans, M., & Kaufman, G. (2023). How TikTok served as a platform for young people to share and cope with lived COVID-19 experiences. *MedieKultur: Journal of Media and Communication Research*, *38*, 152–170. https://doi.org/10.7146/mk.v38i73.128463

Kobayashi, S., Pinto de Carvalho, O., & Schultz, W. (2010). Adaptation of Reward Sensitivity in Orbitofrontal Neurons. *The Journal of Neuroscience*, *30*(2), 534–544. https://doi.org/10.1523/JNEUROSCI.4009-09.2010

Kouvonen, A., Kivimäki, M., Elovainio, M., Pentti, J., Linna, A., Virtanen, M., & Vahtera, J. (2006). Effort/reward imbalance and sedentary lifestyle: An observational study in a large occupational cohort. *Occupational and Environmental Medicine*, *63*(6), 422–427. https://doi.org/10.1136/oem.2005.020974

Krigolson, O. E., Hassall, C. D., Satel, J., & Klein, R. M. (2015). The impact of cognitive load on reward evaluation. *Brain Research*, *1627*, 225–232. https://doi.org/10.1016/j.brainres.2015.09.028

Krystal, A. D., & Edinger, J. D. (2008). Measuring sleep quality. *Sleep Medicine*, *9*, S10–S17. https://doi.org/10.1016/S1389-9457(08)70011-X

Kunkel, T., Hayduk, T., & Lock, D. (2023). Push it real good: The effects of push notifications promoting motivational affordances on consumer behavior in a gamified mobile app. *European Journal of Marketing*, *57*(9), 2592–2618. https://doi.org/10.1108/EJM-06-2021-0388

Lacreuse, A., Schatz, K., Strazzullo, S., King, H. M., & Ready, R. (2013). Attentional biases and memory for emotional stimuli in men and male rhesus monkeys. *Animal Cognition*, *16*(6), 861–871. https://doi.org/10.1007/s10071-013-0618-y

Laskowski, C. S., Dorchak, D. L., Ward, K. M., Christensen, D. R., & Euston, D. R. (2019).

Can Slot-Machine Reward Schedules Induce Gambling Addiction in Rats? *Journal of Gambling Studies*, *35*(3), 887–914. https://doi.org/10.1007/s10899-019-09852-1

Legaspi, C. (2020). *The Effect of High and Low Usage of Social Media on Pain Perception and Heart Rate Variability* [D.P.T., Azusa Pacific University]. https://www.proquest.com/docview/2478603825/abstract/6B96B985F45F45EBPQ/1

Levey, K. (2025). The Role of Platform Design in Excessive Short Form Video Use and the Resulting Impacts on Cognitive Processes. *Senior Theses*, 1–49.

Li, J., Gao, T., & Ye, Y. (2023). How college students' social media information overload affects sleep quality: The mediating effect of social fatigue and irrational procrastination. *Journal of Psychology in Africa*, *33*(5), 440–447. https://doi.org/10.1080/14330237.2023.2245222

Linden, W., Earle, T. L., Gerin, W., & Christenfeld, N. (1997). Physiological stress *reactivity* and *recovery*: Conceptual siblings separated at birth? *Journal of Psychosomatic Research*, *42*(2), 117–135. https://doi.org/10.1016/S0022-3999(96)00240-1

Liu, Y., Ni, X., & Niu, G. (2021). Perceived Stress and Short-Form Video Application Addiction: A Moderated Mediation Model. *Frontiers in Psychology*, *12*. https://doi.org/10.3389/fpsyg.2021.747656

Loftus, E. F., & Palmer, J. C. (1974). Reconstruction of automobile destruction: An example of the interaction between language and memory. *Journal of Verbal Learning and Verbal Behavior*, *13*(5), 585–589. https://doi.org/10.1016/S0022-5371(74)80011-3

Lora, S. K., Purba, S. A., Hossain, B., Oriana, T., Seum, A., & Sharmin, S. (2025). *Infinite Scrolling, Finite Satisfaction: Exploring User Behavior and Satisfaction on Social Media in Bangladesh* (No. arXiv:2408.09601). arXiv. https://doi.org/10.48550/arXiv.2408.09601

Lorette, P., & Dewaele, J.-M. (2024). Valence and arousal perception among first language users, foreign language users, and naïve listeners of Mandarin across various communication modalities. *Bilingualism: Language and Cognition*, *27*(5), 874–885. https://doi.org/10.1017/S1366728923000925

Maier, S. U., & Hare, T. A. (2017). Higher Heart-Rate Variability Is Associated with Ventromedial Prefrontal Cortex Activity and Increased Resistance to Temptation in Dietary Self-Control Challenges. *The Journal of Neuroscience: The Official Journal of the Society for Neuroscience*, *37*(2), 446–455.

https://doi.org/10.1523/JNEUROSCI.2815-16.2016

Margousian, M. (2020). *The Effects of High Versus Low Social Media Usage on Depression and Heart Rate Variability in Young Adults* [D.P.T., Azusa Pacific University]. https://www.proquest.com/docview/2479424193/abstract/482F39C30B334812PQ/1

Markarian, S. A., Pickett, S. M., Deveson, D. F., & Kanona, B. B. (2013). A model of BIS/BAS sensitivity, emotion regulation difficulties, and depression, anxiety, and stress symptoms in relation to sleep quality. *Psychiatry Research*, *210*(1), 281–286. https://doi.org/10.1016/j.psychres.2013.06.004

Maza, M. T., Fox, K. A., Kwon, S.-J., Flannery, J. E., Lindquist, K. A., Prinstein, M. J., & Telzer, E. H. (2023). Association of Habitual Checking Behaviors on Social Media With Longitudinal Functional Brain Development. *JAMA Pediatrics*, *177*(2), 160–167. https://doi.org/10.1001/jamapediatrics.2022.4924

McCraty, R., & Shaffer, F. (2015). *Heart Rate Variability: New Perspectives on Physiological Mechanisms, Assessment of Self-regulatory Capacity, and Health Risk*. https://doi.org/10.7453/gahmj.2014.073

McEwen, B. S. (2003). Mood disorders and allostatic load. *Biological Psychiatry*, *54*(3), 200–207. https://doi.org/10.1016/S0006-3223(03)00177-X

Medrano, V. (2022). The Effects of Social Media on Anxiety, Reward Sensitivity, and Risk-Taking on Emerging Adults. *Master's Theses*. https://doi.org/10.58809/HLSU6505

Meier, A., & Reinecke, L. (2021). Computer-mediated communication, social media, and mental health: A conceptual and empirical meta-review. *Communication Research*, *48*(8), 1182–1209. https://doi.org/10.1177/0093650220958224

Metzler, H., & Garcia, D. (2024). Social Drivers and Algorithmic Mechanisms on Digital Media. *Perspectives on Psychological Science: A Journal of the Association for Psychological Science*, *19*(5), 735–748. https://doi.org/10.1177/17456916231185057

Meyerson, W. U., Fineberg, S. K., Andrade, F. C., Corlett, P., Gerstein, M. B., & Hoyle, R. H. (2023). The association between evening social media use and delayed sleep may be causal: Suggestive evidence from 120 million Reddit timestamps. *Sleep Medicine*, *107*, 212–218. https://doi.org/10.1016/j.sleep.2023.04.021

Milyavskaya, M., Inzlicht, M., Johnson, T., & Larson, M. J. (2019). Reward sensitivity following boredom and cognitive effort: A high-powered neurophysiological investigation. *Neuropsychologia*, *123*, 159–168. https://doi.org/10.1016/j.neuropsychologia.2018.03.033

Misra, S., & Stokols, D. (2012). Psychological and health outcomes of perceived information overload. *Environment and Behavior*, *44*(6), 737–759. https://doi.org/10.1177/0013916511404408

Mobbs, D., Hagan, C. C., Dalgleish, T., Silston, B., & Prévost, C. (2015). The ecology of human fear: Survival optimization and the nervous system. *Frontiers in Neuroscience*, *9*. https://doi.org/10.3389/fnins.2015.00055

Molteni, L. (2022). *Impact of nudges on digital well-being for the smartphone* [Laurea, Politecnico di Torino]. https://webthesis.biblio.polito.it/25550/

Moon, A. (2019, May 20). Exclusive: Google suspends some business with Huawei after Trump blacklist - source. *Reuters*. https://www.reuters.com/article/world/exclusivegoogle-suspends-some-business-with-huawei-after-trump-blacklist-souidUSKCN1SP0N7/

Moretta, T., & Buodo, G. (2018). Autonomic stress reactivity and craving in individuals with problematic Internet use. *PloS One*, *13*(1), e0190951. https://doi.org/10.1371/journal.pone.0190951

Mowbray, F. I., Fox-Wasylyshyn, S. M., & El-Masri, M. M. (2018). Univariate Outliers: A Conceptual Overview for the Nurse Researcher. *Canadian Journal of Nursing Research*, *51*(1), 31–37. https://doi.org/10.1177/0844562118786647

Mullin, B. C., Phillips, M. L., Siegle, G. J., Buysse, D. J., Forbes, E. E., & Franzen, P. L. (2013). Sleep deprivation amplifies striatal activation to monetary reward. *Psychological Medicine*, *43*(10), 2215–2225. https://doi.org/10.1017/S0033291712002875 Mystakidis, S. (2022). Metaverse. *Encyclopedia*, *2*(1), 486–497. https://doi.org/10.3390/encyclopedia2010031

Narvaez Linares, N. F., Charron, V., Ouimet, A. J., Labelle, P. R., & Plamondon, H. (2020). A systematic review of the Trier Social Stress Test methodology: Issues in promoting study comparison and replicable research. *Neurobiology of Stress*, *13*, 100235.

https://doi.org/10.1016/j.ynstr.2020.100235

Nasti, L., Michienzi, A., & Guidi, B. (2021). *Discovering the Impact of Notifications on Social Network Addiction* (pp. 72–86). https://doi.org/10.1007/978-3-030-70650-0_5

Nazir, A., Iqbal, Z., & Muhammad, Z. (2025). ZTA: A novel zero trust framework for detection and prevention of malicious android applications. *Wireless Networks*, *31*(4), 3187–3203. https://doi.org/10.1007/s11276-025-03935-1

Ohiagu, O., & Okorie, V. (2014). SOCIAL MEDIA: SHAPING AND TRANSMITTING POPULAR CULTURE. *Covenant Journal of Communication*, *2*.

Okeke, C., Thomas, A., & Botha, A. (2023). The impact of learners' disruptive behaviour on teachers' well-being: A qualitative approach. *International Journal of Research in Business and Social Science (2147- 4478)*, *12*, 504–511. https://doi.org/10.20525/ijrbs.v12i8.2917

Oppenheimer, S., Bond, L., & Smith, C. (2024). Social media does not elicit a physiological stress response as measured by heart rate and salivary cortisol over 20-minute sessions of cell phone use. *PloS One*, *19*(4), e0298553. https://doi.org/10.1371/journal.pone.0298553

Orben, A. (2020). The Sisyphean Cycle of Technology Panics. *Perspectives on Psychological Science*, *15*(5), 1143–1157. https://doi.org/10.1177/1745691620919372

Orben, A., Dienlin, T., & Przybylski, A. K. (2019). Social media's enduring effect on adolescent life satisfaction. *Proceedings of the National Academy of Sciences*, *116*(21), 10226–10228. https://doi.org/10.1073/pnas.1902058116

Orben, A., Meier, A., Dalgleish, T., & Blakemore, S.-J. (2024). Mechanisms linking social media use to adolescent mental health vulnerability. Nature Reviews Psychology, 3(6), 407–423. https://doi.org/10.1038/s44159-024-00307-y

Orcan, F. (2020). Parametric or Non-parametric: Skewness to Test Normality for Mean Comparison. *International Journal of Assessment Tools in Education*, *7*(2), 255–265. https://doi.org/10.21449/ijate.656077

Oshri, A., Liu, S., Duprey, E. B., & MacKillop, J. (2018). Child Maltreatment, Delayed Reward Discounting, and Alcohol and Other Drug Use Problems: The Moderating Role of Heart Rate Variability. *Alcoholism, Clinical and Experimental Research*, *42*(10), 2033–2046. https://doi.org/10.1111/acer.13858

Otrar, M., & Argin, F. (2015). *Students' Social Media Attitude Scale | TOAD*. https://toad.halileksi.net/olcek/ogrencilerin-sosyal-medya-tutum-olcegi/

Özbay, Ö. (2026). 'Brain Rot' Among University Students in the Digital Age: A Phenomenological Study. Current Psychiatry Reports, 28(1), 11. https://doi.org/10.1007/s11920-025-01658-w

Palmwood, E. N., & McBride, C. A. (2019). Challenge vs. Threat: The Effect of Appraisal Type on Resource Depletion. *Current Psychology*, *38*(6), 1522–1529. https://doi.org/10.1007/s12144-017-9713-6

Panek, E. (2014). Left to their own devices: College students' "guilty pleasure" media use and time management. *Communication Research*, *41*(4), 561–577. https://doi.org/10.1177/0093650213499657

Petko, B., & Tadi, P. (2023). Neuroanatomy, Nucleus Ambiguus. In *StatPearls*. StatPearls Publishing. http://www.ncbi.nlm.nih.gov/books/NBK547744/

Philip, P., Taillard, J., Sagaspe, P., Valtat, C., Sanchez-Ortuno, M., Moore, N., Charles, A., & Bioulac, B. (2004). Age, performance and sleep deprivation. *Journal of Sleep Research*, *13*(2), 105–110. https://doi.org/10.1111/j.1365-2869.2004.00399.x

Pielot, M., & Rello, L. (2015). The Do Not Disturb Challenge: A Day Without Notifications. *Proceedings of the 33rd Annual ACM Conference Extended Abstracts on Human Factors in Computing Systems*, 1761–1766. https://doi.org/10.1145/2702613.2732704

Pielot, M., Vradi, A., & Park, S. (2018). Dismissed! A detailed exploration of how mobile phone users handle push notifications. *Proceedings of the 20th International Conference on Human-Computer Interaction with Mobile Devices and Services*, 1–11. https://doi.org/10.1145/3229434.3229445

Plass, J. L., & Kalyuga, S. (2019). Four Ways of Considering Emotion in Cognitive Load Theory. *Educational Psychology Review*, *31*(2), 339–359. https://doi.org/10.1007/s10648-019-09473-5

Potarca, G., & Sauter, J. (2023). *Chapter 21: The mental health cost of swiping: is dating app use linked to greater stress and depressive symptoms?* https://www.elgaronline.com/edcollchap/book/9781789906769/book-part-9781789906769-31.xml

Pradhan, S., Qiu, L., Parate, A., & Kim, K.-H. (2017a). Understanding and managing notifications. *IEEE INFOCOM 2017 - IEEE Conference on Computer Communications*, 1–9. https://doi.org/10.1109/INFOCOM.2017.8057231

Pradhan, S., Qiu, L., Parate, A., & Kim, K.-H. (2017b). Understanding and managing notifications. *IEEE INFOCOM 2017 - IEEE Conference on Computer Communications*, 1–9. https://doi.org/10.1109/INFOCOM.2017.8057231

Prakash, G., & Sabharwal, D. (2024). AI Revolution in Online Media: Transforming Content Creation, Distribution, and Consumption. Media and Al: Navigating, 179.

Primack, B. A., Bisbey, M. A., Shensa, A., Bowman, N. D., Karim, S. A., Knight, J. M., & Sidani, J. E. (2018). The association between valence of social media experiences and depressive symptoms. *Depression and Anxiety*, *35*(8), 784–794. https://doi.org/10.1002/da.22779

Proverbio, A. M., Zani, A., & Adorni, R. (2008). Neural markers of a greater female responsiveness to social stimuli. *BMC Neuroscience*, *9*(1), 56. https://doi.org/10.1186/1471-2202-9-56

Putting a Finger on Our Phone Obsession. (2016). Dscout Inc. https://web.archive.org/web/20250126081136/https://dscout.com/people-nerds/mobiletouches

Reinecke, L., Hartmann, T., & Eden, A. (2014). The Guilty Couch Potato: The Role of Ego Depletion in Reducing Recovery Through Media Use. *Journal of Communication*, *64*(4), 569–589. https://doi.org/10.1111/jcom.12107

Richards, J. S., Arias Vásquez, A., von Rhein, D., van der Meer, D., Franke, B., Hoekstra, P. J., Heslenfeld, D. J., Oosterlaan, J., Faraone, S. V., Buitelaar, J. K., & Hartman, C. A. (2016). Adolescent behavioral and neural reward sensitivity: A test of the differential susceptibility theory. *Translational Psychiatry*, *6*(4), e771–e771. https://doi.org/10.1038/tp.2016.37

Richter, M., & Gendolla, G. H. E. (2009). The heart contracts to reward: Monetary incentives and preejection period. *Psychophysiology*, *46*(3), 451–457. https://doi.org/10.1111/j.1469-8986.2009.00795.x

Rieger, D., Reinecke, L., & Bente, G. (2017). Media-induced recovery: The effects of positive versus negative media stimuli on recovery experience, cognitive performance, and energetic arousal. *Psychology of Popular Media Culture*, *6*(2), 174–191. https://doi.org/10.1037/ppm0000075

Robinson, T. E., & Berridge, K. C. (2003). Addiction. *Annual Review of Psychology*, *54*(Volume 54, 2003), 25–53. https://doi.org/10.1146/annurev.psych.54.101601.145237

Rodway, G., & Sanders, M. (2003). The efficacy of split-night sleep studies. *Sleep Medicine Reviews*, *7*(5), 391–401. https://doi.org/10.1053/smrv.2002.0272

Ruge, O., Hoppe, J. P. M., Dalle Molle, R., & Silveira, P. P. (2025). Early environmental influences on the orbito-frontal cortex function and its effects on behavior. *Neuroscience & Biobehavioral Reviews*, *169*, 106013. https://doi.org/10.1016/j.neubiorev.2025.106013

Rus, H. M., & Tiemensma, J. (2017). "It's complicated." a systematic review of associations between social network site use and romantic relationships. *Computers in Human Behavior*, *75*, 684–703. https://doi.org/10.1016/j.chb.2017.06.004

Rus, H. M., & Tiemensma, J. (2018). Social media as a shield: Facebook buffers acute stress. *Physiology & Behavior*, *185*, 46–54. https://doi.org/10.1016/j.physbeh.2017.12.021

Safer smartphones and social media: What do Britons want? (n.d.). Retrieved 25 September 2025, from https://www.moreincommon.org.uk/our-work/research/safer-smartphonesand-social-media/

Sahami Shirazi, A., Henze, N., Dingler, T., Pielot, M., Weber, D., & Schmidt, A. (2014). Large-scale assessment of mobile notifications. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 3055–3064. https://doi.org/10.1145/2556288.2557189

Salim, S. (2014). Oxidative stress and psychological disorders. *Current Neuropharmacology*, *12*(2), 140–147. https://doi.org/10.2174/1570159X11666131120230309

Sasson, H., & Mesch, G. (2016). Gender Differences in the Factors Explaining Risky Behavior Online. *Journal of Youth and Adolescence*, *45*(5), 973–985. https://doi.org/10.1007/s10964-016-0465-7

Sawyer, S. M., Azzopardi, P. S., Wickremarathne, D., & Patton, G. C. (2018). The age of adolescence. *The Lancet Child & Adolescent Health*, *2*(3), 223–228. https://doi.org/10.1016/S2352-4642(18)30022-1

Schwab, K. (n.d.). *Schwab, K. (2017) The Fourth Industrial Revolution. Crown Publishing*

Group, New York. - References—Scientific Research Publishing. Retrieved 25 September 2025, from https://www.scirp.org/reference/referencespapers?referenceid=2097936

Schwabe, L., & Wolf, O. T. (2009). Stress Prompts Habit Behavior in Humans. *Journal of Neuroscience*, *29*(22), 7191–7198. https://doi.org/10.1523/JNEUROSCI.0979-09.2009

Scott-Parker, B., & Weston, L. (2017). Sensitivity to reward and risky driving, risky decision making, and risky health behaviour: A literature review. *Transportation Research Part F: Traffic Psychology and Behaviour*, *49*, 93–109. https://doi.org/10.1016/j.trf.2017.05.008

Seery, M. D. (2013). The Biopsychosocial Model of Challenge and Threat: Using the Heart to Measure the Mind. *Social and Personality Psychology Compass*, *7*(9), 637–653. https://doi.org/10.1111/spc3.12052

Sevil, M., Rashid, M., Hajizadeh, I., Maloney, Z., Samadi, S., Askari, M. R., Brandt, R., Hobbs, N., Park, M., Quinn, L., & Cinar, A. (2019). Assessing the Effects of Stress Response on Glucose Variations. *2019 IEEE 16th International Conference on Wearable and Implantable Body Sensor Networks (BSN)*, 1–4. https://doi.org/10.1109/BSN.2019.8771094

Shannon, H., Bush, K., Villeneuve, P. J., Hellemans, K. G., & Guimond, S. (2022). Problematic Social Media Use in Adolescents and Young Adults: Systematic Review and Meta-analysis. *JMIR Mental Health*, *9*(4), e33450. https://doi.org/10.2196/33450

Sharma, M., Kacker, S., & Sharma, M. (2016). A Brief Introduction and Review on Galvanic Skin Response. *International Journal of Medical Research Professionals*, *2*. https://doi.org/10.21276/ijmrp.2016.2.6.003

Siegwarth, N., Larkin, K. T., & Kemmner, C. (2012). Experimenter Effects on Cardiovascular Reactivity and Task Performance During Mental Stress Testing. *The Psychological Record*, *62*(1), 69–82. https://doi.org/10.1007/BF03395787

Smit, A. S., Eling, P. A. T. M., & Coenen, A. M. L. (2004). Mental effort causes vigilance decrease due to resource depletion. *Acta Psychologica*, *115*(1), 35–42. https://doi.org/10.1016/j.actpsy.2003.11.001

Social media mindsets: A new approach to understanding social media use and psychological well-being | Journal of Computer-Mediated Communication | Oxford Academic. (n.d.). Retrieved 25 September 2025, from https://academic.oup.com/jcmc/article/29/1/zmad048/7612379

Software—MindWare Technologies. (n.d.). Retrieved 24 September 2025, from https://www.mindwaretech.com/product-category/software/

Store atmosphere and purchasing behavior—ScienceDirect. (n.d.). Retrieved 25 September 2025, from https://www.sciencedirect.com/science/article/pii/002243599490037X

Sümen, A., & Evgin, D. (2021). Social Media Addiction in High School Students: A CrossSectional Study Examining Its Relationship with Sleep Quality and Psychological Problems. *Child Indicators Research*, *14*(6), 2265–2283. https://doi.org/10.1007/s12187021-09838-9

Termann, S. (2025). The Dopamine Collapse Hypothesis: Foundations of Macro-Neuroeconomics (SSRN Scholarly Paper No. 5168672). Social Science Research Network. https://papers.ssrn.com/abstract=5168672

The co-evolution of two Chinese mobile short video apps: Parallel platformization of Douyin and TikTok—D. Bondy Valdovinos Kaye, Xu Chen, Jing Zeng, 2021. (n.d.). Retrieved 25 September 2025, from https://journals.sagepub.com/doi/abs/10.1177/2050157920952120?casa_token=3NhjHPFmskAAAAA%3Ax9eKisPU0XHGDsJmCMpttDFpAUo26fSg31Yay5q4j0SlJtpb44E0rXCpsTDnD4RZSEQMtsSYgxDRRKY

The relationship between short-form video use and depression among Chinese adolescents: Examining the mediating roles of need gratification and short-form video addiction: Heliyon. (n.d.). Retrieved 25 September 2025, from https://www.cell.com/heliyon/fulltext/S2405-8440(24)06377-1?uuid=uuid%3Adc9223d4-9577-49a6-82d4-8c777fb6831c

Thomas, M. F., Binder, A., Stevic, A., & Matthes, J. (2023). 99 + matches but a spark ain't one: Adverse psychological effects of excessive swiping on dating apps. Telematics and Informatics, 78, 101949. https://doi.org/10.1016/j.tele.2023.101949

Tian, Y., Chan, T. J., Liew, T. W., Chen, M. H., & Liu, H. N. (2025). Overwhelmed online: Investigating perceived overload effects on social media cognitive fatigue via stressorstrain-outcome model. *Library Hi Tech*. https://doi.org/10.1108/LHT-03-2024-0145

Toma, C. L. (2015). Online Dating. In *The International Encyclopedia of Interpersonal Communication* (pp. 1–5). John Wiley & Sons, Ltd. https://doi.org/10.1002/9781118540190.wbeic118

Tulumen, E., Khalilayeva, I., Aytemir, K., Ergun Baris Kaya, F. E. S. C., Sinan Deveci, O., Aksoy, H., Kocabas, U., Okutucu, S., Tokgozoglu, L., Kabakci, G., Ozkutlu, H., & Oto, A. (2011). The Reproducibility of Heart Rate Recovery after Treadmill Exercise Test. *Annals of Noninvasive Electrocardiology : The Official Journal of the International Society for Holter and Noninvasive Electrocardiology, Inc*, *16*(4), 365–372. https://doi.org/10.1111/j.1542-474X.2011.00464.x

Vandersmissen, B., & Godin, F. (2014). *The Rise of Mobile and Social Short-Form Video: An In-depth Measurement Study of Vine*. https://web.archive.org/web/20220121014855id_/http://ceur-ws.org/Vol-1198/vandersmissen.pdf

Vuorre, M., & Przybylski, A. K. (2023). A multiverse analysis of the associations between internet use and well-being. A Multiverse Analysis of the Associations between Internet Use and Well-Being. https://doi.org/10.31234/osf.io/jp5nd

Wadsley, M., & Ihssen, N. (2025). The psychophysiology of Instagram – Brief bouts of Instagram use elicit appetitive arousal and attentional immersion followed by aversive arousal when use is stopped. *Computers in Human Behavior*, *166*, 108597. https://doi.org/10.1016/j.chb.2025.108597

Wang, F., Pan, F., Tang, Y., & Huang, J. H. (2021). Editorial: Early Life Stress-Induced Epigenetic Changes Involved in Mental Disorders. *Frontiers in Genetics*, *12*, 684844. https://doi.org/10.3389/fgene.2021.684844

Wang, X., Zhao, X., & Yu, C. (2025). The influence of information and social overload on academic performance: The role of social media fatigue, cognitive depletion, and self-control. *Revista de Psicodidáctica (English Ed.)*, *30*(2), 500164. https://doi.org/10.1016/j.psicoe.2025.500164

Wheelwright, T. (2025, January 1). Cell Phone Usage Stats 2025: Americans Check Their Phones 205 Times a Day. *Reviews.Org*. https://www.reviews.org/mobile/cell-phoneaddiction/

When shoppers don't have enough self-control resources: Applying the strength model of self-control | Journal of Consumer Marketing | Emerald Publishing. (n.d.). Retrieved 25 September 2025, from https://www.emerald.com/jcm/articleabstract/34/4/328/209602/When-shoppers-don-t-have-enough-self-control

Whiting, A., & Williams, D. (2013). Why people use social media: A uses and gratifications approach. *Qualitative Market Research: An International Journal*, *16*(4), 362–369. https://doi.org/10.1108/QMR-06-2013-0041

Williams, R. A., Hagerty, B. M., & Brooks, G. (2004). Trier Social Stress Test: A method for use in nursing research. *Nursing Research*, *53*(4), 277–280. https://doi.org/10.1097/00006199-200407000-00011

Wolfers, L. N., & Utz, S. (2022). Social media use, stress, and coping. *Current Opinion in Psychology*, *45*, 101305. https://doi.org/10.1016/j.copsyc.2022.101305

Wolff, C. B. (2008). Normal Cardiac Output, Oxygen Delivery And Oxygen Extraction. In D. J. Maguire, D. F. Bruley, & D. K. Harrison (Eds), *Oxygen Transport to Tissue XXVIII* (pp. 169–182). Springer US. https://doi.org/10.1007/978-0-387-71764-7_23

Wu, S., Shafait, Z., & Bao, K. (2024). The relationship between proactive personality and college students' short-form video addiction: A chain mediation model of resilience and self-control. *PloS One*, *19*(11), e0312597. https://doi.org/10.1371/journal.pone.0312597

Xie, T., & Wang, Y. (2025). Too much social media to sleep: The chained mediation effect of information strain and depressive symptoms on the relationship between social media overload and insomnia. *BMC Public Health*, *25*(1), 1404. https://doi.org/10.1186/s12889-025-22698-0

Yaochen, L., & Van Der Blom, J. (2025). *Triggered by Design: How Algorithmic Features of Social Media Disrupt Emotions and Academic Outcomes*. http://lup.lub.lu.se/studentpapers/record/9203490

Yiend, J. (2010). The effects of emotion on attention: A review of attentional processing of emotional information. *Cognition and Emotion*, *24*(1), 3–47. https://doi.org/10.1080/02699930903205698

Yin, C., Wa, A., Zhang, Y., Huang, R., & Zheng, J. (2025a). *Exploring the Dark Patterns in User Experience Design for Short-Form Videos* (pp. 330–347). https://doi.org/10.1007/978-3-031-92977-9_21

Yin, C., Wa, A., Zhang, Y., Huang, R., & Zheng, J. (2025b). Exploring the Dark Patterns in User Experience Design for Short-Form Videos. *Distributed, Ambient and Pervasive Interactions: 13th International Conference, DAPI 2025, Held as Part of the 27th HCI International Conference, HCII 2025, Gothenburg, Sweden, June 22–27, 2025, Proceedings, Part I*, 330–347. https://doi.org/10.1007/978-3-031-92977-9_21

Yousef, A. M. F., Alshamy, A., Tlili, A., & Metwally, A. H. S. (2025). Demystifying the New Dilemma of Brain Rot in the Digital Era: A Review. Brain Sciences, 15(3), 283. https://doi.org/10.3390/brainsci15030283

Zhang, H., & Scheibe, K. (2023). Multi-platform Distribution of Video Content: An Analysis of Video Content Cross-Posted by YouTubers on Bilibili. In C. Stephanidis, M. Antona, S. Ntoa, & G. Salvendy (Eds), HCI International 2023 Posters (pp. 149–156). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-36001-5_20

Zheng, B., Yu, J., Zhang, B., & Shen, C. (2023). Reconceptualizing translation and translators in the digital age: YouTube comment translation on China's Bilibili. Translation Studies, 16(2), 297–316. https://doi.org/10.1080/14781700.2023.2205423

Zhou, K., Constantinides, M., Quercia, D., & Šćepanović, S. (2023). How Circadian Rhythms Extracted from Social Media Relate to Physical Activity and Sleep. *Proceedings of the International AAAI Conference on Web and Social Media*, *17*, 948–959. https://doi.org/10.1609/icwsm.v17i1.22202

Zhu, M., & Ghodsi, A. (2006). Automatic dimensionality selection from the scree plot via the use of profile likelihood. *Computational Statistics & Data Analysis*, *51*(2), 918–930. https://doi.org/10.1016/j.csda.2005.09.010

APPENDICES

Appendix A - Perceived information overload from social media scale

(as adapted from Misra and Stokols (2012)):

These questions in this scale ask you about your feelings and thoughts during the last month. In each case, please indicate on a scale from [1 = never] to [5 = very often] how often you have felt or thought a certain way. Although some of the questions are similar, there are differences between them, and you should treat each one as a separate question. The best approach is to answer each question quickly. That is, do not try to count up the number of times you felt a particular way, but rather indicate the answer that seems like a reasonable estimate.

1. In the last month, how often have you felt overwhelmed by video or images online?
2. In the last month, how often have you felt overwhelmed with the social media messages you have received?
3. In the last month, how often have you forgotten to respond to important online messages or texts?
4. In the last month, how often have felt pressured to respond to messages/texts quickly?
5. In the last month, how often have you received more social media notifications than you can handle?
6. In the last month, how often have you felt that maintaining your social media account is too much too handle?

Appendix B - Behavioural Activation Scale Items

BAI from Carver and White (1994)

<u>Directions:</u>

Each item on this questionnaire is a statement that a person may either agree with or disagree with. For each item, indicate how much you agree or disagree with what the item says. Please respond to all of the items; do *not* leave any blank. Choose only *one* response to each statement. Please be as accurate and honest as you can be. Choose from the following four response options:

1	2	3	4
Strongly disagree	Disagree	Agree	Strongly Agree

~~Even if something bad is about to happen to me, I rarely experience fear or nervousness.~~	~~1~~	~~2~~	~~3~~	~~4~~
I go out of my way to get things I want	1	2	3	4
When I'm doing well at something, I love to keep at it	1	2	3	4
I'm always willing to try something new if I think it will be fun	1	2	3	4
When I get something I want, I feel excited and energized	1	2	3	4
~~Criticism or scolding hurts me quite a bit~~	~~1~~	~~2~~	~~3~~	~~4~~
When I want something, I usually go all-out to get it	1	2	3	4
I will often do things for no other reason than that they might be fun	1	2	3	4
If I see a chance to get something I want, I move on it right away	1	2	3	4
~~I feel pretty worried or upset when I think or know somebody is angry at me~~	~~1~~	~~2~~	~~3~~	~~4~~
When I see an opportunity for something I like, I get excited right away	1	2	3	4
I often act on the spur of the moment	1	2	3	4
~~If I think something unpleasant is going to happen, I usually get pretty "worked up."~~	~~1~~	~~2~~	~~3~~	~~4~~
When good things happen to me, it affects me strongly	1	2	3	4
~~I feel worried when I think I have done poorly at something~~	~~1~~	~~2~~	~~3~~	~~4~~
I crave excitement and new sensations	1	2	3	4

When I go after something, I use a "no holds barred" approach 1
2
3
4

~~I have very few fears compared to my friends~~ ~~1~~
~~2~~
~~3~~
4

It would excite me to win a contest 1
2
3
4

~~I worry about making mistakes~~ ~~1~~
~~2~~
~~3~~
4