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Neurocognitive Correlates of Internet Use: Psychological Measures and Electrophysiological Signatures from Resting-State and Task-Based EEG in a Sample of Healthy Regular Internet Users

DOCTORAL DISSERTATION

Natural Sciences,
Biophysics (N 011)

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VILNIAUS UNIVERSITETAS

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Neurokognityviniai interneto naudojimo ypatumai: psichologinių rodiklių ir EEG parametrų, išmatuotų ramybės būsenoje bei atliekant užduotį, tyrimas, tiriant sveikų, reguliariai internetu besinaudojančių asmenų imtį

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CONTENTS

LIST OF ABBREVIATIONS

ADHD	Attention Deficit Hyperactivity Disorder
BAI	Beck Anxiety Inventory
BDI	Beck's Depression Inventory
CBOCI	Clark-Beck Obsessive-Compulsive Inventory
DPIU	Dimensions of Problematic Internet Use questionnaire
DSM-5	Diagnostic and Statistical Manual of Mental Disorders, 5^{th}
EEG	Electroencephalography
ERP	Event-Related Potential
FAA	Frontal Alpha Asymmetry
FDR	False Discovery Rate
FFT	Fast Fourier transformation
IA	Internet Addiction
ICA	Independent component analysis
ICD-11	International Classification of Diseases, 11^{th} Revision
IGD	Internet Gaming Disorder
MAIA	Multidimensional Assessment of Interoceptive Awareness
MS	Microstate
NEO PI-R	NEO Personality Inventory-Revised
PG	Pathological Gambling
PIU	Problematic Internet Use
PIUQ-9	Nine-Item Problematic Internet Use Questionnaire
SST	Stop Signal Task

1. INTRODUCTION

The internet has become nearly ubiquitous in modern life, with users accounting for over two-thirds of the global population (Statista, 2025). This rapid expansion has made digital interactions integral to daily life, particularly among younger demographics who report near-constant connectivity with digital platforms (Massarat, 2022; Pew Research Center, 2024). The widespread integration of the internet into everyday activities offers unprecedented benefits, including instant information access, global communication, enhanced education, and streamlined services (Huang et al., 2021; Lemenager et al., 2020; Nimrod, 2020). However, the design of many digital platforms – featuring mechanisms like endless scrolling, immersive environments with variable reward systems, attention-focused elements, and algorithm-driven personalized content – often encourages prolonged use beyond initial intentions (Fineberg et al., 2025; Liu, 2005; Nicholas et al., 2009; Robbins & Clark, 2015). Consequently, the psychological and behavioral outcomes of internet use vary significantly depending on the nature and extent of individual engagement.

While thoughtful and purposeful usage may foster personal growth and social connections, excessive or maladaptive engagement – broadly categorized as Problematic Internet Use (PIU) – can result in notable psychological and functional impairments, (Fineberg et al., 2022; Ioannidis et al., 2019; Kuss & Lopez-Fernandez, 2016; Lissak, 2018; Sun et al., 2020; Weinstein & Lejoyeux, 2010). PIU, estimated to affect approximately 7% of the global population (Pan et al., 2020), has been recognized by the World Health Organization as an emerging public health concern (World Health Organization, 2015). Thus, the internet is indispensable for daily tasks yet capable of fostering maladaptive behaviors that negatively impact individual functioning and well-being.

PIU is typically characterized by impaired control over internet use and significant negative outcomes, manifesting along a continuum that ranges from healthy to problematic involvement (Anderson et al., 2017; Billieux et al., 2015; Fineberg et al., 2018; Ioannidis et al., 2019; Kaess et al., 2021; Kuss & Lopez-Fernandez, 2016). Key addiction-like symptoms (e.g., compulsive engagement, impaired self-control, craving states, withdrawal symptoms, continuation of engagement despite adverse consequences) are commonly reported (American Psychiatric Association, 2013; Griffiths, 2019; Ioannidis et al., 2019; Mihajlov & Vejmelka, 2017). However, the expression and interpretation of these symptoms can vary considerably across specific online contexts, contributing to ongoing conceptual and diagnostic ambiguity surrounding PIU (Aarseth et al., 2017; Baggio et al., 2022; Billieux et al., 2019; Gullo et al., 2022; Kardefelt-Winther, 2017; Kuss & Lopez-Fernandez, 2016; Starcevic & Aboujaoude, 2017).

To date, PIU lacks formal recognition, and a lack of consensus within the field complicates research comparability, clinical assessment, and the development of treatment protocols. Nevertheless, the scope of the problem has prompted extensive exploration of physical, psychological, social, cognitive, and neurophysiological PIU correlates, consistently revealing dynamic interactions among these factors (Fineberg et al., 2022; Kuss & Lopez-Fernandez, 2016; Lissak, 2018; Mihajlov & Vejmelka, 2017). Yet, considerable gaps persist in understanding the mechanisms that underlie its onset and maintenance, and more subtle constructs are only beginning to receive attention.

One such factor is interoception – the ability to sense and interpret internal bodily signals (such as heart rate, hunger, or visceral emotional cues) (Craig, 2002; Khalsa et al., 2018). Interoception is fundamental to emotional awareness and regulation, yet its role in PIU has been largely overlooked. Theoretically, individuals with poor interoceptive awareness might struggle to recognize internal states like stress or boredom, with consequences extending beyond emotion mismanagement, as it can also impair decision-making (Herman, 2023; Khalsa et al., 2018; Namkung et al., 2018). Integrating underexplored constructs like interoception into PIU research could illuminate novel pathways that contribute to the development of maladaptive usage patterns, positing that a disconnection between mind and body might render individuals more vulnerable to excessive online behavior.

Beyond psychological traits, cognitive performance and neurophysiological measures are important factors for characterizing PIU, paralleling findings in substance and behavioral addictions (D'Hondt et al., 2015; Kuss & Griffiths, 2012; Yuan et al., 2011). A central cognitive component implicated in many addictive and compulsive behaviors is a deficit in inhibitory control – the reduced ability to suppress inappropriate impulses or actions (Beppi et al., 2020; Kozak et al., 2019; Winstanley et al., 2006; Zhang et al., 2017). In the context of heavy internet use, researchers have similarly observed that individuals with PIU or specific internet-related addictions often show signs of impaired response inhibition, findings supported by both behavioral and neuroimaging evidence (Anderson et al., 2017; Argyriou et al., 2017; D'Hondt & Maurage, 2017; Dong & Potenza, 2014). However, these findings are not entirely consistent. For instance, electroencephalography (EEG) studies on event-related potentials (ERPs) report alterations in amplitudes of the N2 and P3 components during inhibition tasks in high-PIU groups. P3 component is considered to reflect allocation of attentional resources and impulse control efficiency, while N2 is linked to conflict detection and early inhibition (Fogarty et al., 2020a; Luijten et al., 2014; Pires et al., 2014). Some studies of individuals with PIU show reduced amplitudes of these ERPs, others – increased, and some report only subtle or no deviations at all (e.g., Dong et al., 2010; Kim et al., 2017; Li et al., 2020; Littel et al., 2012; Luijten et al., 2014). Incorporating a well-established reaction-time paradigm, such as the Go/NoGo task designed to assess inhibitory control (Fogarty et al., 2020a), and combining behavioral measures and direct neurophysiological indicators (e.g., ERPs) in a healthy sample of regular internet users might reveal insights into how the brain processes information and controls impulses along the continuum from regular to problematic internet use.

In addition to task-based experimental paradigms, resting-state brain activity provides another window into the brain's baseline functioning in high internet users. EEG and functional magnetic resonance imaging (fMRI) studies have revealed characteristic alterations during rest, indicating their potential suitability as candidate biomarkers for identifying and monitoring PIU progression (Burleigh et al., 2020; Lee et al., 2014; Sun et al., 2019; Wang & Griskova-Bulanova, 2018; Wang et al., 2015). Microstate analyses – offering scalable and temporally precise neural metrics (Khanna et al., 2015; Tarailis et al., 2024) – have revealed distinguishable network dynamics in PIU, IGD and internet-related behaviors (Cui et al., 2021; Li et al., 2021; Qi et al., 2023; Wang et al., 2021). However, to date, research on PIU microstates analysis is scarce, and virtually no research has applied this approach to non-clinical PIU populations – a notable gap, since it could have the potential to illuminate large-scale neural dysregulation before problematic involvement fully develops.

Another commonly investigated resting-state EEG metric is alpha oscillatory activity. Alpha activity is thought to inversely reflect cortical activity, contributing to inhibitory processes by facilitating the synchronization of large-scale neural brain networks (Reznik & Allen, 2018; Smith et al., 2017). Measures like alpha asymmetry – reflecting hemispheric imbalance in alpha power – have been consistently associated with affective, motivational, and cognitive processes, with atypical patterns observed in various neuropsychiatric and neurodevelopmental conditions (Ocklenburg et al., 2024; Reznik & Allen, 2018; Smith et al., 2017). Several studies have already linked altered alpha activity and its measures to PIU and internet-related disorders (Burleigh et al., 2020; Sun et al., 2019; Wang & Griskova-Bulanova, 2018; Wang et al., 2017); however, findings are limited, and the parietal region is largely overlooked. To date, no studies have specifically examined parietal alpha asymmetry in the context of PIU, leaving an unaddressed gap in understanding how (if) lateralized neural activity contributes to early-stage maladaptive internet engagement.

In summary, PIU arises against a backdrop of ubiquitous internet access, manifesting along a continuum from adaptive engagement to maladaptive overuse. Yet, current empirical research frequently characterizes PIU as a binary state – either severely expressed or absent – thereby overlooking the nuanced progression from casual or excessive use to problematic engagement. This perspective risks neglecting early-stage or subclinical forms of PIU, which can significantly impact daily life, even if they do not reach clinical thresholds. Moreover, regular internet users constitute a much larger segment of the population, outnumbering clinical populations, yet knowledge regarding how internet use manifests within this broader, non-clinical population remains limited.

A more comprehensive, integrative approach – combining psychological characteristics, behavioral performance, and neurophysiological data – may yield substantial benefits to the field. The present work adopts such an integrative methodology, investigating PIU within a non-clinical sample in search of subtle psychological and neurophysiological markers of problematic internet engagement. Ultimately, this approach broadly aims to advance the conceptual understanding of PIU, enhance early detection strategies, and support the development of preventive interventions before maladaptive internet use escalates into significant impairment or disorder.

1.1. Aim and objectives

This work aimed to investigate internet use patterns and their associations with psychological, personality, interoceptive, and neurophysiological correlates (ERPs, alpha asymmetry, and microstates) in a non-clinical population, using an integrative approach that combined self-report measures, a behavioral inhibition task, and EEG-based methods. The objectives were as follows:

- To investigate associations between the level and type of internet engagement and self-reported symptoms of anxiety, depression, and obsessive-compulsiveness.
- To investigate associations between internet use patterns, interoceptive awareness, and personality traits by employing a network analysis approach.
- To evaluate behavioral performance during an auditory equiprobable Go/NoGo task in relation to the severity and type of internet use.
- To investigate associations between internet use patterns and ERP components (N1, P2, N2, P3) during an auditory equiprobable Go/NoGo task.
- To investigate associations between internet use patterns and resting-state alpha asymmetry at frontal and parietal regions.
- To investigate associations between internet use patterns and resting-state microstates parameters.

1.2. Scientific novelty

For the first time, EEG-based correlates (ERPs, microstates, alpha asymmetry) were examined in relation to a spectrum of internet engagement levels and domain-specific patterns (e.g., social media, gaming, messaging) in a non-clinical population, moving beyond binary and uniform diagnostic models of PIU.

This study is the second to examine interoceptive variables in the context of PIU, and the first to integrate a network analysis approach to both interoception and personality traits in relation to internet use within a non-clinical sample.

This study is the first to examine parietal alpha asymmetry as a potential neural marker of internet use severity in the context of PIU.

1.3. Practical implications

Broadening PIU research to regular, non-clinical internet users by linking psychological variables, personality traits, and EEG markers across the full spectrum of internet engagement could:

- Support early PIU recognition efforts, which aim to identify subtle, preclinical markers signaling the risk before it escalates into a clinically significant disorder.
- Contribute to the development of brief, non-invasive screening measures capable of differentiating early-stage PIU profiles in both research and mental health contexts, thereby enabling timely intervention.
- Provide insights into ongoing conceptual debates by clarifying whether psychological and neurophysiological correlates commonly associated with PIU also apply to regular internet users, thereby supporting efforts to distinguish maladaptive use from normative high engagement.
- Highlight predisposing vulnerabilities that may go unnoticed in non-clinical populations, offering a foundation for preventative mental health strategies and resilience-building efforts.
- Provide insights for mental health professionals, educators, policymakers, and users themselves to improve PIU recognition, self-monitoring, and more adaptive screen time management.

1.4. Statements to be defended

1. Not-Distracting and Trusting domains of interoceptive awareness were linked to internet use severity indicating an association between lower interoceptive awareness and greater internet use, with neuroticism linking reduced bodily awareness to excessive digital behavior patterns.
2. Behavioral performance measures from the auditory equiprobable Go/NoGo task do not differentiate between levels of internet use severity.
3. The N1 in both Go and NoGo conditions, and NoGo-P3 components show domain-specific associations with internet use; however, none of the components differentiate between levels of internet use severity.
4. Parietal EEG alpha asymmetry correlates with internet use, indicating an association between greater left parietal hemisphere activity and higher levels of internet use.
5. Microstate E parameters (occurrence rate and coverage) correlate with higher internet use, indicating an association between greater MS E activity and higher levels of internet use.

2. LITERATURE REVIEW

2.1. Internet use & Problematic Internet Use (PIU)

2.1.1. Internet use: the rise and integration in daily life

The rapid proliferation of internet technology has significantly enhanced global connectivity, with internet users reaching 5.56 billion by 2025, representing approximately two-thirds of the world's population (Statista, 2025). Furthermore, forecasts suggest continued expansion, projecting an additional increase to approximately 7.3 billion internet users by 2029 (Global, Statista). This notable advancement reflects a steady decline in the number of internet non-users, particularly when considering historical data indicating that the global internet penetration rate was below 1% in 1995 (Internet Live Stats), reaching around 35% of the population in 2014 and rising to approximately 67.5% in 2024 (Petrosyan, 2025). In developed countries, internet usage has already reached near-universal levels. For instance, as of 2024, approximately 96% of adults in the United States actively use the internet (Pew Research Center, 2024). Regionally, Northern Europe records the highest internet penetration rate, reaching 97.3% in 2024, whereas East Asia accounts for the highest absolute number of internet users globally (Statista, 2024).

This rapid growth and widespread adoption of the internet have been largely driven by advancements in mobile broadband technology, which played a crucial role in making connectivity an integral and pervasive part of human life. Approximately 59% of global internet traffic originates from mobile devices (Pelchen, 2024). Particularly noteworthy is the extent of mobile internet usage among younger demographics; for example, 46% of American teenagers report using the internet almost constantly (Massarat, 2022). Moreover, 95% of youths aged 13–17 utilize social media platforms, with more than one-third indicating near-constant engagement (Massarat, 2022). The proliferation of smartphones and wireless networks has facilitated continuous and portable online access, thereby effectively blurring the boundaries between online and offline life.

Today, internet technology has permeated nearly all facets of society, fundamentally transforming communication, education, employment practices, commerce, healthcare services, governance, and entertainment. Additionally, the COVID-19 pandemic further accelerated reliance on digital platforms (Huang et al., 2021; Lemenager et al., 2020; Nimrod, 2020), driving the widespread adoption of remote solutions for activities that traditionally required in-person interactions, such as work meetings, classes, and social gatherings.

2.1.1.1. Positive impacts of internet use

Enhancing social, emotional, and psychological well-being

A substantial body of research highlights that thoughtful internet use positively impacts social, emotional, and psychological well-being for individuals and communities.

Socially, the internet facilitates global connectivity, enabling supportive networks previously limited by geographical, physical, or social barriers. Online interactions characterized by meaningful social support, social connectedness, and positive interaction quality effectively reduce depression, anxiety, and loneliness, while simultaneously boosting psychological well-being, perceived companionship support, self-esteem, and overall life satisfaction (Oh et al., 2014; Seabrook et al., 2016). Adolescents, for example, report feeling greater acceptance, increased support during difficult periods, and a closer connection to friends through social media use (Gelles-Watnick & Vogels, 2023). Similarly, broadband access and moderate internet use are linked to better mental health among middle-aged and older adults by alleviating loneliness and reducing the risk of depressive symptoms (Luo et al., 2025; Yu et al., 2021; Zhang et al., 2023), with particularly notable benefits for those who moved from no access to having internet access (Zhang et al., 2023). This improvement has, in turn, been associated with lower levels of inflammation related to mental health issues (Walker et al., 2019). Cross-national and longitudinal studies further support the positive relationship between internet use and higher self-reported health, especially in mitigating social isolation, increasing social engagement, and reducing socioeconomic disparities, thereby enhancing well-being in later life (Luo et al., 2025; Mu et al., 2021; Szabo et al., 2019). Research also indicates that online communication tools positively impact mental health and overall well-being among underserved or vulnerable populations facing challenges such as social anxiety or marginalization (e.g., gender, racial, sexual minorities) by facilitating peer connections, social support, and opportunities for identity exploration (Berger et al., 2022; Office of the U.S. Surgeon General, 2023). Importantly, these beneficial outcomes depend more strongly on the quality rather than the frequency or intensity of online communication platforms use (Seabrook et al., 2016).

Additionally, various internet-based entertainment platforms (e.g., online gaming or video streaming) can enhance psychological well-being by providing avenues for psychological distress relief and emotional regulation. Individuals prone to seeking such relief through psychoactive substances or potentially addictive behaviors – often due to boredom, stress, or mental health conditions such as schizophrenia – may find adaptive coping through these platforms, experiencing reductions in anxiety, depression, tension, and self-stigma (Chen & Lin, 2018; Chang et al., 2020). Moreover, internet technology may support psychological well-being through the mindful and purposeful use of digital tools such as mental health apps, online counseling platforms, and virtual support groups, which address conditions like anxiety, depression, addiction, schizophrenia, and suicidal ideation (Gega et al., 2022).

Consequently, through facilitating meaningful social interactions, enhancing perceived support and connectedness, and providing opportunities for entertainment, self-expression, and mental health resources, internet-based platforms may significantly contribute to improved emotional and psychological well-being across diverse populations.

Cognitive benefits and neuroadaptive potential

The widespread use of the internet provides numerous cognitive benefits by stimulating neural adaptation and enhancing specific mental skills. Even basic interactions, such as using a smartphone's touchscreen, can induce lasting neurocognitive changes in cortical regions associated with sensory and motor processing (Gindrat et al., 2015). These adaptations reflect the brain's well-established capacity for neuroplasticity, allowing it to respond dynamically to new stimuli and environmental demands, particularly with regard to learning new processes (Draganski et al., 2004; Osterhout et al., 2008; Scholz et al., 2009). Firth et al. (2019) emphasize that extensive internet engagement provides both the necessity and opportunity for acquiring new digital skills, likely inducing meaningful neural changes.

Certain forms of online engagement have been shown to specifically enhance cognitive performance. For instance, action video games and other interactive digital media usage led to improvements in visual-spatial skills and reaction times. Habitual gamers exhibit superior visual attention compared to non-gamers, and training non-gamers in action games significantly enhances their cognitive performance, suggesting direct causal benefits (Green & Bavelier, 2003). Further corroborating these findings, Dye et al. (2009) reported that action video gaming significantly reduced reaction times across a variety of tasks beyond games without compromising accuracy, highlighting its potential as an effective training method to increase cognitive processing speed. Expanding upon these behavioral outcomes, Kühn et al. (2014) demonstrated that two months of daily video game training increased gray matter volume in brain regions related to spatial navigation, strategic planning, working memory, and motor performance. Such behavioral and neuroanatomical changes indicate video gaming's potential to enhance key cognitive functions and mitigate cognitive decline linked to conditions like schizophrenia or neurodegenerative disorders.

Further, experimental evidence suggests that targeted digital interventions might effectively counteract cognitive deterioration. For instance, Oh et al. (2018) showed that older adults engaging in daily 15-20 minute smartphone-based cognitive training significantly improved working memory within eight weeks. Similarly, Anguera et al. (2013) demonstrated that older adults participating in multitasking training via a custom-designed video game not only surpassed the cognitive performance of untrained individuals in their twenties but also maintained these gains for at least six months. These enhancements encompassed sustained improvements in cognitive control, multitasking performance, attention, and working memory, accompanied by enhanced neural functioning.

Navigating the internet's extensive information landscape also requires users to develop sophisticated search strategies and critical evaluation skills, thereby enhancing their ability to efficiently locate and assess relevant information. For example, Dong et al. (2017) demonstrated that six days of structured internet search training significantly increased white matter integrity in neural pathways essential for cognitive functioning. Dong & Potenza (2016) reported improved behavioral efficiency following internet search training, evidenced by faster response times without a loss in accuracy, alongside decreased neural activation in brain regions linked to long-term memory and executive processing. These findings reflect a shift toward more efficient cognitive processing, and this phenomenon aligns with the concept of transactive memory, in which individuals depend on external systems—such as the internet—for information storage and retrieval (Sparrow et al., 2011). Rather than remembering the information itself, individuals are more likely to recall how and where to access it, thus optimizing cognitive functioning (Kang & Malvaso, 2024; Sparrow et al., 2011). This cognitive offloading strategy reduces the demand on internal memory systems, freeing cognitive resources for other tasks, as demonstrated by Kang & Malvaso (2024) who reported that individuals with higher internet use frequency consistently outperformed low-frequency users on episodic memory tasks.

Therefore, evidence suggests that adaptive use of internet technologies facilitates meaningful neural adaptations and enhances cognitive efficiency under appropriate conditions.

2.1.1.2. Negative effects & emerging risks of internet use

The integration of internet technology into daily life presents a dual-edged phenomenon, offering unprecedented access to information and connectivity while simultaneously posing significant risks associated with excessive or maladaptive use. As digital engagement becomes increasingly embedded in everyday routines, growing empirical evidence points to the emergence of significant adverse outcomes related to internet use. The COVID-19 pandemic, along with associated quarantines, further intensified these concerns, increasing susceptibility to problematic online behaviors (Li et al., 2021; Sun et al., 2020).

In line with the World Health Organization's (1948) holistic definition of health, which is defined as "a state of complete physical, mental, and social well-being, and not merely the absence of disease or infirmity" – maladaptive internet use can negatively affect multiple life domains. Specifically, maladaptive engagement may impair interpersonal relationships, induce negative physical, mental, and emotional states, decrease academic or professional performance, and lead to severe disruptions such as job loss or educational failure (Kuss et al., 2013; Weinstein & Lejoyeux, 2010). These impacts are broad, encompassing physical, psychological, cognitive, and social dimensions. However, societal normalization of extensive internet use complicates the identification of negative effects related to internet use, as individuals and communities often overlook or underestimate early behavioral warning signs (Duong et al., 2020; Kapus et al., 2021; Kuss & Lopez-Fernandez, 2016).

Physical and psychological health risks

Excessive internet use has been consistently linked to a broad range of physical and psychological health issues. Physically, prolonged screen time is associated with increased risks of cardiovascular disease, impaired stress regulation, obesity, insulin resistance, visual impairments, and reduced bone density (Lissak, 2018). In rare but extreme cases, prolonged online gaming sessions with minimal rest, primarily among young males, have resulted in fatalities due to thromboembolism, cerebral hemorrhage, and fatal cardiac arrhythmias, precipitated by dehydration, sleep deprivation, and chronic stress (Kuperczko et al., 2022).

Psychologically, while some internet-related activities may yield benefits, evidence supporting long-term mental health improvements is limited. In contrast, robust findings from correlational, longitudinal, and experimental studies underscore the psychological risks of heavy internet use. For example, a large-scale survey of South Korean adolescents revealed that increased recreational internet use was associated with poorer mental health outcomes; the more time spent online, the greater the severity of psychological symptoms experienced (Khan et al., 2021). Individuals predisposed to emotional difficulties , as well as people with existing mental health issues or disorders (e.g., ADHD, autism spectrum disorders) (Fineberg et al., 2025), appear especially susceptible to the detrimental effects of excessive internet usage, especially when it fails to fulfill users' social or emotional needs (Oh et al., 2014). Common consequences include heightened symptoms of depression, anxiety, loneliness, and low self-esteem, often exacerbated by cyberbullying, social comparison, fear of missing out (FoMO), and emotional contagion (Khalaf et al., 2023; Pop et al., 2022; Seabrook et al., 2016). A systematic review by Khalaf et al. (2023) encompassing cross-sectional, longitudinal, and empirical studies reported that excessive smartphone and social media use among adolescents is associated with increased mental distress, self-harming behaviors, and suicidality. Pop et al. (2022) also observed that the younger the user of social networks, the higher reported levels of loneliness and depressive symptoms, and consequently, the higher the number of hours spent on social networking sites. Moreover, increased reliance on online tools may displace offline interactions, potentially weakening real-world social bonds and contributing to the erosion of traditional social relationships (Al-Sanaa, 2009; Twenge et al., 2019), thus contributing to poorer mental health.

Another among the most consistently reported consequences of excessive internet use is sleep disturbance, a key mediator of physical, psychological, and cognitive dysfunction. High levels of internet use are associated with disrupted sleep habits, including difficulties initiating and maintaining sleep, delayed bedtimes, frequent nighttime awakenings, greater sleep fragmentation, and subsequent daytime fatigue (Ekinci et al., 2014). These effects are largely attributed to blue light emission, cognitive hyperarousal, and digital notifications disrupting circadian rhythms. For example, Hartmann et al. (2019) demonstrated that intense evening video gaming (specifically, a five-hour session of the violent video game "Counter Strike: Global Offensive") resulted in slightly reduced sleep efficiency, impaired memory recall, lower melatonin levels at bedtime, and increased cortisol levels during gameplay (compared to playing the board game "Monopoly"). These findings indicate that excessive evening gaming contributes to poorer sleep quality and cognitive functioning, reinforcing the role of excessive screen exposure and heightened arousal as key mechanisms linking maladaptive online behaviors with disturbed sleep patterns. Chronic sleep deprivation, in turn, impairs memory, attention, executive functioning, emotional regulation, and academic and occupational performance (Owens et al., 2014; Tarokh et al., 2016). Over time, insufficient sleep negatively impacts physiological systems, contributing to weight gain, metabolic dysfunction, immune suppression, and other health problems (Owens et al., 2014). Sleep problems also co-occur with nearly all major psychiatric and developmental disorders (Kotagal, 2015; Tarokh et al., 2016; Tesler et al., 2013), and its comorbidity with mood disturbances is particularly troubling (Goldstone et al., 2020), While internet overuse is also consistently linked to greater mental distress, including depression, anxiety and psychological distress (Alonzo et al., 2021), sleep's role and impact is also evident: individuals with earlier bedtimes report fewer depressive symptoms and lower suicidality (Tarokh et al., 2016), while limiting screen use after 9:00 p.m. leads to earlier sleep onset, longer sleep duration, and improved daytime alertness (Perrault et al., 2019), contributing to overall well-being.

Cognitive and attentional impairments

Heavy internet use has also been linked to attentional deficits and impairments in cognitive control, largely driven by sensory overload, frequent interruptions, and online media multitasking (Firth et al., 2019). Constant switching between tasks and platforms is associated with shallow engagement with content, while continuous exposure to fragmented, rapidly shifting digital stimuli reduces an individual's ability to sustain attention, impairs executive functioning, and increases distractibility (Firth et al., 2019). To illustrate, Ophir et al. (2009) found that heavy media multitaskers are more susceptible to interference from irrelevant environmental stimuli, easily distracted by multiple concurrent media streams, less effective at filtering out distractions, and, surprisingly, perform worse on task-switching activities compared to light media multitaskers. Authors discuss that heavy multitaskers tend to rely on a bottom-up attentional control style, favoring exploratory over exploitative and focused top-down information processing. In contrast, top-down attentional control exhibited by light multitaskers allowed them to maintain focus more effectively in distracting environments.

Notably, adolescents appear particularly vulnerable. Research indicates that frequent internet use exerts more pronounced adverse effects in early adolescence than in later teenage years; for instance, higher frequencies of internet use over a three-year period among children have been linked to reduced verbal intelligence at follow-up (Firth et al., 2019). Among so-called "Digital Natives" – those who grow up immersed in internet technology – a shift toward shallow information processing, marked by rapid attention shifts and superficial engagement, linked to increased distractibility and poor executive control have been documented, potentially hindering deeper learning and memory retention (Loh & Kanai, 2016; Prensky, 2001). Such findings indicate that the rapidly growing societal trend of digital media engagement corresponds to a distinct cognitive processing style and likely reduces the ability to suppress irrelevant distractions.

Patterns of online reading further support these findings. Users increasingly engage in scanning, keyword spotting, and non-linear reading, favoring speed over deep comprehension; additionally, online platforms' designs – characterized by hypertext navigation and instant search access – further discourage deep cognitive processing, reinforcing a fragmented approach to learning and information retention (Liu, 2005; Nicholas et al., 2009). Skowronek et al. (2023) found that even the mere presence of a smartphone significantly lowered cognitive performance, suggesting that visible digital devices drain limited cognitive resources.

Collectively, these findings suggest that habitual internet use may fundamentally reshape cognitive functioning, privileging speed and breadth over depth and reflection.

2.1.1.3. Conclusion

In summary, the internet provides substantial benefits across social, emotional, psychological, and cognitive domains. Purposeful use of various online platforms and digital interventions fosters essential social support, promotes mental well-being, and enhances cognitive function through neural adaptation. Recognizing the internet's critical role in current technology-driven daily life functioning, the United Nations has advocated for internet access as a fundamental human right (United Nations, 2016) underscoring its importance for societal participation, inclusion, and the safeguarding of basic freedoms (Reglitz, 2020).

Nevertheless, widespread and often unregulated internet use also introduces significant public health challenges. Physical health issues – such as disrupted sleep patterns and increased sedentary behavior – intersect with psychological distress and impaired cognitive control, disproportionately affecting younger users. Simultaneously, excessive engagement with online platforms may also heighten emotional vulnerabilities and weaken meaningful social ties.

Taken together, these insights emphasize the necessity for balanced and mindful internet use, highlighting the critical importance of clearly differentiating adaptive from maladaptive forms of digital engagement.

2.1.2. PIU: conceptual foundations and diagnostic challenges

Problematic Internet Use (PIU) encompasses a range of maladaptive online behaviors that may lead to significant distress or functional impairment (Fineberg et al., 2018; Ioannidis et al., 2019). While extensive internet use is not inherently pathological, a growing body of evidence links excessive and dysregulated online behavior to adverse physical, psychological, and social outcomes (Lissak, 2018). From its initial recognition in the mid-1990s – when cases of people spending untenable amounts of time in chat rooms or online games were described as "Internet Addiction" (Young, 1998) to contemporary debates over terminology, PIU remains a complex and multifaceted phenomenon, identified as a global public health concern by the World Health Organization (WHO) (Kuss et al., 2013; Lissak, 2018; World Health Organization, 2015). However, despite a broad diagnostic and research landscape in the field, not much is globally agreed upon (Duong et al., 2020).

2.1.2.1. Umbrella term and heterogeneity of PIU

Early work by psychologist Kimberly Young (1998) adapted pathological gambling criteria to assess Internet Addiction, framing it as an impulse-control disorder. Since then, diverse definitions have been proposed, such as Internet Addiction (IA), Internet Use Disorder, Pathological/ Maladaptive/ Excessive/ Problematic/ Compulsive Internet Use; however, consensus on definitions has been elusive. To date, there is no single, universally accepted definition or diagnostic criterion set, which has hindered research comparability (discussed below). However, current terminology generally favors "Problematic Internet Use" (PIU) to recognize the heterogeneity of online activities (Fineberg et al., 2022; Kuss & Lopez-Fernandez, 2016; Mihajlov & Vejmelka, 2017) and avoid premature classification under addiction models (Shapira et al., 2003).

The term PIU encompasses various problematic online behaviors, such as online gaming and gambling, shopping, social media use and online messaging, video streaming and sexual content use among others, each potentially involving addictive, impulsive, and/or compulsive elements (Brand, 2022; Fineberg et al., 2018; Ioannidis et al., 2019). However, it is important to note that heterogeneity of these behaviors has also led to criticism that such an umbrella term as PIU is too broad and conceptually imprecise to serve as a unified diagnostic category for all the problem behaviors (Starcevic, 2013; Starcevic & Aboujaoude, 2017). Similarly, some authors propose that individuals are not *hooked* to the internet per se, but rather to the activities it provides, arguing that individuals go online primarily to engage in preferred activities, making the technology and device merely a delivery mechanism

(Baggio et al., 2022). For instance, M. G. Kim & Kim, (2010) claimed that "internet users are no more addicted to the internet than alcoholics are addicted to bottles", asserting that problematic internet users are driven by content or services, not the internet medium itself. However, a distinction was proposed by Davis (2001), by presenting a cognitive-behavioral model of pathological internet use differentiating between generalized PIU, where individuals engage excessively in a wide array of online activities, and specific PIU, characterized by problematic use tied to a particular application (e.g., gaming or social networking). Moreover, generalized and specific PIUs can co-occur, and their boundaries may not always be distinct. Research shows that generalized PIU often overlaps with problematic use of several specific applications like social networking, although some activities, such as gaming, appear to follow a more distinct pattern (Montag et al., 2015; Sánchez-Fernández et al., 2024). In response, several authors have advocated for replacing terms like PIU or IA with behavior-specific classifications (e.g., Internet Gaming Disorder, Pathological Gambling) when sufficient evidence supports the addictive potential of those behaviors (Griffiths & Szabo, 2014; Starcevic, 2013). As a response, the research focus has shifted over time from generalized internet use (which was the main focus until 2000) toward examining discrete online behaviors, treating the internet more as a medium for a variety of activities (Mihajlov & Vejmelka, 2017).

Despite definitional debates, a large body of research supports the clinical relevance of PIU. Whether viewed as a unified construct or a cluster of related behaviors, consensus holds that certain patterns of internet use can become pathological and warrant clinical attention. Researchers generally agree that PIU is characterized by a loss of control over internet use, compulsive behavior, and negative consequences across various life domains (Billieux et al., 2015; Kaess et al., 2021; Weinstein & Lejoyeux, 2010). It is also agreed that excessive engagement in online behaviors for some individuals results in significant functional impairments (Ioannidis et al., 2019) and mental health issues (Ioannidis et al., 2019; Kuss & Lopez-Fernandez, 2016).

2.1.2.2. Distinguishing high engagement from pathological use

A central challenge in addressing PIU lies in differentiating pathological behavior from high internet engagement, which is not necessarily pathological (Peng & Liao, 2023). While some individuals may spend prolonged hours online yet remain well-adjusted, others may experience marked impairments in functioning indicative of disordered usage. As deep penetration of the internet into daily life often masks the recognition of misuse and its warning signs, problematic patterns can go unrecognized, both by users and their communities.

Importantly, time spent online alone is not a reliable indicator of pathology. Király et al. (2015) demonstrated that time online is a weak predictor of problematic use, highlighting the need to consider contextual factors and functional outcomes. Laconi et al. (2019) further observed that problematic behavior most likely arises when individuals neglect responsibilities or meaningful offline activities, particularly during free time, as time spent online during the weekend significantly better predicted PIU than time spent online during the weekdays. As Peng & Liao (2023) noted, context and consequences are therefore critical. The immersive and reward-based design of many digital platforms – featuring mechanisms like endless scrolling and personalized content – can gradually lead users toward maladaptive patterns, even in the absence of initial intent.

Researchers thus stress the importance of distinguishing normal, habitual internet engagement from truly pathological use without pathologizing normative behaviors (Kuss & Lopez-Fernandez, 2016). The Research Domain Criteria (RDoC) framework, proposed by the U.S. National Institute of Mental Health (Insel et al., 2010), encourages the conceptualization of mental health disorders along of normal-to-pathology spectra. Instead of rigid categorical diagnoses, this approach recognizes that individuals fluctuate over time in their level of vulnerability and symptom severity (Figure 2.1.). At any given point, some individuals may be symptom-free, others may show early warning signs or emerging vulnerabilities, while some experience acute symptoms or crises; of these, some recover fully, whereas others develop persistent, recurrent problems (Gega et al., 2022). Applied to PIU, this approach suggests a nuanced spectrum of online engagement, categorizing internet-related behaviors on a developmental continuum from healthy to excessive or problematic (Anderson et al., 2017; Kaess et al., 2021). Consequently, it enables the capture of fluctuating symptom severity, allows subthreshold identification, and recognition of emerging and acute presentations, particularly within non-clinical populations.

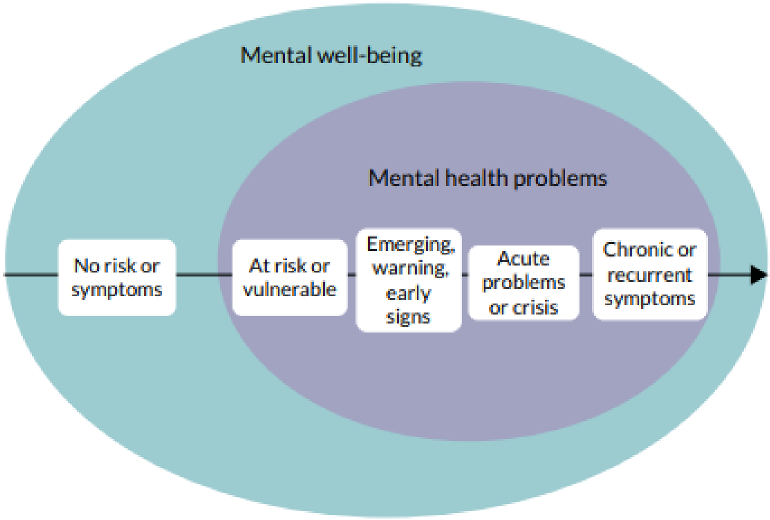

Figure 2.1. Conceptual continuum of mental health and well-being, illustrating the progression from no symptoms through varying degrees of vulnerability, early signs, acute problems, and chronic or recurrent symptoms of various mental health problems. This model emphasizes a dimensional view of mental health rather than categorical distinctions. In the context of Problematic Internet Use (PIU), such continuum-based frameworks are increasingly referenced to hypothetically conceptualize PIU not as a discrete disorder, but as a dynamic condition that may fluctuate across stages of risk, symptom emergence, and severity (image source: Gega et al., 2022).

2.1.2.3. Diagnostic recognition: addictive, impulsive, or compulsive?

Ongoing efforts to classify PIU have led to debates over its conceptual alignment: is PIU best understood as an addictive disorder, or does it fall more accurately under the categories of impulse-control or obsessive-compulsive spectrum disorders (OCD) (Brand, 2022; Fineberg et al., 2018; Ioannidis et al., 2018). Due to the lack of clear physiological markers, PIU has been conceptualized through multiple frameworks (Mihajlov & Vejmelka, 2017).

Behavioral addictions, described as non-chemical dependencies that do not involve the consumption of psychoactive substances (Griffiths, 2013), may share the same psychological and neurobiological features as substance use disorders (SUDs), with the “substance” in this case being a behavior that produces euphoria or relief. Core features – such as the desire to engage in a rewarding behavior, loss of control, withdrawal, and unsuccessful effort to cut down certain behavior, despite the negative consequences – are common to both behavioral and substance-related addictions (American Psychiatric Association, 2013; Lejoyeux et al., 2000; Smith & Seymour, 2004; Sussman & Sussman, 2011; WHO, 2019). These similarities have led scholars to suggest that behavioral addictions should be conceptualized based on the diagnostic criteria outlined in the fifth edition of Diagnostic and Statistical Manual of Mental Disorders (DSM-5; American Psychiatric Association, 2013). Consequently, PIU has increasingly been framed within this addiction paradigm. In a meta-analysis of 40 studies, Ioannidis et al. (2019) concluded that PIU shares multiple core features with addictions, including escalating use over time, repetitive behavior patterns (also characteristic of OCD), short-term gratification and reduction or loss of control (also feature of impulse disorders as inability to resist urges), long-term personal and social problems, failed attempts to cut back, high relapse rates, psychological distress when/if prevented from internet use (Ioannidis et al., 2019; Mihajlov & Vejmelka, 2017). Attempts to identify core addiction-like components have provided some structure. Griffiths (2005) proposed a six-component model of addiction – salience, mood modification, tolerance, withdrawal, conflict, and relapse – which has been applied to both substance and behavioral addictions. However, emerging evidence suggests that these components do not apply uniformly across all forms of online behavior. For instance, Fournier et al. (2023) found that in the context of Problematic Social Media Use (PSMU), salience and tolerance were not reliably linked to psychological outcomes. Similarly, Kaptsis et al. (2016) observed that negative emotional states during abstinence from gaming do not equate to the physiological withdrawal observed in psychoactive substance use. There was also criticism that these components might not differentiate high engagement from problematic use, and using such criteria risks pathologizing high, yet normative, media use (Cataldo et al., 2022; Peng & Liao, 2023).

To date, only a limited subset of internet-related behaviors – namely, Gambling Disorder and Gaming Disorder – has achieved formal diagnostic recognition. Problematic online gambling is recognized in both main classification systems – DSM-5 and International Classification of Diseases, 11th Revision (ICD-11; WHO, 2019) – as addictive behavior corresponding to the diagnosis of Gambling Disorder. Internet Gaming Disorder (IGD), sharing similarities with Pathological Gambling (PG) and Substance Use Disorders (SUDs) (Müller et al., 2014; Sanders & Williams, 2019), in DSM-5 is specified as the next candidate for inclusion and appears as a condition for further study. Meanwhile, ICD-11 already classifies Gaming Disorder under “disorders due to addictive behaviors”, characterized by impaired control over gaming, increased priority given to gaming over other activities to the extent that gaming takes precedence over other interests and daily activities, and continuation or escalation of gaming despite the occurrence of negative consequences. Beyond these, other problematic online behaviors –

such as excessive social media or internet-communication usage, pornography consumption, or online shopping – occupy a “gray zone” and remain informal and diagnostically unclassified (Baggio et al., 2022; Fineberg et al., 2025). However, there is growing evidence suggesting they can lead to addiction-like symptoms, including craving, functional impairment, failed attempts to reduce use (Billieux et al., 2017; Ho et al., 2014; Kardefelt-Winther, 2017; Lortie & Guitton, 2013; Wegmann et al., 2018) and have potential to cause severe life impairments comparable to those observed in formally recognized addictions (Ioannidis et al., 2019). To illustrate, Love et al. (2015) argue that problematic pornography use aligns with the addiction framework, as it mirrors substance addiction mechanisms by stimulating the brain’s reward circuitry. On contrary, other scholars criticize the confirmatory approach that applies SUDs criteria to behavioral addictions. They contend that excessive pornography use, gaming, or related behaviors is a result of underlying disorders, maladaptive coping mechanisms for low mood and life dissatisfaction, or consequences of voluntary choices rather than true addictive disorders (Billieux et al., 2019; Gullo et al., 2022; Kardefelt-Winther, 2017). Responding to these critiques, Griffiths (2019) emphasizes that if such exclusion criteria were strictly applied, few behaviors – including substance use itself – would qualify as addictions. He notes that many addictive behaviors begin as voluntary activities and often function as coping strategies or manifestations of underlying psychological issues yet still progress to significant functional impairments. However, as a result of such debates, all problematic behaviors – except IGD and PG – remain classified under "Other specified disorders related to addictive behaviors" (6C5Y) in the ICD-11, a category designed to code emerging addictive behaviors beyond gambling and gaming.

Neurobiological research supports the addiction framework to some extent. Neuroimaging studies have identified increased activation in all main brain regions linked to craving and reward processing, including the nucleus accumbens, amygdala, prefrontal cortex (PFC), and insula, particularly among individuals with IGD (Kuss et al., 2018). Additionally, dopaminergic function impairments and structural alterations in areas such as the dorsolateral PFC have been documented, mirroring neurobiological patterns observed in SUDs (Balodis & Potenza, 2020; Kayser, 2019; Sun et al., 2017). Nevertheless, there is also criticism that current neurobiological data are insufficient to establish PIU as equivalent to substance-based addictions, and directly comparing behavioral and chemical addictions is still speculative (Aarseth et al., 2017; Billieux et al., 2015; Deleuze et al., 2017; Starcevic & Aboujaoude, 2017; Van Rooij & Prause, 2014).

Alternative perspectives emphasize compulsivity and impulsivity as central mechanisms in PIU. Some forms of PIU, such as repetitive email checking, excessive video streaming or shopping, or cyberchondria, reflect compulsive patterns driven by attentional bias, intolerance of uncertainty or difficulty with decision-making (Fineberg et al., 2018; Liu et al., 2024). The overlap with impulse-control disorders is also notable, particularly in cases marked by the inability to resist urges despite adverse consequences. Repetitive, short-term reward-seeking behavior is characteristic of both domains [impulsivity discussed in detail in 2.1.4.2]. While PIU shares certain features with obsessive-compulsive disorder (OCD; e.g., repetitive behaviors) and impulse disorders (e.g., inability to resist urges) (Fineberg et al., 2018; Ioannidis et al., 2019), key differences exist: in OCD, compulsions are ego-dystonic and anxiety-relieving, whereas PIU behaviors are typically ego-syntonic and reward-seeking. However, both impulsivity and compulsivity, as dimensional variables, play an important role in both SUDs and behavioral addictions, including PIU (Ioannidis et al., 2016).

Some researchers further suggest that PIU may function as a compensatory mechanism to manage psychological distress or as a manifestation of underlying disorders (e.g., depression, social anxiety) rather than as a standalone disorder (Kardefelt-Winther, 2017; Mihajlov & Vejmelka, 2017; Schimmenti & Caretti, 2010). Such a position urges focusing on root causes instead of studying the addiction framework, which, according to Kardefelt-Winther (2017) "does not contribute much to an improved understanding of the antecedents and etiology of internet use disorders". Nevertheless, researchers and clinicians reveal cases where uncontrolled internet behavior presents as a primary complaint, including withdrawal-like symptoms and life disruptions akin to other addictions, supporting the notion that PIU can manifest independently, even if comorbidities are present (Fineberg et al., 2022; Smirni et al., 2023).

2.1.2.4. PIU prevalence estimates

Estimating the prevalence of PIU remains methodologically challenging due to conceptual inconsistencies, diverse diagnostic thresholds, and variation in measurement tools. Reported prevalence rates vary widely, for example, ranging from 1% to 36.7%, depending on the sample characteristics, instruments used, and cultural context (Ko et al., 2012). One key contributor to this variability is the inconsistency in PIU assessment. A systematic review by Laconi et al. (2014) identified 45 distinct instruments developed to measure PIU, yet only 17 had undergone repeated psychometric evaluation. Discrepancies in validation techniques across studies, alongside previously discussed challenges related to definitions and characterization, further undermine the comparability of prevalence estimates.

However, large-scale surveys and meta-analyses have attempted to produce more representative figures. For example, Durkee et al. (2012) reported an overall PIU prevalence of 4.4% among 11,956 adolescents across 11 European countries, with higher rates in males (5.2%) than females (3.8%). A systematic review and meta-analysis by Pan et al. (2020) estimated that approximately 7% of the global population may meet criteria for PIU. During the COVID-19 pandemic, this rate initially appeared to increase to 25%, but stricter criteria later adjusted the prevalence to 7.9% (Burkauskas et al., 2023). Notably, non-representative samples often yield inflated rates, representing frequencies in specific populations, rather than overall prevalence. For instance, a Hungarian study found a 19.1% PIU prevalence among high school students under age 25 (Feher et al., 2023), emphasizing the need for caution when interpreting prevalence data (Fineberg et al., 2022; Kapus et al., 2021; Pan et al., 2020).

Specific online activity subtypes also show substantial variability in usage and disorder prevalence. Social media remains the most popular online activity, with over five billion users worldwide as of 2024 and usage rates exceeding 95% among USA adolescents, a third of whom report near-constant use (Dixon & Statista, 2024; Office of the U.S. Surgeon General, 2023). A meta-analysis across 32 countries estimated the pooled prevalence of social media addiction at 5% for very severe symptoms, 13% for severe, and 25% for moderate-to-severe; however, estimates across studies varied from 0% to 82% (Cheng et al., 2021). Gaming is also highly prevalent worldwide, with approximately 2.6 billion global gamers reported in 2023; more than 80% of internet users aged 16 to 44 engage in gaming on any device (Clement & Statista, 2024). Gaming Disorder affects an estimated 3.05% of the global population (Stevens et al., 2021), though meta-analyses report pooled prevalence rates up to 8.6% among adolescents, with higher rates in some countries, such as China at 11.7% (Satapathy et al., 2025), and broader estimates ranging from 0.21% to 91% depending on sample and severity (Darvesh et al., 2020). Gambling prevalence studies estimate that 46.2% of adults and 17.9% of adolescents engaged in some form of gambling within the past year, with men exhibiting higher rates of risk gambling than women (11,9% vs. 5.5%, respectively). These figures suggest that nearly 450 million adults worldwide may be affected, with approximately 80 million individuals experiencing a gambling disorder or problematic gambling (Wardle et al., 2024). Regarding pornography use, prevalence exceeds 85% across all age groups, from individuals under 18 to those over 60 years old (Ballester-Arnal et al., 2023), with the risk of problematic pornography use estimated between 3.2% and 16.6% across 42 countries (Bőthe et al., 2024).

2.1.2.5. Contextual factors in PIU

Existing literature identifies multiple PIU influencing factors, including gender, age, socioeconomic status, cultural norms, and family environment.

Meta-analytic findings suggest that males are generally more prone to PIU than females, particularly regarding specific behaviors such as online gaming, gambling, and pornography use. In contrast, females more frequently exhibit problematic patterns of social media use, often classified as Social Network Use Disorder (Anderson et al., 2017; Durkee et al., 2012; Fineberg et al., 2025; Fineberg et al., 2022; Ioannidis et al., 2018; Kapus et al., 2021). A comprehensive meta-analysis of 115 samples from 34 countries with over 200,000 participants reported a higher overall tendency for PIU among males, with a small but significant effect size (Su et al., 2019). Notably, gender gaps were mostly pronounced in samples of Asian countries, while those in North America and Europe were minimal. Interestingly, meta-regression analyses indicated that nations with higher GDP per capita and broader internet access had smaller gender disparities. Cultural values and norms further influenced PIU patterns. Likely, societies that endorse gendered behavioral expectations or restrict internet use among women tend to exhibit more pronounced gender gaps in PIU, particularly when combined with differential access to digital resources (Su et al., 2019). These findings support both the “internet availability” and “social norms” hypotheses, suggesting that observed gender differences in PIU might be shaped by contextual factors.

Considering age-related factors, young individuals, particularly those under the age of 25, consistently exhibit the highest rates of PIU. Some studies report prevalence rates of up to 20% in this age group, further supporting the notion that the younger the age of the individual engaging with digital devices, the greater the susceptibility to addictive patterns (Feher et al., 2023; Kapus et al., 2021; Kuss & Lopez-Fernandez, 2016; Mihajlov & Vejmelka, 2017). Conversely, adults over 50 remain understudied; however, research suggests that the purpose of internet use also influences risk (Fineberg et al., 2022; Ioannidis et al., 2018). For instance, “time-wasting” activities or streaming content can exacerbate PUI among middle-aged and older adults; however, watching pornography content is more commonly reported by younger individuals (Ioannidis et al., 2018).

In regard to socioeconomic and cultural influences, living in metropolitan areas is associated with a higher risk of PIU (Durkee et al., 2012). As well, factors such as mobile device ownership, after-dark use, number of devices, and media type also shape screen time effects (Lissak, 2018). Lower family income, rural residence, and limited social support from school or work settings may increase vulnerability to PIU (Dahl & Bergmark, 2020). Additionally, a greater ratio for PIU is also observed in nations with higher pollution, higher traffic times, and lower life satisfaction (Cheng & Li, 2014).

Moreover, family environment and social support also play important role. For instance, the quality of parent–child relationship significantly influences the risk of compulsive internet use. Emotional distance, low parental involvement, and unsatisfactory family environments may drive adolescents toward maladaptive online coping strategies (Kardefelt-Winther, 2017). Shi et al. (2023) found that psychological distress mediates the relationship between family atmosphere and PIU, and the family atmosphere-self-esteem-internet addiction pathway plays a key intermediary role. Behaviors such as parental "phubbing" (ignoring a child in favor of a phone) may indirectly predict PIU risk by undermining adolescents' psychological needs (Liu et al., 2024). However, Pew Research (Auxier et al., 2020) reported that 17% of American parents often feel distracted by their phones while spending time with their children, and an additional 52% acknowledge being sometimes distracted. In such circumstances, young individuals may struggle to regulate their internet use, compounding the risks of developing PUI. Furthermore, students living apart from parents, those with unemployed caregivers, or those reporting low parental engagement are at elevated risk for both moderate and severe PIU (Durkee et al., 2012). On the contrary, supportive family environments appear to serve as protective factors. Yu & Shek (2013) demonstrated that adolescents from positive home environments showed a significant reduction in PIU symptoms over two years.

2.1.2.6. Conclusion

Problematic Internet Use (PIU), defined as maladaptive online behavior, is characterized by impaired control over use and negative consequences, with prevalence estimates varying considerably due to inconsistent definitions and assessment tools. While high internet engagement is not inherently pathological, distinguishing it from clinically significant use remains central and is best viewed along a continuum. PIU is heterogeneous, manifesting in both generalized and specific forms (e.g., gaming, social media), and overlapping with addictive, impulsive, and compulsive disorders. Although only Gaming and Gambling Disorders have received formal recognition, many PIU behaviors share features of behavioral addictions. However, applying a uniform addiction model to all forms of PIU risks oversimplification. A dimensional approach that accounts for both shared characteristics and distinct symptom profiles offers a more precise and clinically relevant understanding. These insights provide a foundation for exploring the psychological, cognitive, and neurobiological impacts of PIU.

2.1.3. Psychology of PIU and mental health correlates

2.1.3.1. Motivational factors in internet use behaviors

Motivational factors play an important role in understanding the development and maintenance of PIU. As considered in a systematic review by Kuss & Lopez-Fernandez (2016) based on 46 clinical studies, initial motivations for engaging with online platforms – such as seeking social interaction, emotional escapism, or achievement – may drive intensified internet activity. Over time, this intensified engagement can displace alternative offline activities and interpersonal interactions, reducing opportunities for healthier coping strategies. Consequently, what initially serves as an adaptive method for managing real-life stress or emotional discomfort may gradually evolve into maladaptive avoidance coping, further exacerbating mental health disorders and promoting longer-term adverse effects (Feher et al., 2023).

Motivations for internet engagement also differ substantially across platform types. For example, use of social networking platforms is often driven by motives such as social interaction, information seeking, and self-enhancement (Al-Menayes, 2015; Masciantonio & Bourguignon, 2023). In contrast, online gaming is more closely linked to emotional escapism, achievement striving, and competitive urges (Bäcklund et al., 2022; Wang & Cheng, 2022). However, motives for engagement might vary even within the same platforms. For example, considering internet gaming, Lee et al. (2017) proposed a typology for individuals with Internet Gaming Disorder (IGD), identifying emotionally vulnerable players as one key subgroup among impulsive/aggressive, socially conditioned, and unspecified types. Among emotionally vulnerable gamers, gaming serves both as a source of positive reinforcement and as a self-remedy for emotional suffering or self-dissatisfaction. Empirical findings indicate that nearly one-third of online gamers report using gaming to escape negative feelings and everyday problems (Hussain & Griffiths, 2009). Although these online activities (e.g. video games or social media) may temporarily fulfill these needs or relieve negative emotions by providing relief or escape (Brand et al., 2019; Mehroof & Griffiths, 2010), persistent maladaptive use is associated with worsened symptoms of depression, anxiety, loneliness, and self-discrepancy (Brand et al., 2019), Moreover, certain platform features, particularly image-centric social media, contrary to expectations may independently contribute to negative emotional outcomes, for example by fostering upward social comparisons, thereby amplifying anxiety and depressive symptoms (Brand et al., 2019; Dahl & Bergmark, 2020; Fineberg et al., 2022).

However, the relationship between online engagement and engagement motives (e.g., escapism or mood modification) is not inherently pathological. Using online activities to alleviate daily stress may function as an adaptive coping strategy; for instance, individuals who use gaming to alleviate stress from daily life, thereby enhancing their daily functioning, may not necessarily indicate problematic behavior (Lee et al., 2017). Yet, over-reliance on the online world, when online activities become the primary or exclusive means of coping, the risk of developing maladaptive patterns and problematic behaviors increases (Lee et al., 2017). Thus, motivational factors must be interpreted with caution, recognizing that online engagement can range from adaptive coping to maladaptive dependency depending on broader psychosocial circumstances.

2.1.3.2. Psychological impact and comorbidities of PIU

The clinical significance of PIU is underscored by its profound psychological impacts, supported by extensive research into its consequences. It is generally acknowledged that PIU rarely occurs in isolation; rather, it frequently coexists with various psychiatric comorbidities such as depression, anxiety disorders, impulse control disorders, substance use disorders (SUDs), and Attention Deficit Hyperactivity Disorder (ADHD) (Carli et al., 2013; Fineberg et al., 2022; Ho et al., 2014; Kuss & Lopez-Fernandez, 2016; Petersen et al., 2009; Weinstein & Lejoyeux, 2010). Particularly pronounced in problematic internet users are impulsivity and obsessive-compulsive symptoms, highlighting the complex interplay between psychological distress and compulsive online behaviors (Cao et al., 2007; Carli et al., 2013; Fineberg et al., 2022; Wang et al., 2017). Multiple studies further emphasize that mood and anxiety disorders are particularly prevalent, suggesting that comorbidity between PIU and these conditions is more typical than exceptional (Kuss & Lopez-Fernandez, 2016). For instance, Carli et al. (2013) conducted a systematic review showing psychiatric comorbidity rates in PIU ranging from 57% for anxiety, 75% for depression, and up to 100% for ADHD. In contrast, Ho et al. (2014) reported lower rates, ranging from 13.3% to 21.7% with ADHD, 23.3% with anxiety and highest rates (26.3%) with depression, supporting the view that psychiatric comorbidity in PIU mirrors patterns observed in substance use and addictive disorders, where comorbidity typically ranges from 20% to 30%. Moreover, as summarized by Fineberg et al. (2025), individuals with emotional and behavioral disorders or ADHD are often driven by impulsivity and the pursuit of positive reinforcement online; those with obsessive-compulsive or autism-related symptoms and attentional inflexibility may struggle to disconnect; while individuals with internalizing disorders are more likely to use the internet as a means of escaping real-life distress through negative reinforcement.

However, high online involvement alone does not necessarily indicate psychological issues. Recent research on problematic social media use identified distinct user subgroups, with only problematic users showing severe symptoms of depression, anxiety, and stress, while highly engaged but low-risk users exhibited minimal psychological distress (Peng & Liao, 2023), suggesting that it is not mere internet engagement, but the presence of problematic use patterns that is strongly associated with psychiatric comorbidities. On the other hand, the clinical picture also points to the possibility of more severe psychiatric outcomes. A scoping review by Huot-Lavoie et al. (2023) summarized cases of gaming disorder associated with psychotic episodes, identifying intensified gaming time and abrupt gaming withdrawal as possible triggers. Although rare, these findings highlight the potential for severe psychiatric outcomes in extreme cases and underscore the need for further research. Taken together, these findings illustrate that the relationship between PIU and mental health problems is neither simple nor unidirectional, indicating a cyclical dynamic where internet use both exacerbates and stems from psychological distress (Fineberg et al., 2022). On the other hand, this highlights the possibility that interventions targeting either PIU or comorbid psychiatric symptoms may positively influence the other (Kuss & Lopez-Fernandez, 2016).

Beyond clinical psychiatric comorbidities, PIU is also associated with significant impairments in quality of life and functional outcomes. Severe mental health impairments resulting from PIU are linked to substantial reductions in overall quality of life, with meta-analyses consistently demonstrating associations between PIU, diminished well-being, and impaired physical health (Feher et al., 2023; Noroozi et al., 2021). Reductions in life satisfaction have been observed across multiple domains, including family relationships, friendships, academic experiences, and living environment (Noroozi et al., 2021). As discussed in 0, individuals with PIU also frequently exhibit irregular sleep patterns and reduced sleep duration, prioritizing online activities over rest, which exacerbates daytime fatigue, insomnia symptoms, and reliance on sleep medication (Exelmans & Van den Bulck, 2015; Feher et al., 2023). Emotional exhaustion, depersonalization, and reduced personal accomplishment – key features of burnout – also frequently co-occur with PIU (Feher et al., 2023), potentially reinforcing maladaptive online behaviors or, conversely, arising as a consequence of stress exacerbated by excessive internet use. Critically, these patterns may not only impair daily functioning but also exacerbate existing psychiatric vulnerabilities or contribute to the development of additional mental health disorders.

2.1.3.3. Personality traits as risk and protective factors for PIU

Personality traits – defined as relatively stable habitual patterns of attitude, behavior, emotion, and thought (Eysenck, 1991) - provide a useful framework for a deeper understanding of individual susceptibility to problematic internet behaviors. Research consistently shows that certain personality dimensions and specific traits confer vulnerability, whereas others may offer protection, while a combination of dysfunctional traits may result in personality disorders (American Psychiatric Association, 2013).

Big Five personality dimensions and PIU

A substantial body of evidence highlights the influence of the Big Five traits – neuroticism, extraversion, agreeableness, conscientiousness, and openness – on PIU. Traits such as extraversion, agreeableness, conscientiousness, and openness often function protectively, whereas neuroticism substantially elevates risk. These findings are supported by a wide range of studies, including a 2016 meta-analysis involving more than 12,000 individuals (Kayiş et al., 2016) and a comprehensive 2021 meta-analysis of over 34,000 participants (Mak et al., 2021), both identifying neuroticism - and, in the latter case, psychoticism – as critical risk factors for problematic internet behaviors. Further reviews converge on similar patterns. Floros & Siomos (2014) noted positive correlations between internet overuse and neuroticism, psychoticism, sensation seeking, and openness, but negative correlations with extraversion, agreeableness, conscientiousness, reward dependence, and self-directedness. Likewise, Gervasi et al. (2017) confirmed that high neuroticism and low extraversion, agreeableness, conscientiousness, and openness to experience increase vulnerability to pathological internet use and online gaming addiction. A more recent review focusing on internet gaming by Şalvarlı & Griffiths (2022), based on more than 16,500 gamers, yielded parallel findings, again underscoring neuroticism and diminished levels of other Big Five traits as key risk indicators.

As summarized by Kayiş et al. (2016), extraverted individuals typically maintain positive in-person interactions, reducing the need for excessive online engagement. Conscientious individuals, with their stronger impulse control and rule-bound approach, are more likely to adequately control internet use habits. Similarly, agreeable individuals' empathy and tolerance appear to buffer them from compulsive online behaviors, while those high in openness, being curious, flexible, and open to novelty, often prefer real-world experiences over exclusively virtual alternatives. However, findings regarding openness and extraversion have been inconsistent. Several studies report either a positive association or no significant correlation between these traits and PIU (Andreassen et al., 2013; Floros & Siomos, 2014; Papastylianou, 2013; Rahmani & Lavasani, 2011). For instance, Andreassen et al. (2013) found that agreeableness was negatively associated with multiple behavioral addictions – including Facebook use, gaming, internet use, exercise, mobile phone use, compulsive buying, and study addiction – while neuroticism showed positive associations. However, extraversion demonstrated positive correlations with all measured behavioral addictions. Also, Floros & Siomos (2014) reported that curiosity and novelty-seeking traits in individuals high in openness may also foster certain forms of problematic online engagement.

Taken together, these findings suggest that while some personality traits generally serve as risk (e.g., neuroticism) or protective factors against PIU, their effects are not uniform across all individuals or contexts.

Neuroticism as a core vulnerability factor for PIU

Growing evidence identifies neuroticism as a psychological trait of profound public health significance (Marciano et al., 2020). A meta-analysis of longitudinal and prospective studies encompassing over 440,000 participants concluded that neuroticism not only correlates with psychological issues but also significantly predicts the onset of common mental disorders, including anxiety, depression, and general psychological distress (Jeronimus et al., 2016). Moreover, neuroticism was defined as the strongest longitudinal predictor of internalizing – and, to a lesser extent, externalizing – psychopathology (Jeronimus et al., 2016). Extensive research has shown that neuroticism affects virtually all aspects of personality functioning, fostering a persistently negative and anxious view of oneself and the environment (Costa & McCrae, 2008).

Neuroticism – characterized by frequent negative emotions and affects, abnormal stress reactivity, poor coping mechanisms, heightened threat perception, and emotional instability (Widiger & Oltmanns, 2017) – was linked to various forms of problematic internet behaviors, such as general PIU, smartphone addiction, social media addiction, and gaming disorder (Brand et al., 2016; Floros & Siomos, 2014; Gervasi et al., 2017; Kayiş et al., 2016; Mak et al., 2021; Marciano et al., 2020; Smirni et al., 2023). In these cases, internet-related behaviors may serve as maladaptive coping strategies, offering temporary relief from distress by providing a more manageable and comfortable environment (Kayiş et al., 2016; Marciano et al., 2020).

Moreover, Marciano et al. (2020) proposed that PIU may reflect deeper dysfunctional aspects of character and behavior, aligning with the "vulnerability model." According to this framework, high levels of neuroticism intensify the negative impact of stressors through cognitive mechanisms such as negativity biases in attention, memory, and interpretation, as well heightened emotional reactivity, and ineffective coping strategies. This may both directly and indirectly facilitate the onset of common mental health disorders. As a result, internet engagement alleviates negative emotions by offering immediate emotional rewards and reducing real-world distress (Smirni et al., 2023). These observations align with theoretical models like the I-PACE model[1] (Brand et al., 2016), which posits that maladaptive internet use stems from negative affective states and deficits in self-regulation. Over time, these factors strengthen the association between negative emotional states and specific online activities through conditioning processes.

In support, a longitudinal study by Tian et al. (2021) examined the relationships among the personality traits, maladaptive cognitions, and internet addiction. Neuroticism positively correlated with vulnerability factors for internet addiction (such as low self-esteem, loneliness, depression, and social anxiety), while the rest of the traits correlated negatively. Tian et al. (2021) further highlighted the role of maladaptive cognitions (cognitive distortions about the self and the world, and the internet serving as the only place where one feels good about themselves) in mediating the link between personality traits and PIU. These cognitions serve as “proximal sufficient causes,” channeling broader psychopathology (the “distal necessary cause”, such as depression, social anxiety, and substance dependence) into internet-based addictive behaviors. When negative beliefs about oneself and one’s environment intensify, individuals may retreat further into online contexts, limiting social support and increasing isolation and interpersonal issues. Over time, this “vicious cycle” can further affect personality traits and exacerbate existing personality vulnerabilities, reinforcing the maladaptive cycle of excessive internet engagement.

[1] The Interaction of Person-Affect-Cognition-Execution (I-PACE) model (Brand et al., 2016) is a comprehensive theoretical framework, conceptualizing problematic internet-related behaviors as the outcome of dynamic interactions among individual predispositions, cognitive and affective responses to situational cues, diminished executive functioning, and the reinforcing effects of conditioning processes.

These associations suggest that dysfunctional internet behaviors may, in many cases, reflect broader emotional and interpersonal vulnerabilities of highly neurotic individuals, rather than solely indicating problematic internet engagement.

2.1.3.4. Interoception and its role in PIU

Beyond traditional psychological and personality factors, cognitive–perceptual mechanisms such as interoception have also emerged as a potential contributor to addictive behaviors.

Interoception, broadly defined as the ability to perceive and interpret internal bodily signals arising from external and internal stimuli, plays a critical role in maintaining homeostasis and regulating emotional and behavioral responses (Craig, 2002; Khalsa et al., 2018). It encompasses three empirically distinct facets: interoceptive accuracy (the objective recognition of bodily changes, such as heartbeat detection), interoceptive sensibility (associated with the subjective experience and trust in these internal bodily signals), and interoceptive awareness (defined as the metacognitive insight into the accuracy of one’s bodily perceptions) (Forkmann et al., 2016; Garfinkel et al., 2015). Emerging evidence suggests that deficits in interoceptive functioning may contribute to heightened stress sensitivity, emotional dysregulation, impulsivity, loneliness, depression, anxiety, and increased vulnerability to impulsive and addictive behaviors (Herman, 2023; Khalsa et al., 2018; Namkung et al., 2018; Wei et al., 2017). According to Naqvi & Bechara (2010), interoception contributes to addiction by modulating the subjective experience of pleasure, the recall of these experiences, and the decision-making processes weighing anticipated rewards against costs. As interoceptive awareness influences decisions based on the body's need to maintain homeostasis, inadequate interoceptive processing contributes to dysfunctions in approach–avoidance behaviors, disrupting craving regulation and self-control, thus increasing vulnerability to maladaptive behaviors (Herman, 2023; Paulus & Stewart, 2014).

At the neurobiological level, interoception is associated with brain structures that have been implicated in addictive disorders (Droutman, Read, et al., 2015; Naqvi et al., 2007; Naqvi & Bechara, 2009, 2010). The insula is considered as the central hub for interoceptive processing (Barrett & Simmons, 2015), involved in integration of emotional regulation (Wiebking & Northoff, 2014), decision-making (Droutman, Bechara, et al., 2015), cravings (Naqvi et al., 2007; Wei et al., 2017), the balance between impulsive and reflective systems maintenance (Cai et al., 2014), and the coordination among brain networks involved in processing salient and motivational cues

(Droutman, Bechara, et al., 2015; Droutman, Read, et al., 2015). Early studies demonstrated that lesions disrupting the insular cortex can halt addictive behaviors. For instance, Naqvi et al. (2007) reported, that previously smoking patients with insular damage effectively "forgot the urge to smoke"[2]. Since then, alterations in insular activity have been consistently reported in substance use disorders (Droutman, Read, et al., 2015; Naqvi et al., 2007; Naqvi & Bechara, 2009, 2010) and across behavioral addictions, suggesting that interoceptive dysfunction may represent a shared vulnerability factor[3].

Notably, interoception, as a function of the insula, has been investigated to some extent in Internet Gaming Disorder (IGD). Neuroimaging studies have identified several alterations in the insula among individuals with IGD, including decreased gray matter volume (Jeong et al., 2016), disrupted resting-state functional connectivity (Chen et al., 2016; Li et al., 2023; Zhang et al., 2015), and increased activity in response to gaming cues following periods of gaming deprivation (Turel et al., 2021). Additionally, insula activation has been positively associated with the intensity of gaming cravings (Ko et al., 2009). Intervention studies further demonstrated that targeting craving-related processes can modulate insula activity and alleviate IGD symptoms (Zhang et al., 2016).

Similar patterns have been observed across other problematic internet-related behaviors as well. Namely, decreased insular activity during the

[2] To illustrate, smoking-associated airway sensations are encoded as pleasurable experiences by the insula and are stored in memory. Absence of these sensations triggers cravings through somatic marker representations, leading to the insular cortex generating a physical craving and urge for the desired sensation (Droutman, Read, et al., 2015; Naqvi & Bechara, 2010). These processes involve insular connections with the "impulsivity network" (e.g., ventral striatum, amygdala, nucleus accumbens) and the "reflection-oriented system" (e.g., dorsolateral and ventromedial prefrontal cortices).

[3] Historically, neurocognitive models have framed addiction as an imbalance between two interacting systems: an impulsive network (the amygdala-striatum dopamine pathway) and a reflective system (the prefrontal cortex), which handles planning and inhibitory control (Herman, 2023). However, such a perspective was challenged by the previously mentioned studies indicating that insular damage can disrupt addictive behaviors and prompted an expanded triadic neurocognitive model of addiction (Noël et al., 2013). Within this framework, interoception is an integral component, bridging bodily signals with impulsive and reflective processes. Wei et al. (2017) applied this model to Internet Gaming Disorder (A Tripartite Neurocognitive Model of Internet Gaming Disorder), proposing that an interoceptive system mediates both physical and psychological cues, ultimately shaping bodily signals into craving states and contributing to addiction.

processing of pornographic images in internet pornography users (Antons & Matthias, 2020), excessive recruitment of insula circuitry in problem gambling (Clark et al., 2014), negative associations between insula activity and social media addiction symptoms (Turel et al., 2018), and distinct patterns of insular connectivity between problematic online sport bettors and non-problematic users (Brevers et al., 2024). Such findings further confirm the insula's involvement in reward-driven behaviors and support the role of interoceptive dysfunction across diverse forms of PIU.

Despite these insights, direct investigations of interoceptive processes in problematic internet behaviors remain limited (Droutman, Read, et al., 2015). To date, there's only one recent study (Di Carlo et al., 2024) that directly touches upon interoceptive awareness and PIU. A notable study by Di Carlo et al. (2024) investigated this relationship through self-report questionnaires, including the Multidimensional Assessment of Interoceptive Awareness (MAIA), among a sample of 1076 participants. The findings reveal that participants at risk for PIU displayed reduced interoceptive capabilities across three MAIA dimensions: (1) noticing, or perceiving body sensations; (2) not-distracting, or responding to negative bodily signals; and (3) not-worrying, or worrying excessively about these body sensations. Interestingly, the study found that the severity and impact of PIU may not only depend on individual interoceptive abilities but also on how these capacities interact. According to the authors, individuals with PIU demonstrated a tendency to distract themselves from unpleasant bodily sensations, indicating an avoidance-based coping style. By turning to the internet instead of addressing discomfort, these individuals may reinforce the cycle of PIU. Over time, these patterns can undermine executive functioning, decision-making, and inhibitory control, potentially altering the interoceptive insular system.

Taken together, current findings suggest that impaired interoceptive functioning may constitute an important vulnerability mechanism in problematic behaviors, as disruptions in bodily awareness and regulation may contribute to emotional dysregulation and maladaptive coping patterns. However, the relationship between interoceptive awareness and internet usage behaviors appears to be a relatively unexplored area in the literature, with limited previous research available.

2.1.3.5. Conclusion

Taken together, a wide range of motivational, psychological, personality, and interoceptive factors contribute to the development and maintenance of PIU. Maladaptive coping motives, psychiatric comorbidities, personality vulnerabilities – particularly neuroticism – and disturbances in interoceptive processing appear to interact in a dynamic and often cyclical manner, exacerbating both internet-related and broader psychological difficulties. While a significant amount of research efforts has clarified some of these mechanisms, further research is needed to disentangle the conditions under which internet use shifts from adaptive engagement to maladaptive dependency and to better understand the underlying underpinnings of these transitions.

2.1.4. Cognitive control, impulsivity, and inhibition in PIU

The impacts of PIU extend beyond psychological disturbances into neurophysiological domains, as evidenced by neuroimaging findings. Emerging data suggest that shifting lifestyles, particularly reduced engagement in real-world activities in favor of virtual environments, may diminish cognitive reserve and potentially accelerate neurocognitive decline (Firth et al., 2019).

2.1.4.1. Cognitive control impairments in PIU

PIU has been linked to a broad range of cognitive impairments, including deficits in attentional and motor inhibition, decision-making, working memory, risk-taking choices, emotional regulation, conflict detection, information processing efficiency, and heightened reward sensitivity (D'Hondt et al., 2015; Weinstein, 2017; Yuan et al., 2011). Growing evidence thus suggests that individuals with PIU may be best characterized by a "loss of control" over online behaviors (Brand et al., 2014; D'Hondt et al., 2015).

At the neurocognitive level, PIU appears to produce structural and functional brain alterations that resemble patterns seen in substance-related addictions and gambling disorders, all characterized by maladaptive reward-seeking behaviors and executive function impairments (D'Hondt et al., 2015; Kuss & Griffiths, 2012; Yuan et al., 2011). For instance, research on IGD shows that excessive gaming may lead to diminished impulse control (due to the dysregulation of reward pathways and increased dopamine release, resembling SUDs), alongside disruptions in learning, memory, and processing of auditory, visual, and somatosensory stimuli (Lissak, 2018; Weinstein, 2017).

These findings reinforce theories positing that cognitive impairments – indicating underlying frontostriatal dysfunction – play a key role in the pathophysiology of PIU and suggest shared neurobiological vulnerabilities across various online behaviors (Ioannidis et al., 2019). Structural and functional brain alterations, particularly in frontostriatal regions, have been consistently reported in individuals with PIU, especially during executive function and cue-reactivity tasks (Brand et al., 2014; Yuan et al., 2011). Specifically, grey matter volume alterations in areas such as the orbitofrontal cortex (OFC), dorsolateral prefrontal cortex (dlPFC), dorsal anterior cingulate cortex (dACC), and insula correlate with both the severity and duration of PIU (Weng et al., 2013; Yuan et al., 2011; Zhou et al., 2024). Such associations suggest that brain alterations may arise as consequences, rather than causes of prolonged excessive engagement. For example, Zhou et al. (2019) reported that excessive gamers exhibited lower right OFC volume compared to gaming-naïve individuals, with reductions correlating with addiction severity. Moreover, a six-week online role-playing game intervention in previously gaming-naïve participants resulted in notable grey matter decreases in the OFC (a region integral to impulse control and decision-making), directly linking excessive gaming to structural deficits.

Moreover, Chang & Lee (2024) proposed that Internet Addiction (IA) induces widespread neural alterations rather than changes restricted to isolated regions. Their review highlights significant disruptions within large-scale brain networks – particularly the default mode network (DMN), executive control network (ECN), salience network (SN), and reward pathways – pointing to shifts in reward valuation, impulsivity, salience attribution, and cue reactivity. These findings underscore the importance of both within-network and between-network dysfunctions in sustaining IA and shaping its behavioral manifestations.

However, a recent longitudinal study by Christensen et al. (2024) introduced an important nuance. Their findings indicate that baseline neurocognitive functions poorly predicted addictive behaviors, including PIU, over a six-month period, except for delay discounting predicting problematic pornography use. This contrasts with prior research that has consistently linked PIU to neurocognitive deficits. A critical methodological difference may explain these discrepancies: Christensen et al. (2024) studied general community samples, compared to clinical or more severe samples in previous studies. Interestingly, when a shorter three-month follow-up timeframe was used, certain neurocognitive functions were able to predict PIU, although with small effect sizes. Notably, greater goal-directed performance (i.e., reduced reward-related attentional bias) and lower risk-taking under uncertainty predicted higher PIU at follow-up. This temporal sensitivity may lend support to the continuum model, suggesting that meaningful neurocognitive variability in PIU emerges primarily at higher symptom severity levels.

Given the broad range of cognitive impairments associated with PIU, the focus of the present work narrows to impulsivity and, in particular, response inhibition as core mechanisms of interest. Accordingly, the following subchapters will explore these domains in greater detail, examining their contribution to the neurocognitive profile of problematic internet use.

2.1.4.2. PIU, impulsivity, and response inhibition

One possible approach to distinguishing problematic from non-problematic internet use is through the lens of response inhibition – the capacity to suppress impulsive reactions incompatible with long-term goals and to maintain goal-directed behavior by resisting internal and external distractions (Brand et al., 2019; Hofmann et al., 2012). Impulsivity and impairments in inhibitory control are central features implicated in the development and maintenance of numerous psychiatric and behavioral disorders, including learning difficulties, mania, schizophrenia, OCD, post-traumatic stress disorder (PTSD), anxiety, and depression (Clarke et al., 2024; Hoptman et al., 2024; Zhang et al., 2017).

Elevated impulsivity and deficits in inhibitory control – alongside impaired reward-based decision-making – are consistently reported in populations with ADHD, SUDs and behavioral addictions such as smoking, alcohol and drug use, and gambling, supported by converging evidence from both behavioral and neurobiological studies (Beppi et al., 2020; Brevers & Noël, 2013; Fillmore & Rush, 2002; Jentsch & Pennington, 2014; Kozak et al., 2019; Spinella, 2002; Winstanley et al., 2006; Zhang et al., 2017).

Similarly, multiple studies have identified impairments in both cognitive and motor inhibition, as well as elevated impulsivity, in individuals with PIU (Carli et al., 2013; Chen et al., 2017; Fineberg et al., 2022; Ioannidis et al., 2019; Meerkerk et al., 2010; Wang et al., 2017). Although these impairments are not specific to addiction, they appear to function as both risk factors and consequences of compulsive and addictive behaviors across the lifespan, among both adolescents and adults (Burnette et al., 2019; Green et al., 2023; Kozak et al., 2019; Rømer Thomsen et al., 2018).

Conceptualizing impulsivity

Impulsivity is a complex, multidimensional construct broadly defined as a predisposition toward rapid, unplanned responses to internal or external stimuli, or a tendency to prematurely act on immediate desires, often undertaken without adequate consideration of potential negative consequences (Dalley et al., 2011; Herman et al., 2018; Moeller et al., 2001). It is commonly characterized by diminished self-control, heightened sensation-seeking behavior, poor impulse control, and behavioral tendencies such as urgency, risk-taking, aggression, and impaired planning (Winstanley et al., 2006). At its core, impulsivity reflects a "failure of the inhibitory process" (Bari & Robbins, 2013). However, due to the use of varied definitions under the umbrella term “impulsivity”, the construct has been a source of conceptual confusion in the literature (Sanders et al., 2020).

Current evidence indicates that impulsivity is not a unitary construct, but rather encompasses multiple distinct dimensions, making the singular use of the term scientifically imprecise (MacKillop et al., 2016). Conceptually, impulsivity manifests across trait and state dimensions. Trait impulsivity refers to a relatively stable personality characteristic, while state impulsivity reflects context-dependent increases in impulsive behavior in response to emotional or situational triggers (Winstanley et al., 2006).

At the behavioral level, impulsivity is commonly divided into three domains: motor impulsivity (also referred as impulsive action), cognitive impulsivity (or impulsive choice) and non-planning impulsivity (reflecting trait-level executive dysfunction)[4] (MacKillop et al., 2016; Winstanley et al., 2006). Within this framework, motor impulsivity refers to failure to inhibit a prepotent or to withhold from making a motor response. Cognitive impulsivity reflects impaired decision-making and a preference for immediate rewards over delayed but more advantageous ones. Non-planning impulsivity involves a lack of foresight and difficulties in attention regulation, risk evaluation, and future planning (MacKillop et al., 2016; Winstanley et al., 2006).

Taken together, impulsivity comprises a constellation of interrelated yet distinct tendencies. Deficits across these domains contribute to impairments in executive functioning and behavioral regulation, often manifesting as an inability to anticipate long-term outcomes and resist emotionally salient cues – patterns commonly observed in individuals with psychiatric and addictive disorders (Barratt, 1985; Stanford et al., 2009).

[4] Another widely adopted framework dissecting distinct impulsivity dimensions is the UPPS model (Whiteside & Lynam, 2001). The original model identifies four core dimensions differing in expression and psychological correlates: (negative) urgency, defined as a tendency to act rashly under emotional distress and linked to neuroticism; (lack of) premeditation, reflecting a tendency to act without considering consequences, related to poor executive function and low conscientiousness; (lack of) perseverance, referring to difficulties in maintaining attention or effort on challenging and monotonous tasks, also linked to conscientiousness; and sensation seeking, defined as a preference for novel and stimulating experiences, linked to extraversion and positive affect (Sperry et al., 2016; Whiteside & Lynam, 2001). A fifth dimension, positive urgency, was added in the updated UPPS-P model to capture rash actions in response to extreme positive emotions (Cyders et al., 2007).

Inhibition as a core executive function

Executive control is a fundamental domain of cognitive functioning, responsible for regulating attention, working memory, information processing, and inhibitory control (Beppi et al., 2020). Inhibitory control is described as an active mechanism that modulates internally or externally driven urges toward primary reinforcers – such as food, sex, or other rewarding stimuli. When functioning properly, this mechanism suppresses conditioned, reflexive, irrelevant, or maladaptive responses, thereby enabling slower, deliberative processes to guide goal-directed behavior (Winstanley et al., 2006).

Cognitive control is supported by two interrelated mechanisms: proactive inhibition and reactive inhibition (Beppi et al., 2020; Borgomaneri et al., 2020; Braver, 2012; Mäki-Marttunen et al., 2019). Proactive inhibition refers to an anticipatory form of control that involves the sustained maintenance of task-relevant information in working memory, which directs attention, perception, and motor responses toward goal-consistent behavior. Although it helps prevent interference and optimizes performance, proactive inhibition is cognitively demanding and heavily reliant on attentional and working memory resources (Beppi et al., 2020; Braver, 2012). In contrast, reactive inhibition operates as a late-stage corrective mechanism, recruited in response to unexpected events or interference (Braver, 2012; Mäki-Marttunen et al., 2019). It functions through conflict detection and episodic memory processes, enabling the rapid suppression of already-initiated actions and the reconfiguration of behavior in response to immediate contextual demands (Beppi et al., 2020).

Although proactive and reactive inhibition differ in timing, function, and their underlying neural mechanisms, they are interdependent and complementary (Beppi et al., 2020; Borgomaneri et al., 2020; Mäki-Marttunen et al., 2019). Proactive inhibition is more resistant to distraction but requires greater cognitive resources, whereas reactive inhibition offers flexibility and speed at the cost of greater vulnerability to interference (Beppi et al., 2020; Braver, 2012). For example, as illustrated by Borgomaneri et al. (2020), a driver may engage proactive inhibition by reducing speed in anticipation of a pedestrian crossing, or rely on reactive inhibition to brake suddenly if a pedestrian unexpectedly steps onto the road. Together, these mechanisms form a dynamic regulatory system that adjusts behavior according to changing environmental and cognitive demands (Beppi et al., 2020; Braver, 2012).

Inhibitory control is further categorized into two domains: behavioral inhibition and cognitive inhibition (Beppi et al., 2020). Behavioral inhibition – also referred to as motor inhibition, response inhibition, or impulsive action – involves the active suppression of automatic, habitual, or prepotent motor responses when they become inappropriate or goal-incongruent (Aron, 2007). In research settings, this domain is typically divided into action withholding (which refers to inhibiting a response before it is initiated) and action cancellation (terminating an already initiated response). By contrast, cognitive inhibition (also referred to as impulsive choice) entails the suppression of mental processes – such as distracting memories, inappropriate attentional shifts, or irrelevant stimuli and external intrusions – that interfere with goal-directed behavior (Winstanley et al., 2006). In experimental research, cognitive inhibition is typically subdivided into incongruency and decision-making domains.

In summary, inhibitory control reflects a dynamic, multidimensional system involving anticipatory and corrective processes that regulate behavior in changing contexts. Deficits in either domain can compromise goal-directed control, with implications for a wide range of psychiatric and behavioral conditions.

Assessment of impulsivity: self-report and behavioral measures

Trait impulsivity is frequently assessed using self-report questionnaires, which are widely employed in both clinical and research settings (Vassileva & Conrod, 2019; Winstanley et al., 2006). Among the most prominent tools are the Barratt Impulsiveness Scale (BIS-II) (Barratt, 1959; Patton et al., 1995), which comprises attentional (cognitive), motor, and non-planning impulsivity (Stanford et al., 2009), and the UPPS Impulsive Behavior Scale (Whiteside & Lynam, 2001), derived from the Five-Factor Model of Personality. Both scales have gained recognition as gold standards for capturing distinct facets of impulsive behavior (Sanders et al., 2020; Stanford et al., 2009).

Beyond self-report instruments, the study of state impulsivity and response inhibition heavily relies on behavioral paradigms designed to isolate specific deficits in cognitive and motor control (Vassileva & Conrod, 2019). These paradigms provide objective, task-based metrics and are widely used in cognitive neuroscience and clinical research to examine inhibitory control function across healthy and clinical populations. Key paradigms include Go/NoGo and Stop Signal Tasks (SST), Delay Discounting tasks, Rule inhibition, and cognitive interference paradigms (such as Stroop task, Eriksen Flanker task, Simon task, etc.)[5].

These tasks target distinct aspects of inhibitory control. Cognitive inhibition is commonly examined via delay-discounting tasks, which typically assess reward-based decision-making by requiring individuals to choose between smaller-sooner and larger-later rewards (Burnette et al., 2019; Zhang et al., 2024). A steeper discounting curve reflects a greater tendency to devalue future rewards, indicating a preference for immediate gratification (Winstanley et al., 2006). Another broad domain of cognitive inhibition is typically assessed using incongruency tasks (e.g., interference suppression and rule inhibition), which usually require individuals to selectively respond to task-relevant stimuli amidst distracting or conflicting information (Zhang et al., 2017). Meanwhile, response inhibition is typically assessed through response suppression tasks (e.g., Go/NoGo, SST). As this work focuses on response inhibition, these paradigms are discussed in greater detail in the following subchapter.

Together, both self-report instruments and behavioral paradigms offer a comprehensive framework for investigating the behavioral and neural mechanisms underlying maladaptive behaviors.

Measuring response inhibition: Go/NoGo and SST paradigms

Two classical paradigms – the Go/NoGo and Stop-Signal Tasks – are widely employed to measure response inhibition and are used extensively in both clinical and non-clinical populations to assess inhibitory control and impulsivity (Beppi et al., 2020; Winstanley et al., 2006).

In the Stop-Signal Task (SST), participants are instructed to make speeded responses to “Go” signals but occasionally must inhibit their response upon presentation of a “Stop” signal (Zhang et al., 2017). The primary outcome of the SST is the Stop-Signal Reaction Time (SSRT), which estimates the time required to halt an already initiated response; failure to inhibit the “Stop” signal results in an inappropriate, impulsive response (Dalley et al., 2011).

[5] Even though indirectly, other behavioral tasks also invoke inhibitory processes at some stage and can also be used for behavioral impulsivity assessment. For instance, a commonly used paradigm that indirectly assesses impulsive action is the Five-Choice Serial Reaction Time Task (5CSRTT; M. Carli et al., 1983), developed to measure sustained and divided attention in rodents, however, also requires response inhibition. Originally, this task required subjects to respond to brief light stimuli in one of five apertures. Responses made during the inter-trial interval – prior to stimulus onset – are considered premature and are punished, serving as indicators of motoric impulsivity (Winstanley et al., 2006).

During the Go/NoGo task, participants are instructed to respond quickly to "Go" stimuli and to withhold responses to "NoGo" stimuli (Zhang et al., 2017; see Chapter 2.2.4.1 for an in-depth discussion of the Go/NoGo paradigms).

Although the SST and Go/NoGo tasks appear similar, as in both individuals respond to "Go" stimuli and must withhold responses to NoGo or Stop signals – they engage distinct processes (Dalley et al., 2011; Zhang et al., 2017). The Go/NoGo task involves action withholding, meaning the inhibition of a prepotent but not yet initiated response, making it a standard measure of motor impulsivity. In contrast, the SST measures reactive inhibition, as it requires action cancellation – the ability to cancel a motor response that has already been initiated. In other words, the Go/NoGo task resembles a SST trial with a stop signal delay of 0 s. While this may seem like a small procedural difference, evidence clearly demonstrates that different subprocesses are involved, as discussed in the following subchapter.

However, both tasks align with the Horse Race Model (Logan et al., 1984), which conceptualizes inhibitory control as a race between two competing processes: one initiating the "Go" response and the other halting it ("NoGo" or "Stop" response). Based on this model, inhibitory success during NoGo or Stop trials depends on the relative speed of these processes: successful inhibition occurs if the Stop process finishes before the Go process reaches its execution threshold. However, while the latency and variability of the Go response can be observed directly, the NoGo and Stop response is internally generated and cannot be directly measured (Logan et al., 1984; Pires et al., 2014).

Neural mechanisms of inhibition

Neuroimaging and lesion studies consistently associate inhibitory control with the functioning of the prefrontal cortex (PFC) (Aron, 2007; Winstanley et al., 2006). Specifically, the dorsolateral prefrontal cortex (dlPFC), inferior frontal gyrus (IFG), and anterior insula (AI) are frequently identified as key cortical hubs involved in response inhibition (Dalley et al., 2011; Hung et al., 2018; Zhang et al., 2017). Research shows that IFG and AI coordinate the mediation of both proactive and reactive inhibition and are particularly implicated in the suppression of automated responses in SST and Go/NoGo tasks (Beppi et al., 2020; Rubia et al., 2001). Although both structures are critical for stopping a response, they are not exclusively dedicated to motor inhibition. The IFG, which is closely connected to dlPFC, is involved in action selection and competition, and is thought to play a dominant role in initiating inhibitory commands. However, it also contributes to action updating and cognitive flexibility, highlighting its broader involvement in executive control processes (Beppi et al., 2020; Borgomaneri et al., 2020). In contrast, the AI is more closely associated with salience detection and may facilitate conflict resolution and the redirection of attention toward stimuli, including those requiring inhibition (Beppi et al., 2020; Borgomaneri et al., 2020).

A review of inhibitory control and error processing in individuals with substance dependence and behavioral addictions by Luijten et al. (2014) concluded that hypoactivation of PFC regions – namely the anterior cingulate cortex (ACC), IFG, and dlPFC – is among the most consistent findings among addicted individuals compared to healthy controls. However, these neural deficits do not always correspond to impaired task performance.

Functional neuroimaging further reveals that inhibition is not governed by a single brain region but emerges from dynamic interactions within distributed networks. Growing evidence supports functional specialization within the frontoparietal circuit, with activation patterns that vary depending on contextual demands and sensory modality (Beppi et al., 2020; Erika-Florence et al., 2014). Moreover, inhibitory control is also not solely a cortical function. Frontostriatal circuits play a central role in the regulation of impulse control, as demonstrated in both human and animal models. These circuits involve distinct but converging neural pathways comprising both cortical and subcortical structures that regulate various aspects of impulsive behavior (Jupp et al., 2013; Winstanley et al., 2006). Frontal regions may act as modulators of motor output via cortico-striatal–thalamic–cortical loops, relaying inhibitory signals to motor execution areas such as the supplementary motor area (SMA), pre-SMA, and supplementary eye fields (SEF) (Aron, 2007; Zhang et al., 2017). Subcortical structures – especially the striatum, nucleus accumbens (NAc), and subthalamic nucleus (STN) – are particularly important. Impairments in these regions, such as chemical dysregulation, may compromise an individual's capacity to align behavior with long-term goals or contextual demands (Dalley et al., 2011; Pezze et al., 2009). Additionally, dopaminergic transmission within corticostriatal circuits has also been implicated in impulsivity, with evidence suggesting that disrupted dopamine signaling contributes to the impairments of inhibitory control and pathophysiology of impulse control disorders (Jupp et al., 2013).

Meta-analyses further support the view that inhibition is not a unidimensional construct but rather a composite of subcomponents engaging overlapping and distinct neural networks. In a large-scale meta-analysis of 323 experiments, Zhang et al. (2017) identified consistent activations across all inhibition tasks in structures such as the IFG, insula, dlPFC, pre-SMA, and temporo-parietal junction. These regions primarily recruited the frontoparietal and ventral attention networks, as the core neural systems engaged during response inhibition. However, different subtypes of inhibition showed distinct neural signatures. Interference resolution tasks (e.g., Stroop, Flanker) engaged both dorsal and ventral attention networks more than action withholding or cancellation. Action withholding (Go/NoGo task) predominantly activated the frontoparietal network, particularly bilateral insula and right caudate, while action cancellation (SST) engaged both ventral attention and frontoparietal systems, activating regions such as the right IFG, SMA, and right superior parietal gyrus. Hung et al. (2018) extended these findings in a meta-analysis of 66 fMRI studies comparing cognitive, emotional, and motor (response) inhibition. While AI activation was common across domains, distinct neural systems were recruited across all inhibitory domains. Cognitive inhibition (e.g., attention suppression) activated a dorsal frontoparietal network (dACC, dlPFC, parietal cortex) associated with top-down control and attention-driven cognitive control processes. Emotional interference inhibition (e.g., suppressing affective distraction) recruited a ventral frontal-limbic network (including the ventral IFG and amygdala), consistent with bottom-up emotional regulation. Response inhibition (e.g., Go/NoGo, SST) was supported by a frontostriatal system involving dACC, SMA, dlPFC/vlPFC, basal ganglia, midbrain, and parietal regions – highlighting its role in coordination between sensory-motor processes and top-down executive control.

Together, neuroimaging evidence underscores the multidimensional and context-sensitive nature of inhibition. Rather than relying on a single pathway, inhibitory control emerges from dynamic coordination among functionally specialized cortical and subcortical networks tailored to the demands of different inhibitory domains.

Impulsivity and inhibitory deficits in addictive behaviors

Research spanning SUDs, behavioral addictions, and emerging conditions like PIU consistently identifies impaired inhibition and elevated impulsivity, especially its behavioral and emotional dimensions, as a critical vulnerability factor.

Impulsivity traits – such as urgency and lack of perseverance – have been identified as potential predictors of various substance- and addiction-related behaviors (e.g., binge eating, alcohol and other drugs use, problematic pornography use; although the association with IGD is less consistent) (Rømer Thomsen et al., 2018). Meerkerk et al. (2010) reported that impulsivity was a stronger predictor of compulsive internet use than psychosocial well-being, underscoring impulsivity as a core vulnerability trait linked to reduced control over internet use. This is further supported by findings linking PIU with

ADHD, as both conditions are characterized by poor self-control, boredom intolerance, and a preference for immediate rewards (Andreassen et al., 2013; Feher et al., 2023; Wang et al., 2017). ADHD symptoms – particularly inattention and sensation seeking – have been shown to predict PIU severity (Dalbudak et al., 2015), though excessive internet use may also serve as a maladaptive coping mechanism for managing ADHD-related attentional difficulties (Ho et al., 2014)[6].

In IGD, impulsivity plays a critical role in the onset, development, and maintenance of the disorder. A 2-year prospective study by Gentile et al. (2011) identified impulsivity as a significant predictor of pathological gaming in children, along with high gaming frequency and low social competence, while depression, anxiety, social phobia, and academic underperformance appeared as outcomes of IGD. A systematic review by Şalvarlı & Griffiths (2022) further confirmed its role, reporting consistent positive associations between impulsivity and IGD across 32 of 33 studies encompassing 18,128 participants. Other studies show that low impulse control and high anxiety both appear to predispose individuals to excessive gaming habits (Griffiths et al., 2012; Mehroof & Griffiths, 2010; Şalvarlı & Griffiths, 2022). Moreover, as proposed by Lee et al. (2017), online activities such as gaming may themselves exacerbate impulsivity and reduce executive control, creating a vicious cycle in which heightened impulsivity leads to excessive gaming, which in turn further impairs impulse control and contributes to the development of problematic behavior.

Beyond gaming, impulsivity has also been implicated in other forms of PIU. Wéry et al. (2018) found that negative urgency predicted excessive online sexual activity. Similarly, Antons et al. (2019) reported that individuals with problematic internet pornography use exhibited higher delay discounting, attentional impulsivity, dysfunctional coping, and craving compared to recreational users, though no group differences were observed in motor or non-planning impulsivity. Individuals with PIU also share impulsivity with Pathological Gambling (PG) patients, interestingly, with PIU being more impulsive than PG patients (Zhou et al., 2016).

At the behavioral level, individuals with PIU demonstrate deficits in response inhibition, again paralleling impairments seen in ADHD and SUDs, and suggesting shared underlying neurobiological impairments (Anderson et al., 2017; Argyriou et al., 2017). D'Hondt et al. (2015) reported broad executive functioning impairments in individuals with PIU, including

[6] In that regard, Lissak (2018) raised concerns about overdiagnosis, noting that screen-induced ADHD-like behavior may be misinterpreted as clinical ADHD.

deficient cognitive inhibition, impaired behavioral monitoring, and diminished self-error detection. Gervasi et al. (2017) proposed that impaired self-regulation may increase the risk of developing IGD. Supporting this view, a meta-analysis by Argyriou et al. (2017) examined inhibitory control via neurocognitive tasks (namely, Go/NoGo, Stroop, and SST) and found that individuals with IGD performed tasks significantly worse than controls, as evidenced by impaired measures of inhibition, such as increased errors when withholding responses.

Neuroimaging studies further support these behavioral findings, revealing alterations in brain structures associated with inhibitory control and impulse regulation in individuals with PIU, particularly those with IGD (Argyriou et al., 2017; Dong & Potenza, 2014; Petry et al., 2015). From a neurobiological perspective, impulsivity in SUDs is thought to result from an imbalance between bottom-up reward reactivity and top-down regulatory control, mediated by interlinked neural circuits (Kozak et al., 2019). There is a broad consensus in the field of substance addiction that initial substance use primarily affects the PFC and mesolimbic reward system, involved in goal-directed behavior and reinforcement, respectively. With continued substance use, behavioral control progressively shifts from the PFC to the dorsal striatum, which supports the development of habitual, compulsive behaviors (Kuhn et al., 2019). This trajectory aligns with the Dual-Process model, an influential theoretical framework proposed by Bechara (2005). The model conceptualizes the dynamic nature of inhibitory control, posing that behavior emerges from the competition between two competing systems: an impulsive system (bottom-up control) and a reflective system (top-down control). Impulsivity arises when bottom-up drives overwhelm top-down control[7]. Furthermore, both trait impulsivity and deficits in inhibitory control have been linked to increased cue-elicited craving (Papachristou et al., 2013). For

[7] Based on this model, addiction arises from an imbalance between two interacting neural systems: a hyperactive impulsive system centered in the amygdala, which responds to immediate rewards and punishments, and a weakened reflective system in the prefrontal cortex, which is responsible for goal-directed behavior and evaluates long-term consequences. Normally, reflective system controls the impulsive system, however the imbalance between the systems, potentially present before drug use, impairs decision-making by allowing bottom-up signals from the amygdala to override reflective top-down control, thereby hijacking cognitive resources necessary for self-regulation and willpower and increasing susceptibility to substance use (Bechara, 2005; Kozak et al., 2019). As one could expect, in adolescents, an immature inhibitory control system due to underdeveloped prefrontal top-down control and hyperactive ventral striatal response makes them especially vulnerable to addictive behaviors (Chambers et al., 2003).

instance, sensation seeking has been associated with increased frontostriatal reactivity in response to addiction-related cues (potentially reflecting stronger craving responses), while lower delay reward discounting correlates with increased frontoparietal activation to these cues (potentially indicating increased cognitive control to maintain less impulsive decision making) (Burnette et al., 2019).

Similar patterns are evident in PIU. Review of electrophysiological studies shows a hypoactive reflective-control system and a hyperactive impulsive system in individuals with internet addiction (D'Hondt & Maurage, 2017). These individuals display reduced prefrontal efficiency during cognitive tasks and exaggerated reward system activation when exposed to addiction-related cues. This imbalance may contribute to heightened craving and arousal when confronted with internet-related stimuli, combined with a reduced ability to control this urge and inhibit addictive behavior. Individuals high in impulsivity and low in inhibitory control also often exhibit impaired emotional regulation and are more likely to exhibit problematic internet behaviors, such as excessive gaming, gambling, digital bingeing, and compulsive social media use (Jupp & Dalley, 2014; Moretta & Buodo, 2021; Rømer Thomsen et al., 2018; Yen et al., 2017).

Moreover, impaired activity in the dlPFC and ACC, along with heightened striatal activation, has been documented in IGD (Chen et al., 2020). A meta-analysis by Meng et al. (2015) also reported that hyperactivity in the dlPFC and cingulate gyrus (including the ACC) was positively associated with IGD severity, as indexed by weekly hours online, reflecting a failure of self-regulation and elevated gaming urges. Additionally, reduced gray matter volume in the ACC and SMA has been linked to impulsivity, while structural alterations in the ventrolateral PFC were associated with lifetime gaming duration in excessive internet gamers who began gaming in early adolescence (Lee et al., 2018). The ACC – often identified as one of the most affected regions in IGD – is involved in conflict monitoring and error processing and may contribute to impaired impulse control and a disrupted balance between goal-directed behavior and reward-seeking (Lee et al., 2018), consistent with the I-PACE model (Brand et al., 2019).

Furthermore, as discussed by Chen et al. (2020), the high-level reward stimuli embedded in online games – and similar reward-sensitive design features in other platforms (e.g., variable reinforcement or infinite scroll, exploiting bottom-up impulsive systems (Fineberg et al., 2025; Robbins & Clark, 2015)) – may activate dorsal striatum reward pathways and suppress prefrontal activity. Over time, dysfunctional prefrontal-striatal connectivity and disrupted dopaminergic signaling within mesolimbic circuits further exacerbate inhibitory deficits and compulsive reward-seeking, reinforcing maladaptive impulsive behavior, such as prolonged gaming.

However, findings across studies are not entirely consistent. For example, while Dong et al. (2010) and Kim et al. (2017) reported increased cognitive resource allocation during successful inhibition in individuals with PIU and IGD, Littel et al. (2012) failed to replicate these effects, instead observing compromised error processing in excessive computer gamers. Furthermore, Christensen et al. (2024) identified a negative relationship between delay discounting and problematic pornography use (PPU) severity (though this may be attributable to low overall PPU severity within the sample and sample attrition, as participants who failed to return for a 6-month follow-up had higher baseline PPU scores and steeper delay discounting). Nevertheless, Wegmann et al. (2018) found no direct association between general executive functioning or specific inhibitory control domains and symptom severity in problematic social network users; however, interaction effects suggested that attentional impulsivity combined with reduced executive or social-networking domain-specific inhibitory control increases susceptibility to problematic use.

2.1.4.3. Conclusion

Taken together, converging evidence positions impulsivity and inhibitory control impairments as significant factors contributing to PIU and related behaviors (Brand et al., 2019; Zhang et al., 2017). These impairments closely parallel dysfunctions observed in both substance use disorders and behavioral addictions, suggesting overlapping neurocognitive mechanisms, particularly including dysregulated frontostriatal circuitry and altered prefrontal functioning.

Yet, despite robust cross-sectional associations, findings remain inconsistent – longitudinal data are inconclusive, and neurobiological markers of impaired inhibition in high internet users vary across studies (Christensen et al., 2024; Kozak et al., 2019; MacKillop et al., 2011). It remains unclear whether observed alterations reflect stable neurocognitive deficits, compensatory adaptations, or functional reorganization within cognitive control systems (Argyriou et al., 2017). A more nuanced understanding of the neurobiological dynamics underlying inhibitory dysfunction, especially across different stages and severities of internet use, may help refine diagnostic models and inform more effective, targeted interventions for PIU.

2.2. Electrophysiological correlates of PIU: insights from EEG

The pathophysiology of various disorders is often preceded by neurophysiological impairments that manifest prior to the onset of overt clinical symptoms, underscoring the utility of neurophysiological monitoring in early diagnosis and disorder management. Identifying cost-effective, reliable, and clinically translatable biomarkers is essential for facilitating early detection and intervention (Khanna et al., 2015). While various neuroimaging methods can elucidate brain changes associated with problematic behaviors, most of these methods are expensive, and their use in wide-scale or multiple-testing studies is cost-ineffective. Electroencephalography (EEG) presents a viable alternative due to its non-invasive, affordable, and real-time recording capabilities of bioelectrical brain activity (Bunge & Kahn, 2009). The method is well-suited for large-scale or repeated assessments and has shown promise in exploring neurophysiological mechanisms underlying various conditions and behaviors (Arjoonsingh et al., 2024), including PIU (D'Hondt et al., 2015).

Initially developed by Hans Berger in 1924, EEG was first employed to document cortical oscillations from the human scalp, including the alpha rhythm, also known as the Berger wave, and beta waves (İnce et al., 2021). Since then, subsequent research has associated distinct frequency bands – delta (1–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), beta (13–30 Hz), and gamma (>30 Hz) – with a variety of cognitive functions, physiological and consciousness states, behaviors, and psychiatric conditions (Anderson & Perone, 2018; Donoghue et al., 2022). These oscillations play a fundamental role in coordinating sensory and cognitive processes and have been linked to over 50 distinct functions, including perception, motor control, attention, learning, and memory, underscoring their central importance in neural communication and integration (Başar et al., 2001).

However, given the multidimensional nature of EEG signals, diverse analytical approaches have been developed to extract meaningful neural features and evaluate their functional significance (Anderson & Perone, 2018; Khanna et al., 2015). Nevertheless, EEG is now a well-established method for capturing temporally precise recordings of superficial postsynaptic brain activity both at rest and during cognitive tasks (Bunge & Kahn, 2009; Khanna et al., 2015).

2.2.1. Resting-state EEG & neural network alterations in PIU

Resting-state EEG refers to the recording of intrinsic brain activity in the absence of sensory or task-driven stimulation, typically conducted under eyes-open or eyes-closed conditions without active cognitive engagement (Anderson & Perone, 2018; Deco et al., 2011; Khanna et al., 2015). Broadly, it serves as an index of the brain's spontaneous electrical activity, generated by the synchronized firing of neuronal populations within a specific frequency range (Anderson & Perone, 2018). In contrast to task-based recordings, resting-state measures are less influenced by momentary cognitive fluctuations and thus offer a robust framework for detecting stable alterations in functional brain organization (Babiloni et al., 2021).

Notably, rest is an active brain state. Resting-state fMRI studies have revealed multiple simultaneously engaged brain networks, showing fluctuating activity in regions associated with various functions and typically active during task performance (e.g., executive functioning, auditory processing, motor activity, among others) (Damoiseaux et al., 2006; Mantini et al., 2007). Such results confirms that the brain typically does not produce isolated rhythms confined to specific frequency bands or localized neural circuits, but rather exhibits a convergence of overlapping rhythmic activities across distributed networks (Mantini et al., 2007). However, the default mode network (DMN) is the only network consistently active in the absence of external tasks (Damoiseaux et al., 2006). While the precise function of the DMN remains to be fully understood, growing evidence suggests that it may coordinate prior task-related activity and support the consolidation of recent experiences (Anderson & Perone, 2018). Moreover, the DMN is linked to alpha-band activity (Bonnard et al., 2016; Mantini et al., 2007), which is the dominant frequency observed during relaxed wakefulness (Grandy et al., 2013; Reznik & Allen, 2018; Smith et al., 2017). As demonstrated by Bonnard et al. (2016), applying transcranial magnetic stimulation to the medial prefrontal cortex (mPFC) – a key node of the DMN – enhances alpha power in occipital regions. This supports the notion that the DMN may play a mechanistic role in generating or sustaining alpha rhythms during rest.

Given the involvement of large-scale networks like the DMN in shaping spontaneous brain activity at rest, resting-state EEG provides a valuable approach for examining these intrinsic neural dynamics. It captures fluctuations across multiple frequency bands and has been widely used to investigate both typical and disordered neural functioning (Anderson & Perone, 2018; Newson & Thiagarajan, 2018). As a baseline measure, it allows researchers to identify patterns that may reflect underlying neural mechanisms of various psychological disorders (Anderson & Perone, 2018), including addictive behaviors (Liu et al., 2022). Although relatively few studies have examined resting-state EEG in individuals with PIU (Burleigh et al., 2020), this line of research is expanding, offering unique insights into baseline brain functioning in these populations. For example, Choi et al. (2013) found that increased gamma power and decreased beta power were associated with higher PIU and impulsivity levels. Similarly, Lee et al. (2014) reported that treatment-seeking individuals with Internet Addiction (IA) and no comorbid depression exhibited reduced delta and beta power, suggesting deficits in information processing and inhibitory control, respectively. In contrast, those with comorbid depression demonstrated elevated theta and decreased alpha power, indicating divergent EEG profiles depending on comorbid affective states. These findings suggest that specific EEG frequency bands may hold the potential to differentiate between pure and comorbid forms of PIU.

Alterations in functional brain network organization have also been observed. For instance, Sun et al. (2019) reported that individuals with PIU exhibited more random network organization in the beta and gamma bands, suggesting disrupted neural integration and balance. Hong et al. (2022) further showed that underlying neurophysiological networks during the resting-state in individuals with IGD varies among gamers. Alterations in beta and delta activity, along with reduced intrahemispheric coherence in the theta, delta, and beta bands – which were linked to impaired visuospatial working memory – differ based on gaming patterns (a single game vs. multiple games) and the type of games they play (first-person shooters vs. massively multiplayer online role-playing games (MMORPGs)).

Findings from resting-state fMRI further corroborate EEG-based observations. For example, Wang et al. (2015) identified reduced homotopic connectivity between prefrontal areas among individuals with IGD. Notably, reduced connectivity in the superior frontal gyrus (orbital part) was specifically associated with higher scores on the Chen Internet Addiction Scale (CIAS), and not with anxiety, depression, or impulsivity, underscoring the potential specificity of these disruptions to PIU-related processes rather than general psychopathology.

Together, resting-state studies provide converging evidence of functional disruptions in PIU, revealing frequency-specific and network-level alterations that reflect both shared and distinct features of neurocognitive functioning in addictive behaviors. Since resting-state EEG may reflect stable, trait-like neural patterns rather than transient state effects, these findings suggest that specific EEG markers could help identify individuals at risk for PIU and track its progression over time.

2.2.2. EEG resting-state alpha asymmetry

2.2.2.1. Characteristics and functional role of alpha oscillations

Alpha waves, typically ranging from 8 to 12 Hz, are the most prominent in posterior cortical regions, particularly the occipital cortex, during eyes-closed wakefulness and states of reduced cognitive engagement (Cantero et al., 2002). In resting-state studies, alpha activity is commonly viewed as a marker of spontaneous brain dynamics, associated with low arousal and relaxed alertness (Babiloni et al., 2021). Notably, mindfulness practices have been associated with increased alpha power, reflecting cortical 'deactivation' that signifies a state of relaxed alertness and underscores the role of alpha activity in regulating internal cognitive states (Lomas et al., 2015).

While early theories emphasized a link between alpha frequency and information processing speed, more recent frameworks conceptualize alpha oscillations as a mechanism for the timing of neural inhibition and the gating of information flow (Grandy et al., 2013; Olaniyan et al., 2023). In general, alpha activity is thought to inversely reflect cortical activity, supporting inhibitory function in large-scale network dynamics by facilitating the synchronization of these neural networks (Reznik & Allen, 2018; Smith et al., 2017). Moreover, as recently showed by Lombardi et al. (2023), alpha oscillations may serve as an active "pacemaker" for regulating cortical excitability regulation rather than merely reflecting reduced arousal. It is likely that alpha waves modulate both the suppression and enhancement of neural activity during resting wakefulness (Lombardi et al., 2023).

These rhythms appear to be shaped by thalamic inputs via thalamo-cortical loops and modulated through cortico-cortical interactions (Başar et al., 2001; Cantero et al., 2002; Hampel et al., 2018; Olaniyan et al., 2023). Although the exact neural origins of alpha rhythms remain debated, evidence suggests that several cortical generators may be involved in the generation of alpha oscillations (Olaniyan et al., 2023). However, anterior and posterior EEG alpha patterns observed during relaxed wakefulness may represent a single, spatially distributed brain phenomenon across the scalp (Cantero et al., 2002)

Research on alpha oscillations has produced an extensive body of literature encompassing psychophysiological, physiological, developmental and clinical domains (Cantero et al., 2002; Newson & Thiagarajan, 2018). Considering addiction research, alpha waves seem to exhibit substance-specific modulation patterns – for instance, alcohol and opioid dependence correlate with reduced alpha power (although findings across studies are not always consistent), while nicotine consumption produces a widespread alpha increase, and tobacco deprivation leads to an alpha decrease (Domino et al., 2009; Ehlers & Phillips, 2007; Liu et al., 2022). Within PIU, alpha desynchronization and decreased frontal alpha power during eyes-closed resting-state was associated with the severity of internet addiction (Wang & Griskova-Bulanova, 2018), possibly reflecting deficits in inhibitory control (Grandy et al., 2013; Olaniyan et al., 2023) or altered default mode network functioning (Bonnard et al., 2016; Mantini et al., 2007).

2.2.2.2. Concept and measurement of alpha asymmetry

In general, alpha asymmetry refers to the relative difference in alpha power between homologous left and right brain regions (Reznik & Allen, 2018; Smith et al., 2017). Given the inverse relationship between alpha power and cortical activity, greater alpha power in one hemisphere is interpreted as reduced neural activity in that region (Reznik & Allen, 2018). Alpha asymmetry is commonly computed as the log-transformed difference between right and left alpha power values, with positive scores indicating greater relative left hemisphere activity and negative scores indicating relative right hemisphere dominance (Reznik & Allen, 2018; Smith et al., 2017). However, although such alpha asymmetry scores reflect the relative difference in alpha power between hemispheres, they do not specify whether high scores arise from reduced left alpha power, increased right alpha power, or both, thus limiting their interpretive specificity (Smith et al., 2017).

In general, alpha asymmetry can be assessed during both resting-state and task-related conditions (Reznik & Allen, 2018; Smith et al., 2017). In this context, alpha "activity" refers to the absolute level of alpha power during a given time window, whereas "activation" indicates changes in that level in response to task demands or internal states (Reznik & Allen, 2018; Smith et al., 2017). However, most studies examining alpha asymmetry focus on resting-state alpha activity, as opposed to task-evoked activation (Smith et al., 2017) and research has been implicated in affective, motivational, and cognitive processes, with altered asymmetry patterns reported in various psychiatric and neurological conditions (Ocklenburg et al., 2024). Furthermore, approximately 60% of alpha asymmetry variability appears to reflect stable, trait-like neural characteristics that are reliably associated with psychological and neurocognitive constructs (Fox et al., 1995; Hagemann et al., 2002; Stewart et al., 2011).

A prominent theory suggests that lateralized resting-state frontal alpha asymmetry (FAA) reflects trait-like predispositions toward affective (positive vs. negative) and motivational (approach vs. avoidance) orientations, while task-evoked activation represents transient state-related emotional or motivational responses (Smith et al., 2017). According to the approach-withdrawal model (Davidson, 1992), greater relative left frontal activity is associated with approach motivation and positive affect (e.g., self-control, optimism, anger, jealousy, and higher well-being), whereas right frontal dominance is linked to withdrawal motivation and negative affect (e.g., sadness, fear, and empathy) (de Vries et al., 2023; Kelley et al., 2017; Reznik & Allen, 2018; Smith et al., 2017).

However, despite EEG resting-state alpha asymmetry is the most investigated marker of brain lateralization, research has predominantly focused on frontal asymmetry, leaving parietal alpha asymmetry largely underexplored (Metzen et al., 2022; Wang et al., 2025). Although both regions are involved in attention modulation, information processing, and behavioral control, the parietal cortex plays a critical role in attention allocation and polymodal sensory processing (Bush, 2011). Moreover, posterior alpha activity is maximal during rest and shows greater temporal stability and consistency across conditions than frontal asymmetry (Metzen et al., 2022; Schneider et al., 2016; Umemoto et al., 2021). The valence–arousal model (Heller et al., 1997) further highlights distinct regional roles in modulating arousal-related processes; with higher left frontal activity associated with anxious apprehension (i.e., worry), and right parietal activity reflecting anxious arousal (e.g., panic) (Heller et al., 1997; Metzger et al., 2004; Umemoto et al., 2021).

2.2.2.3. Alpha asymmetry as a neural correlate in psychopathology

Alpha asymmetry has also been broadly explored in relation to psychopathology. For instance, greater relative left FAA has been found in individuals with ADHD (higher frontal and central, but not parietal asymmetry), whereas lower relative left FAA has been associated with depressive and anxiety symptoms (Keune et al., 2011, 2015; Reznik & Allen, 2018). Longitudinal studies suggest that reduced relative left FAA (left parietal hypoactivity as well) may act as a vulnerability marker, predicting the later development of depressive symptoms (Mitchell & Pössel, 2012; Pössel et al., 2008). Alterations in brain asymmetry have also been reported in schizophrenia and PTSD (Ocklenburg et al., 2024; Reznik & Allen, 2018), and greater variability in relative left FAA has been linked to trait neuroticism (Minnix & Kline, 2004). In terms of emotional regulation, Papousek et al. (2011) showed that individuals with higher regulation capacity returned to baseline relative left FAA levels after exposure to anxiety-inducing stimuli, while those with lower regulation exhibited sustained relative left frontal alpha asymmetry changes. These results suggest that FAA variability is adaptive and may serve as an index of emotional flexibility and regulation ability, while relative left FAA alterations during rest may indicate inability to regulate emotions and vulnerability to psychopathology.

Beyond affective processing, FAA has also been associated with executive functions, verbal fluency, worry, and cognitive control (Smith et al., 2017). For instance, in a recent study Akil et al. (2024) investigated the relationship between resting-state FAA and inhibitory control using EEG, the Stop-Signal Task (SST), and transcranial direct current stimulation (tDCS) targeting the dlPFC. Although no direct behavioral effects of FAA or tDCS were found, greater relative right frontal activity was associated with reduced early inhibitory responses (as indexed by Stop-N2) and enhanced later inhibitory responses (Stop-P3), suggesting a temporal dissociation in the relationship between FAA and different stages of inhibitory control.

Furthermore, parietal alpha asymmetry has been associated with individual personality differences, emotion processing, and emotional vulnerability, dysregulated behavioral activation, depression, anhedonia, and traits like rumination and self-criticism (Metzen et al., 2022; Schiltz et al., 2018; Umemoto et al., 2021). Notably, parietal asymmetry often exhibits patterns opposite to frontal asymmetry (Metzen et al., 2022; Schiltz et al., 2018) (Schiltz et al., 2018; Metzen et al., 2022). For instance, depressive symptoms, vulnerability for emotional disruption, internalizing symptoms, and greater behavioral activation (BAS) have been attributed to higher relative left-sided activity in parietal areas, as opposed to the observed right hemisphere dominance at frontal sites (Baik et al., 2019; Blackhart et al., 2006; Metzen et al., 2022; Schiltz et al., 2018).

2.2.2.4. Conclusion

In summary, the asymmetrical distribution of alpha power across cortical regions represents a promising neurophysiological marker of both trait-like and state-dependent cognitive and affective processes. Patterns of frontal and parietal alpha asymmetry have been linked to motivational tendencies, emotional regulation, executive functioning – including attention and inhibition control – and a range of psychopathological conditions. While frontal asymmetry has been extensively studied, emerging evidence underscores the relevance of parietal asymmetry and its distinct contributions to emotional and cognitive vulnerabilities.

However, despite these strong associations, alpha asymmetry is not regarded as a sufficient standalone diagnostic biomarker. Rather, it may serve as a meaningful index of symptom expression, risk status, or treatment response (Ocklenburg et al., 2024; Reznik & Allen, 2018). Furthermore, the interpretability of resting-state alpha asymmetry is limited by spontaneous, internally driven cognitive processes that vary across individuals and time, potentially influencing both affective and cognitive components (Reznik & Allen, 2018). Nonetheless, given the established associations between alpha asymmetry, psychopathology, and executive functioning, resting-state alpha asymmetry remains a promising, albeit indirect, underexplored neural correlate for research on PIU.

2.2.3. EEG resting-state microstates

In contrast to traditional region- or frequency-specific EEG analyses, the resting-state EEG microstate (MS) approach provides an alternative method for quantifying spontaneous brain activity, defining momentary brain states based on the topographical configuration of electrical potentials recorded across a multichannel scalp electrode array (Khanna et al., 2015).

The method was first introduced by Lehmann et al. (1987), who transformed the multichannel resting-state EEG signal into a time series of possible scalp topographies. Remarkably, although many configurations are theoretically possible, it was observed that a large portion of the ongoing signal could be captured by a small set of consistently recurring topographic patterns. Each of these patterns reflect a single, specific functional state of the brain, which remains stable for a short duration before rapidly transitioning to the next. These brief states, referred to as microstates, are thought to represent fundamental units of cognitive processing, with transitions marking shifts in the brain's electrical activity (S A et al., 2024). As such, microstates quantifies information from all channels simultaneously, enabling the assessment of spatial dynamics within large-scale cortical networks while preserving EEG's high temporal resolution (Khanna et al., 2015; Michel & Koenig, 2018).

2.2.3.1. Characteristics of EEG microstates

The microstates approach segments the continuous EEG signal into brief, quasi-stable topographies, typically lasting 80–120 ms, and reflecting momentary global functional states of the brain (Khanna et al., 2015; Michel & Koenig, 2018). A small number of highly reproducible topographies explain over 80% of spatial variance and are thought to originate from different underlying sources (Tarailis et al., 2024). Source localization studies, such as Custo et al. (2017), identified seven EEG microstates (A–G), though most resting-state research consistently focuses on four core microstates (A–D) (S A et al., 2024).

As summarized by Tarailis et al. (2024) in a systematic review of the functional aspects of resting EEG microstates, each microstate appears to reflect distinct physiological and functional aspects of cognition and behavior. As such, microstate A is associated with auditory and visual processing and has also been linked to an individual's arousal. Microstate B is primarily involved in visual functions but also shows associations with self-related imagery, autobiographical memory, and other cognitive abilities. Microstate C may be connected to internally directed thought, such as self-reflection and the processing of personally relevant information. Microstate D is implicated in executive control, particularly attention and working memory, and is thought to involve the dorsal attention network. Microstate E appears to engage the salience network and is related to emotional and interoceptive processing. Microstate F likely aligns with the default mode network (DMN), supporting functions such as mental simulation, processing of personally relevant information, and theory of mind. Lastly, microstate G remains the least explored, though preliminary findings suggest a connection to somatosensory processing (Tarailis et al., 2024). Each microstate has a distinct scalp topography, with microstate A showing a right-anterior to left-posterior orientation, B the reverse, C an anterior-posterior layout, D a fronto-central configuration, and E centro-parietal maximum (S A et al., 2024; Tarailis et al., 2024).

Furthermore, microstates are usually defined by a range of parameters that reflect their typical temporal patterns, and commonly reported metrics include the frequency of occurrence, average duration, and overall prevalence (the total percentage of time a microstate is present) (Tarailis et al., 2024; Zanesco, 2024). The mean duration refers to the time a given microstate is present without interruption, indicating synchronous activity of its underlying sources. The occurrence rate represents the number of times per second a given microstate appears independent of the duration, reflecting the tendency of those underlying sources to be synchronously active. Lastly, time coverage reflects the proportion of time a microstate is dominant or active (Tarailis et al., 2024). Importantly, changes in these characteristics can signal altered patterns of brain network functioning (Khanna et al., 2015).

2.2.3.2. EEG microstates as neural correlates of psychopathology

A growing body of evidence suggests that MS temporal parameters are sensitive to a range of clinical (Chivu et al., 2024; Das et al., 2022; Férat, Arns, et al., 2022; Nishida et al., 2013) and task related conditions (Deolindo et al., 2021; Korn et al., 2021; Nazare & Tomescu, 2024; Poskanzer et al., 2021), personality traits (Schiller et al., 2024; Schlegel et al., 2012; Tarailis et al., 2021; Tomescu, Papasteri, et al., 2024; Wu et al., 2020), wakefulness levels (Artoni et al., 2022; Bréchet et al., 2020; Diezig et al., 2024) and are linked with social behavior and emotional dynamics (Schiller et al., 2024).

Moreover, research suggests that EEG microstates are distinct and potentially more sensitive and robust biomarkers compared to spectral characteristics (S A et al., 2024). For instance, a study by Férat et al. (2022) report no significant differences in terms of spectral power in two independent samples of ADHD patients compared to healthy controls, but found increased temporal parameters of MS D and decreased temporal parameters of MS A. Deiber et al. (2024) reported similar results – no differences in relative EEG power averaged across all channels in any frequency band between a sample of patients with borderline personality disorder and healthy controls. However, authors reported significantly decreased MS C and increased MS E activity in the patient group. Likewise, Lassi et al. (2023) did not find any differences in absolute power in any EEG frequency band between individuals with mild cognitive impairment, subjective cognitive decline, and healthy controls, but reported differences for MS B occurrence and MS C duration, concluding that EEG microstates are the most robust marker to differentiate subjective and objective cognitive decline (Lassi et al., 2023). Furthermore, two studies (Britz et al., 2010; Férat, Seeber, et al., 2022) demonstrated that eyes-closed EEG microstates are independent from the power of EEG frequency bands. In a recent review of EEG microstates as biomarkers in neuropsychological processes, S A et al. (2024) identified EEG microstates as one of the most effective electrophysiological indicators of ongoing brain activity and emphasized the need for further research to advance their use in analyzing brain function.

Notably, several recent studies have linked altered microstate dynamics to problematic media and technology use. For example, Qi et al. (2023) observed reduced duration and coverage of microstate C among individuals with PIU; Li et al. (2021) reported weakened microstate D activity in relation to general media use; and Zhang et al. (2024) found enhanced activity of microstate E among individuals with phone addiction. Similarly, gaming-related studies have demonstrated increased presence of microstate D and decreased activity of microstate B in individuals with high gaming exposure or gaming addiction (Cui et al., 2021; Wang et al., 2021).

2.2.3.3. Conclusion

In summary, the EEG microstate approach offers a powerful framework for examining the spatiotemporal dynamics of resting-state brain activity. Importantly, accumulating evidence highlights the clinical relevance of microstate dynamics, with alterations in temporal parameters linked to a range of neuropsychological conditions, cognitive traits, and behavioral patterns. However, microstates are typically analyzed by comparing their characteristics across groups or experimental conditions (Tarailis et al., 2024), and despite the aforementioned findings, no studies to date have specifically examined whether the spatiotemporal properties of EEG microstates vary according to PIU severity in non-clinical populations. Compared to traditional spectral analyses, microstates may offer greater sensitivity in detecting subtle changes in brain function, including those related to problematic internet use.

2.2.4. EEG Event-Related Potentials

Time-locked EEG changes, or event-related potentials (ERPs), derived from EEG data are electrical signals recorded from the scalp that occur in response to specific events, such as a stimulus presentation or a behavioral action (Landa et al., 2014; Picton et al., 2000). These signals are thought to reflect the combined postsynaptic potentials transmitted to the scalp from synchronized firing of cortical pyramidal neuron groups in response to task-relevant stimuli (Sur & Sinha, 2009). Elicited by meaningful sensory, affective, cognitive or motor stimuli, ERPs serve as precise temporal indices of cortical activity (Helfrich & Knight, 2019) and enable the investigation of functional dynamics in neuronal processing (Sur & Sinha, 2009).

Unlike resting-state EEG, which reflects ongoing intrinsic activity, ERP methodology requires participants to engage in structured experimental paradigms (such as oddball, Go/NoGo, Stroop, Cue-reactivity, to name a few), that are specifically designed to isolate cognitive or affective domains (e.g., attention, memory, response inhibition, sensory processing) (Karamacoska, Barry, Steiner, et al., 2018). From its early applications, research has aimed to link distinct ERP waveform features – such as amplitude, latency, time course, polarity, and scalp topography – to specific stages of cognitive processing. ERP components are typically classified into early (e.g., P100, N100, P200) and late (e.g., N200, P300) categories, reflecting sequential phases of information processing from perceptual encoding to stimulus evaluation, respectively (Sokhadze et al., 2017). Such a component-based approach draws on established functional interpretations of ERP markers, thereby enabling inferences about disrupted cognitive processing mechanisms in both clinical and non-clinical populations (Sokhadze et al., 2017). The ERP components relevant to the present work are described in detail in the following sections.

Consequently, ERPs have been widely applied in addiction-related research (Campanella et al., 2014; Houston & Schlienz, 2018; Sokhadze et al., 2017). However, no standardized neurophysiological biomarkers currently exist to reliably characterize or distinguish PIU. Nevertheless, ERPs offer a promising avenue for identifying candidate biomarkers by linking component-level alterations to cognitive dysfunctions observed in PIUs.

2.2.4.1. The equiprobable auditory Go/NoGo task

The Go/NoGo task is a well-established two-choice reaction time paradigm designed to assess inhibitory control by requiring participants to respond to "Go" stimuli and withhold responses to "NoGo" stimuli (Fogarty et al., 2020a). Traditional Go/NoGo paradigms typically involve a higher probability of Go stimuli to prime response activation and thus necessitate deliberate inhibition on infrequent NoGo trials (Fogarty et al., 2018). However, the equiprobable Go/NoGo variant, characterized by equal stimulus probabilities, has gained attention for its ability to delineate sensory and cognitive processes without probability-induced response biases (Barry & De Blasio, 2013; Fogarty et al., 2018, 2020a). While some critics suggest that equiprobable paradigms may elicit weaker inhibitory-related neural activity due to reduced prepotent Go bias (Wessel, 2018), the equiprobable version remains the most commonly used version (Wessel, 2018). Equiprobable design minimizes confounds associated with stimulus frequency, motor preparation, and stimulus–response conflict, thus offering enhanced clarity on cognitive demands (Fogarty et al., 2018; Mizukami et al., 2019).

Electrophysiological studies using ERPs in Go/NoGo paradigms provide a temporally precise view of the neural processes underlying task performance. In the equiprobable auditory Go/NoGo task, ERP waveforms reflect a sequence of sensory, attentional, and cognitive control-related processes that differ between Go and NoGo trials. The processing stages are best conceptualized through the sequential processing schema developed by Barry & De Blasio's (2013) and later refined by Fogarty et al. (2020, 2018), which maps ERP components to specific stages of task performance (Figure 2.2.).

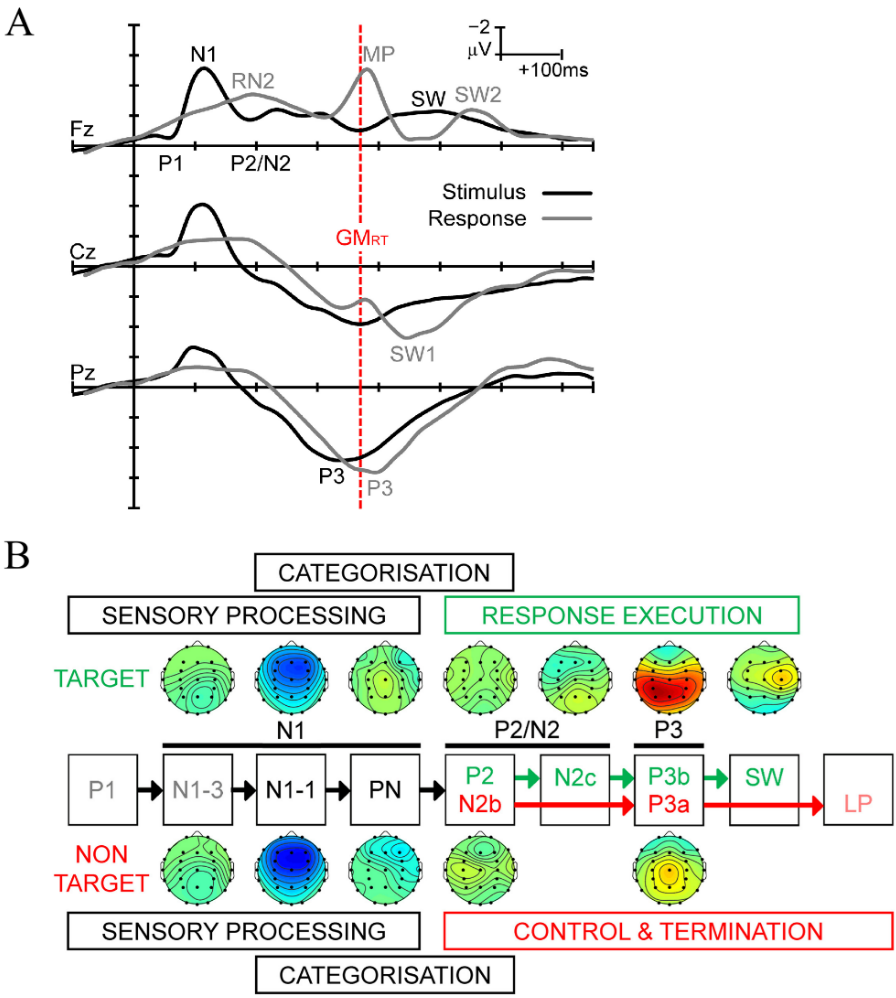

Figure 2.2. A. Grand mean raw stimulus- and response-locked ERPs at three midline sites (Fz, Cz, Pz), with key ERP components labeled. The red dashed GM_{RT} line indicates the grand mean reaction time (Fogarty, 2020). B. The updated sequential processing model illustrating distinct ERP topographies linked to cognitive stages in Go and NoGo processing (Fogarty, 2020).

As depicted in Figure 2.2., early sensory and attentional processes emerge as P1 and N1 components, reflecting automatic initial sensory gating and stimulus discrimination (Fogarty et al., 2018). Subsequently, stimulus identification and categorization into target and nontarget stimuli initiate divergent processing chains for Go and NoGo stimuli. In Go trials, the P2/N2c complex, followed by parietal P3b, reflects sequential stages of response activation, execution, and cognitive evaluation. In NoGo processing, the N2b component is followed by frontocentral P3a, indicating active inhibition and disengagement from response execution[8] (Fogarty et al., 2018, 2019, 2020a). P3 component is further followed by slow-wave components (SW1, SW2), which appear in both trial types but are consistently larger for NoGo stimuli, and are thought to be primarily response related (Fogarty et al., 2020a). Divergent processing of Go and NoGo stimuli is also evident in neural activation patterns. Within the first 200 ms post-stimulus in NoGo trials, the posterior pre-SMA, ACC, and right OFC are activated to resolve response-execution conflict. Successful inhibition is marked by a shift toward anterior pre-SMA and left OFC within approximately 400 ms, while unsuccessful inhibition engages supplementary motor areas within initial 200 ms timeframe, enabling erroneous response execution (Pires et al., 2014). This detailed analysis underscores the paradigm's utility in dissecting the neural substrates of cognitive control.

Behavioral performance metrics in Go/NoGo tasks serve as sensitive indicators of inhibitory control efficiency (Karamacoska, Barry, & Steiner, 2018). Core indices include reaction time (RT), commission errors (responses to NoGo stimuli, reflecting inhibitory failures), and omission errors (missed Go responses, reflecting attentional lapses) (Winstanley et al., 2006). Research further reveals reliable associations between these metrics and specific ERP components. For instance, faster Go RTs are linked to amplified NoGo-N2, NoGo-P3, and SW1 amplitudes, reflecting efficient cognitive and motor preparation processes (Fogarty, 2020; Nakata et al., 2021). In contrast, increased reaction time variability (RTV) correlates with higher error rates, increased Go-N2 amplitudes, diminished Go-P3 and NoGo-P3 amplitudes, delayed NoGo-P3 peak latency, and amplified Go slow wave positivity, signaling inefficient decision-making and increased response control efforts (Fogarty et al., 2018; Karamacoska, Barry, & Steiner, 2018; Nakata et al., 2021). NoGo-N2 amplitudes and latency and P3 amplitudes also have been shown to correlate with commission errors (Fogarty et al., 2018; Karamacoska, Barry, & Steiner, 2018; Nakata et al., 2010). Although behavioral performance remains unaffected by variations in task pace or stimulus probability, neural activity exhibits sensitivity to task modalities and parameters, including interstimulus intervals (ISI) and stimulus modality (Bruin & Wijers, 2002; Falkenstein et al., 1995, 1999, 2002; Nakata et al., 2010, 2021).

[8] That NoGo-related ERP components (e.g., N2b, P3a) index active inhibitory control processes rather than mere cessation of cognitive effort to terminate the Go response (Fogarty et al., 2018). This aligns with earlier findings by Falkenstein et al. (1999) and Rubia et al. (2001), emphasizing the necessity of effortful cognitive control during response inhibition.

Impaired response inhibition, as indicated by elevated reaction times, commission, and omission error rates, has been consistently observed across various populations with addictive behaviors (Ames et al., 2014; Kamarajan et al., 2005; Petit et al., 2012; Yin et al., 2016). Similar patterns appear in PIU and related conditions. For instance, Zhou et al. (2010, 2016) reported higher commission and omission error rates among PIU than in controls or even pathological gamblers (Zhou et al., 2010). Elevated commission errors have also been observed in IGD (Kim et al., 2017; Li et al., 2020; Littel et al., 2012). Littel et al. (2012) further reported that commission errors in excessive gamers were associated with higher self-reported impulsivity and greater weekly gaming time, with faster RTs suggesting a speed–accuracy trade-off.

Nevertheless, findings across PIU studies remain inconsistent, as mixed or conflicting behavioral findings have been reported. For instance, no significant differences in Go/NoGo performance were observed between individuals with PIU (Dong et al., 2010; Vargas et al., 2019) or excessive smartphone users compared to the control group (Chen et al., 2016). Zhang et al. (2024) also reported no group-level RT or accuracy differences between PIU and healthy control groups, although noted that all participants exhibited faster responses and poorer inhibitory control in response to internet-related versus neutral stimuli[9]. These inconsistencies may reflect variability in task design, sample characteristics, or the context-dependence of inhibitory impairment.

In summary, behavioral outcomes from the Go/NoGo task largely support prior research, indicating altered impulse regulation in individuals with PIU. However, inconsistencies across studies highlight the importance of incorporating neurophysiological measures – such as ERPs – to uncover subtle, stimulus-locked differences in cognitive processing, that may not be detectable through behavioral metrics alone. For instance, Houston & Schlienz (2018) observed that while ERP alterations in alcohol use disorder often co-occur with behavioral impairments, similar ERP deviations in binge drinkers occurred without measurable performance deficits. These findings

[9] Investigations employing alternative inhibitory paradigms, such as the SST, further contextualize the complexity of response inhibition-related deficits in PIU. Chamberlain et al. (2017) found no SST performance differences between occasional gamblers with and without PIU, as well no differences in performance observed between internet addiction (IA) and control groups (Tseng et al., 2024). In contrast, Nie et al. (2016) revealed nuanced patterns in IA, ADHD, and comorbid IA/ADHD groups. IA and comorbid IA/ADHD groups demonstrated faster reaction times to internet-related Go stimuli and increased commission errors during internet-related stop trials, indicating stimulus-specific inhibitory impairment linked to internet use

suggest that ERP changes may reflect compensatory neural effort, revealing cognitive strain not evident in overt behavior – an insight particularly relevant for understanding PIU.

2.2.4.2. Early sensory processing (N1, P2)

The first 250 ms following stimulus presentation in auditory Go/NoGo is typically characterized by early ERP components (Fogarty et al., 2020b), including P1, N1, and P2, primarily reflecting early sensory and perceptual processes, including sensory gating, stimulus discrimination, selective attention, and interference control (Barry & De Blasio, 2013; Crowley & Colrain, 2004; Fogarty et al., 2020a, 2020b; Lijffijt et al., 2009; Pires et al., 2014). These components are generally regarded as automatic, exogenous responses, sensitive to physical stimulus parameters (e.g., intensity or loudness) rather than top-down cognitive influences (Pires et al., 2014; Sokhadze et al., 2017).

However, early attention mechanisms might also influence initial sensory processing, with the P1 potentially facilitating sensory processing of attended stimuli and N1 reflecting attentional orientation toward task-relevant targets (Sokhadze et al., 2017). Neurophysiological data further suggest that the Go/NoGo task elicits activity within a core frontal network during this early period, which is implicated in maintaining task-relevant goals in working memory, guiding top-down control, and coordinating early cognitive operations (Fogarty et al., 2020b).

N1 component

The N1 component is an early negative-going ERP waveform that is generally linked to stimulus-driven sensory processing, such as stimulus detection (Fogarty et al., 2020a; Joos et al., 2014). Furthermore, when combined with the subsequent P2 wave, the N1-P2 complex is thought to represent a later phase of sensory gating, contributing to stimulus categorization and discrimination (Fogarty et al., 2020b; Joos et al., 2014).

While traditionally considered an exogenous response to auditory input, N1 is also associated with attention-catching stimulus properties (Joos et al., 2014), likely reflecting early attentional mechanisms (Tomé et al., 2015). Joos et al. (2014) indicated that the N1 component in auditory modality involves both bottom-up (sensory) and top-down (prediction-driven) processing, suggesting that attention can affect the characteristics of this component (Joos et al., 2014). According to Joos et al. (2014) the N1 plays a key role in selective attention mechanisms likely mediated by the ventrolateral prefrontal cortex (vlPFC), which is believed to support attention-switching toward behaviorally relevant stimuli and the ongoing updating of internal auditory representations. In support of this, research in tinnitus populations shows reduced N1 amplitudes and increased latencies, which may reflect impaired attentional switching from internal to external auditory stimuli, leading to suboptimal perceptual encoding (Joos et al., 2014).

Importantly, the N1 may also serve as an early precursor to inhibitory control processes. Specifically, modulation of N1 amplitude has been linked to attentional orientation toward inhibitory signals, and enhanced N1 amplitudes have been associated with successful inhibition compared to failed attempts, suggesting that early attentional allocation may set the stage for effective response suppression, indexed by later N2 component (Pires et al., 2014).

Neuroanatomically, the N1 component is generated by multiple neural sources, with the superior temporal plane (encompassing primary and secondary auditory cortices and auditory association areas) being the primary generator (Fogarty et al., 2020b). However, additional activation in frontal cortical regions – such as the dorsal anterior cingulate cortex (dACC), parietal cortex, and vlPFC – has been implicated, supporting the notion that N1 also reflects cognitive processes related to working memory and behavioral control (Fogarty et al., 2020b; Joos et al., 2014).

In the context of PIU and IGD, the N1 has been explored as a potential neurophysiological marker of altered attentional and perceptual processing, though findings are scarce and mixed. For instance, individuals with IGD exhibit both reduced N1 amplitudes during auditory oddball paradigms (Park et al., 2017b) and increased amplitudes with prolonged latencies during semi-natural gaming tasks (Duven et al., 2015). In contrast, Ge et al. (2011) observed no significant differences in N1 amplitude or latency between individuals with PIU and healthy controls during an auditory binary oddball paradigm. Despite these inconsistencies, a review by Kashif et al. (2021) proposed the N1 as a potential neurophysiological biomarker specifically for IGD.

P2 component

Similarly to N1, the P2 is also considered a primarily stimulus-related component, reflecting sensory and perceptual processing in response to incoming stimuli (Fogarty et al., 2020a). Although its precise cognitive function remains unclear, the P2 has been associated with higher-level perceptual processing, such as early stimulus evaluation, target identification, and classification (Crowley & Colrain, 2004; Sokhadze et al., 2017).

Research further suggests that P2 amplitude is modulated by task demands, with more challenging conditions, such as decreased NoGo probability, associated with enhanced P2 amplitudes, suggesting its involvement in expectancy-related attentional processes and heightened engagement in early cognitive evaluation of stimuli (Bruin & Wijers, 2002; Fogarty et al., 2019; Sokhadze et al., 2017).

Neuroanatomically, auditory P2 generators are located within frontal and temporal brain regions, particularly in the ACC and temporal lobes – structures associated with attention and sensory gating processes (Fogarty et al., 2020b). This anatomical localization further reinforces the link between P2 amplitude modulation and attentional control or expectancy processes influenced by stimulus predictability (Fogarty et al., 2020b).

To date, studies investigating the P2 component in the context of PIU remain limited. One such study by Ge et al. (2011) reported no significant differences in P2 amplitude or latency between individuals with PIU and healthy controls during an auditory oddball task. These findings may suggest that early perceptual discrimination and attentional gating, as reflected by the P2 component, are not markedly altered in PIU. However, further research is needed to determine the sensitivity of this component to PIU-related cognitive alterations and to establish its relevance as a neural correlate.

2.2.4.3. Late cognitive processing (N2, P3)

The N2 and P3 components have been extensively studied as key ERP markers of cognitive control. Traditionally grouped together as the "N2-P3 complex", these components, particularly during NoGo trials, are widely recognized as neural signatures of conflict monitoring and motor inhibition (Bruin & Wijers, 2002; Kamarajan et al., 2005; Pires et al., 2014). Specifically, the NoGo-N2 reflects early conflict detection, while NoGo-P3 is more associated with the inhibition of prepotent motor responses (Detandt et al., 2017; Dong et al., 2010; Huster et al., 2013). In contrast, the ERP sequence elicited during Go trials – Go P3, SW1, and SW2 – is primarily response-related, supporting their interpretation as components linked to motor execution and response evaluation (Fogarty et al., 2020a).

N2 component

The N2 component is a well-studied endogenous ERP, typically emerging between 200 and 350 ms after stimulus onset and most prominent at frontocentral scalp sites (Bruin & Wijers, 2002; Pires et al., 2014). It encompasses several subcomponents with distinct functional implications: frontocentral N2a, often referred to as mismatch negativity (MMN);

frontocentral N2b (commonly labeled as NoGo-N2 in inhibitory paradigms); posterior N2c, also called Go-N2; and posterior N2pc (Balconi & Angioletti, 2021; Fogarty et al., 2018; Folstein & Van Petten, 2008; Larson et al., 2014; Nieuwenhuis et al., 2003; Pires et al., 2014). The N2, particularly the NoGo-N2 subtype, has been linked to neural activity in the OFC and ACC, reflecting engagement of neural circuits involved in conflict monitoring, decision-making, and executive control (Fogarty et al., 2020b; Luijten et al., 2014).

Traditionally, N2 has been interpreted as a classic neural marker of response inhibition, evidenced by larger amplitudes in NoGo versus Go trials (Balconi & Angioletti, 2021; Cheng et al., 2019; Hoyniak & Petersen, 2019; Roche et al., 2005), and by associations between larger, earlier NoGo-N2 and lower error rates and better task performance (Falkenstein et al., 1999).

However, the precise functional significance of N2 remains debated. A substantial body of research suggests that conflict detection, rather than inhibition per se, may be its primary driver (Donkers & van Boxtel, 2004; Enriquez-Geppert et al., 2010). For instance, under conditions such as increased task difficulty that demand heightened cognitive control and therefore a greater need for inhibition (e.g., Go and NoGo responses are perceptually similar, stimuli violate expectations, or stimulus probability decreases), N2 amplitudes typically enhance (Bruin et al., 2001; Bruin & Wijers, 2002; Dong et al., 2010; Nieuwenhuis et al., 2003, 2004; Smith et al., 2010; Smith & Douglas, 2011). In this view, N2 responds to conflict arising from competing responses and reflects higher cognitive demands on implementing inhibitory control (Bruin & Wijers, 2002; Donkers & van Boxtel, 2004; Jodo & Kayama, 1992; Kenemans et al., 2005; Nieuwenhuis et al., 2004; Sokhadze et al., 2017; Wessel, 2018). Supporting this, N2 has been found to increase not only in response to NoGo stimuli but also to unexpected or deviant Go stimuli, reinforcing the idea that it indexes general conflict monitoring rather than inhibition-specific processes (Bruin et al., 2001; Nieuwenhuis et al., 2003; Smith et al., 2010). Moreover, N2 has also been proposed to reflect a modality-specific cognitive control mechanism that operates independently of motor processes. Evidence shows distinct N2 characteristics across auditory, visual, and somatosensory modalities, largely attributable to variations in perceptual overlap, rather than the sensory modality itself (Falkenstein et al., 1995, 1999, 2002; Nakata et al., 2021; Nieuwenhuis et al., 2004; Pires et al., 2014; Smith & Douglas, 2011).

However, although the NoGo-N2 is generally less pronounced in equiprobable Go/NoGo tasks (Barry et al., 2014), the Go/NoGo-N2 effect is still assessed. This further indicates that N2 amplitude is likely shaped by an interaction between cognitive load (e.g., modulated by stimulus deviance or perceptual overlap) and response assignment (Bruin & Wijers, 2002). Furthermore, while stimulus probability modulates the size of N2 amplitude, it appears to have no effect on latency, at least in the somatosensory domain (Nakata et al., 2005). This supports the idea that N2 onset timing may offer a more stable and valid index of early cognitive control (Roche et al., 2005).

In summary, N2 is likely associated with premotor processes and may reflect various cognitive functions, ultimately signaling that a perceptual representation has been formed (Pires et al., 2014; Sokhadze et al., 2017). While NoGo-N2 is likely driven by the early recognition of signals requiring inhibition (Dong et al., 2010; Kenemans et al., 2005; Nieuwenhuis et al., 2004), it may also involve suppression of planned responses (Folstein & Van Petten, 2008; Zhou et al., 2010), thus, reflecting non-motor processes (Pires et al., 2014).

Empirical studies exploring the N2 component across addictive behaviors, including SUDs, PIU, IGD, and excessive smartphone use, report mixed findings. Reduced (less negative) NoGo-N2 amplitudes have been reported in individuals with PIU (Dong et al., 2010; Fathi et al., 2024; Zhou et al., 2010) and IGD (Fathi et al., 2024; Lee & Kang, 2014), suggesting impairments in conflict detection and the early sub-process of response inhibition. In a systematic review on ERP and fMRI studies, Luijten et al. (2014) noted that five out of seven studies evaluating the N2 component in addicted populations reported amplitude reductions and identified blunted NoGo-N2 as one of the most consistent neurophysiological alterations (despite some inconsistencies, particularly in IGD-related research).

Conversely, enhanced (more negative) N2 amplitudes have also been observed in individuals with PIU, IGD, excessive smartphone use, and excessive social network site usage (Chen et al., 2016; Chen et al., 2018; Gao et al., 2019). A recent review by Yu et al. (2024) on EEG markers of inhibitory control in IGD concluded that gamers often exhibit enlarged N2 amplitudes compared to controls, interpreted as increased recruitment of cognitive control resources to inhibit impulsive responses.

Furthermore, a positive correlation between Go-N2 amplitudes and IAT scores was observed in response to gambling stimuli during a modified Go/NoGo task with addiction-related background pictures (e.g., videogames, online gambling, and neutral stimuli) in a healthy general sample, though NoGo-N2 showed no such association (Balconi & Angioletti, 2021). In terms of latency, prolonged N2 latency – but no significant alterations in amplitude – have been reported in both PIU and IGD populations (Ge et al., 2011; Kim et al., 2017), with positive correlations between NoGo-N2 latency and IAT and BIS-11 scores in IGD (Kim et al., 2017).

On the other hand, several studies report null findings. No group differences in NoGo-N2 components were found between control groups and alcoholics (Kamarajan et al., 2005), heavy social drinkers (Petit et al., 2012), smokers (Yin et al., 2016), excessive computer gamers (Littel et al., 2012) and individuals with IGD (Li et al., 2020), further underscoring the heterogeneity of N2 outcomes across populations and paradigms.

P3 component

The P3 component is a well-characterized endogenous ERP that typically emerges between 250–500 ms post-stimulus, exhibits a frontocentral to centroparietal topography (Pires et al., 2014; Sokhadze et al., 2017) and is highly sensitive to the cognitive context in which a stimulus occurs, as well as the level of attention and arousal (Joos et al., 2014).

The P3 is widely regarded as a neural signature of the cognitive mechanisms required to update the mental model of the environment (e.g., sensory, motor, or response-related representations) in order to generate an appropriate response (Fogarty et al., 2020a; Polich, 2003), and generally reflects the involuntary and transient allocation of attentional resources (Park et al., 2017a; Pires et al., 2014). The P3 is also implicated in response evaluation (Dong et al., 2010), encompassing both motor and non-motor inhibition processes, such as conflict resolution (e.g., deciding whether to withhold or execute a response) and performance evaluation (e.g., determining whether inhibition was successfully and appropriately applied to the context) (Pires et al., 2014).

Rather than a unitary phenomenon, P3 also comprises several distinct subcomponents, most notably P3a and P3b, differing in timing, topography, and functional role. P3a tends to peak earlier and is maximal over frontocentral sites, whereas P3b occurs later and shows a stronger parietal distribution (Barry et al., 2014; Bruin & Wijers, 2002; Enriquez-Geppert et al., 2010; Pires et al., 2014; Smith et al., 2008; Zhang et al., 2007). A third subcomponent, Novelty P3 (nP3), is elicited in response to a novel stimulus and is linked to the orienting reflex, marked with a unique set of motor-related activations (Barry et al., 2019). In Go/NoGo tasks, the dissociation between P3a and P3b is particularly pronounced. Go trials elicit a centroparietal Go-P3b, maximal at CP3, P3, and Pz, while NoGo trials evoke a frontocentral NoGo-P3a (Bruin et al., 2001; Bruin & Wijers, 2002; Fogarty et al., 2018; Karamacoska, Barry, & Steiner, 2018). Empirical data show that P3 amplitudes are typically larger on NoGo than Go trials (Nakata et al., 2010).

This topographical distribution reflects further functional differences. The NoGo-P3 – often maximal at the pre-SMA region – serves as a marker of active evaluative and inhibitory processing, triggered by conflict detection (Fogarty et al., 2018) and emerging after the decision to withhold a response has been made (Gajewski & Falkenstein, 2013). It has been linked to the closure and evaluation of the inhibitory performance and the effectiveness of motor suppression within motor or premotor cortices (Bruin et al., 2001; Donkers & van Boxtel, 2004; Gajewski & Falkenstein, 2013; Ramautar et al., 2004, 2004; Roche et al., 2005). Delayed NoGo-P3 onset on error trials (e.g., reaction times significantly exceed the mean) further supports the component's involvement in performance evaluation, error detection, and/or preparation for subsequent trials (Roche et al., 2005). Meanwhile, during successful Go trials, the parietal P3b is related to cognitive attentional processes that are tied to the stimulus evaluation process and reflect response-related updating in working memory, which leads to motor activation and the generation of movement-related sensory feedback (Donkers & van Boxtel, 2004; Fogarty et al., 2020a; Nieuwenhuis et al., 2004; Pires et al., 2014; Randall & Smith, 2011). Anatomical source localization further supports these functional roles, showing that P3 arises from a distributed fronto-temporo-parietal network pathway reflecting top-down control (Enriquez-Geppert et al., 2010; Pires et al., 2014). The neural generators of P3 also overlap with core regions implicated in inhibitory regulation (e.g., ACC, OFC, pre-SMA, insula, medial temporal gyrus, tempoparietal junctions, also deeper structures like the thalamus and striatum) (Joos et al., 2014; Luijten et al., 2014; Pires et al., 2014).

Furthermore, P3 latency has been proposed as an index of the speed of stimulus classification and evaluation, with shorter latencies often interpreted as reflecting greater cognitive efficiency (Kamijo et al., 2004; Kutas et al., 1977; Polich & Criado, 2006). Moreover, P3 characteristics are sensitive to experimental manipulations, including stimulus modality and probability, interstimulus interval (ISI), and response demands. For instance, faster-paced tasks (e.g., ISI of 1.5 ms vs. 4 ms) yield earlier and larger P3 amplitudes (Nakata et al., 2010; Wessel, 2018). Overt responses (e.g., manual response) as opposed to covert ones (e.g., silent counting) also elicit larger amplitudes, suggesting higher cognitive resource demands on manual inhibition and partial P3 dependence on movement-related activity (Bruin & Wijers, 2002; Pires et al., 2014). Rare NoGo trials also elicit larger P3s (Wessel, 2018), supporting the view that in equiprobable designs, NoGo-P3 primarily indexes attentional processing (Fogarty, 2020). Moreover, faster Go responses correlate with larger NoGo-P3 amplitudes, reflecting the interaction between response readiness and inhibition (Smith et al., 2006).

A reduction in NoGo-P3 amplitude is a frequently reported finding across various problematic and addictive behaviors (Colrain et al., 2011; Luijten et al., 2014), including nicotine use (Evans et al., 2009; Luijten et al., 2016; Yin et al., 2016), alcoholism (Kamarajan et al., 2005; Porjesz & Begleiter, 2003), stimulant use (Sokhadze et al., 2008), excessive social network use (Gao et al., 2019), and IGD (Li et al., 2020; Park et al., 2016; Park et al., 2017b). In IGD, reduced P3 amplitude has been proposed as a potential neurophysiological marker, correlating with symptom severity and interpreted as reflecting dysfunctional information processing, either due to impaired inhibitory control or overstimulation from repeated gaming stimuli exposure (Park et al., 2016; Yu et al., 2024). Moreover, problematic Facebook users displayed lower NoGo-P3 amplitudes to Facebook-related, pleasant, and neutral stimuli than to unpleasant stimuli, unlike controls, whose amplitudes varied by all emotional content (Moretta & Buodo, 2021).

However, findings on this component also remain inconsistent. Some studies report increased NoGo-P3 amplitudes in excessive internet users (Dong et al., 2010), while others found no amplitude differences in excessive gamers (Littel et al., 2012), IGD (Kim et al., 2017), PIU (Ge et al., 2011), or excessive smartphone use (Chen et al., 2016). Regarding latency, prolonged NoGo-P3 has been observed in smokers (Yin et al., 2016), heavy social drinkers (to alcohol-related context only) (Petit et al., 2012) and individuals with PIU (Dong et al., 2010). In PIU, Ge et al., (2011) found no amplitude changes but reported longer P3 latency (reduced after a 3-month cognitive behavior therapy) during the auditory binary oddball paradigm, while Yu et al. (2009) noted both reduced P3b amplitude and longer latency. Conversely, Kim et al. (2017) found no latency differences among IGD, OCD, and healthy controls.

Collectively, P3a and P3b provide distinct yet complementary insights into attentional and context-updating processes during action execution and inhibition in the Go/NoGo paradigm. However, consistent with the notion of the systematic review by Luijten et al. (2014) no definitive conclusions can be drawn from current evidence, as findings on P3 amplitudes in addicted individuals, including PIU, remain inconsistent, limiting their interpretability as reliable markers of dysfunction.

2.2.4.4. Conclusion

In sum, although findings from Go/NoGo tasks are not entirely consistent, many studies suggest that individuals with PIU exhibit impaired inhibitory control. However, inconsistencies across behavioral measures highlight the importance of incorporating neurophysiological measures to capture subtler cognitive alterations. ERP findings offer valuable insight into the temporal dynamics of attention and inhibition; yet, while some components, such as N2 and P3, have been widely studied (however, findings remain mixed and often contradictory), research on early components like N1 and P2 remains scarce. Although some studies report reduced amplitudes or delayed latencies indicative of cognitive inefficiency, others suggest compensatory increases or null effects. D'Hondt et al. (2015) emphasize that the most consistent neurophysiological finding in the PIU field is impaired control monitoring, reflected in P3 alterations, while self-control deficits are linked to both error monitoring and inhibition – the latter specifically through changes in conflict detection (reflected by N2) and response evaluation (reflected by NoGo-P3). However, as noted by Luijten et al. (2014), such heterogeneity across findings limits the interpretability of ERP markers as reliable indicators of dysfunction in PIU and points to the need for more nuanced approaches in future research.

2.2.5. Conclusion

The current body of EEG research on PIU reveals promising yet inconclusive evidence of neurophysiological disruptions, including alterations in spectral power, alpha asymmetry, microstate dynamics, and ERP components. Collectively, these findings suggest impairments in cognitive functioning, such as attention allocation and inhibitory control, evident both at rest and during task engagement. While no single neural metric demonstrates diagnostic specificity, their combined patterns may hold potential for advancing the conceptualization of PIU and its underlying mechanisms.

However, the lack of consistency and generalizability across findings, along with a predominant reliance on clinically diagnosed or treatment-seeking individuals versus healthy controls designs, limits the understanding of how PIU-related neural features manifest in the general population or evolve prior to the onset of overt psychopathology. Capturing the trajectory from normative to maladaptive engagement by moving beyond binary clinical classifications toward continuum-based models or longitudinal research, and by investigating neural mechanisms in non-clinical individuals, remains a gap to address in future research.

3. METHODS

A schematic representation of the experimental procedure is provided in Figure 3.1. below. The protocol began with participant preparation for the EEG recording session. EEG acquisition consisted of three consecutive conditions: (1) a 5-minute eyes-closed resting-state recording, (2) a 4-minute alternating state condition comprising 2 minutes of eyes-open followed by 2 minutes of eyes-closed recording, and (3) an equiprobable auditory Go/NoGo task. Upon completion of the EEG session, participants completed a set of self-report questionnaires (4) assessing internet use patterns and psychological constructs, including affective symptoms, personality traits, and interoceptive awareness.

EEG data were preprocessed (5) using standard procedures. Subsequently, paradigm-specific features were extracted (6): event-related potentials (ERPs) for the Go/NoGo task, microstate parameters for eyes-closed resting-state data, and alpha power and asymmetry indices for the alternating resting-state condition.

Finally, statistical analyses (7) were conducted to examine associations between patterns of internet use, electrophysiological measures, and psychological characteristics. All analyses were performed using two complementary approaches: across the full sample and between groups categorized as low and high internet users, based on scores from the Problematic Internet Use Questionnaire (PIUQ-9).

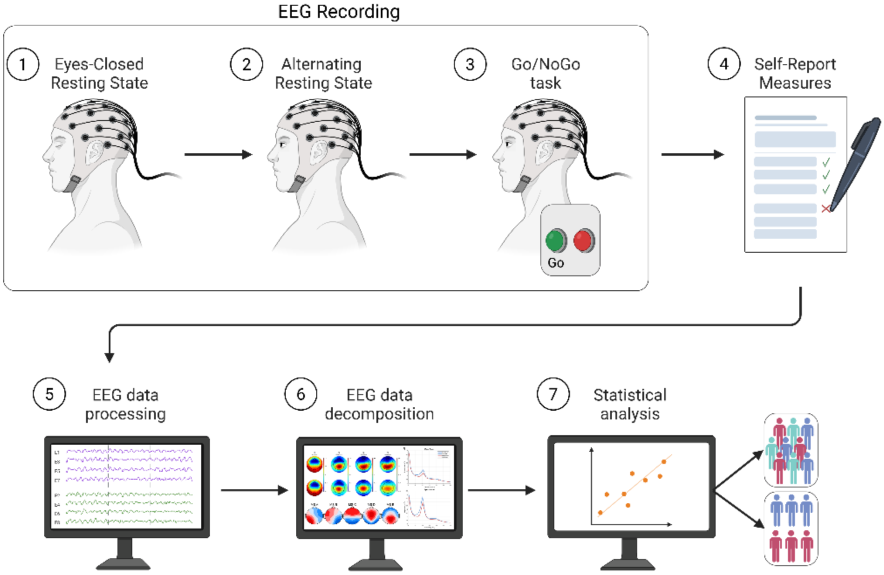

Figure 3.1. Sequence of the experimental procedure.

3.1. Participants

The sample consisted of 161 participants (71 males and 90 females), with an age range of 18 to 35 years and a mean age of 24.21 ± 4.28 years. There was a significant age difference between male and female participants, with males being slightly older (25.56 ± 4.32, 23.14 ± 43.96, $p<.001$). 96.3% of the participants identified as right-handed, with no significant differences observed in hand dominance between genders ($p=0.521$). Physical metrics collected showed an average Body Mass Index (BMI) of 22.68 ± 3.78 kg/m^2, indicative of a predominantly healthy participant demographic. A significant sex-based difference in BMI was observed ($p<.001$), with males presenting a higher BMI compared to females (23.82 ± 4.29 vs. 21.76 ± 3.04 kg/m^2). In terms of educational attainment, the majority of participants (50.3%) reported having received higher education. Statistical analysis yielded no significant difference in the distribution of education levels between male and female participants ($p=0.062$), suggesting an equitable distribution of education levels across sexes. Demographic characteristics of the subjects are provided in Table 3.1 below.

Inclusion criteria required participants to have good self-reported general health, normal or corrected-to-normal vision, and normal hearing. Additionally, female participants were required to have a regular menstrual cycle for at least three months prior to the experiment and could not use hormonal contraception. As hormonal fluctuations across different menstrual phases have been shown to significantly influence cognitive processes and electrophysiological correlates of executive functioning (Griskova-Bulanova et al., 2016), all female participants were tested during the early follicular phase, specifically within the first days of menstruation, to reduce the potential confounding effects and improve the reliability and consistency of neurophysiological data. Individuals with a history or current diagnosis of psychiatric, neurological, or endocrinological disorders, along with those using psychotropic or psychoactive substances (nicotine excepted), and those with self-considered or clinically confirmed addictions, were not eligible to participate in the experiment.

Recruitment of subjects was conducted through advertisements placed within the student community, on social media, and across a variety of other media platforms. All participants were instructed to ensure a good night's sleep before the day of the experiment and to avoid consumption of caffeine, energetic drinks, and nicotine at least two hours prior to their participation. The study was approved by the Vilnius Regional Biomedical Research Ethics Committee (Nr.2019/10-1159-649). All participants provided written informed consent, and the study procedures were thoroughly explained beforehand.

Table 3.1. Demographic characteristics of the subjects.

Category	Subcategory	Frequency (%)	Mean ± SD	Difference between sexes
Gender	**Females**	90 (55.9 %)		
	Age		23.14 ± 3.96	
	BMI		21.76±3.04	
	Males	71 (44.1 %)		
	Age		25.56 ± 4.32	
	BMI		23.82±4.59	
Age (years)			24.21 ± 4.28	p<0.001*
BMI (kg/m^2)			22.68±3.78	p<0.001*
Handedness	Right-handed	155 (96.3%)		χ^2=1.305, p=0.521**
	Left-handed	5 (3.1%)		
	Ambidextrous	1 (0.6%)		
Education	Bachelor or higher	81 (50.31%)		χ^2=7.319, p=0.062**
	Non-university degree	5 (3.11%)		
	Technical school	2 (1.24%)		
	High school	73 (45.34%)		

BMI – Body Mass Index, SD – Standard Deviation. * Independent samples t-test, ** Pearson Chi-Square.

3.1.1. Data loss and final samples

The number of participants retained for each analysis is presented in Table 3.2. Regarding self-report measures, the majority of participants (140 out of 161; 87%) fully completed all questionnaires. Missing data rates ranged from 0% to a maximum of 6.2%. Given the high completion rate and minimal missing data, the pairwise deletion method was applied to handle missing values, following recommendations in the literature (Mirzaei et al., 2022). Accordingly, the full sample of 161 participants was retained for self-report data analyses.

For the EEG datasets, data loss due to technical issues, poor recording quality, or inadequate task performance ranged from 3.1% to 19.25%, depending on the specific paradigm. This resulted in a final sample of 133 participants (mean age 24.19 ± 4.27 years, 74 females) for the Go/NoGo task dataset, 129 participants (mean age 24 ± 4.02 years, 80 females) for the alternating resting-state dataset, and 156 participants (mean age 24.17 ± 4.24 years, 86 females) for the eyes-closed resting-state dataset.

Table 3.2. Sample sizes retained for self-report data and each EEG paradigm used in statistical analysis.

	Full sample size	High PIU score group	Low PIU score group
Psychological measures	161 (90)	46 (30)	45 (22)
Go/NoGo task	133 (74)	38 (24)	35 (17)
Alternating resting-state *(alpha asymmetry)*	129 (80)	33 (24)	36 (22)
Eyes-closed resting-state *(microstates)*	156 (86)	44 (28)	43 (21)

Values in parentheses indicate the number of females within the sample.

3.2. Questionnaires

Participants completed a set of questionnaires to assess various psychological and personality traits. Besides general demographic assessment (sex, age, weight, height, handedness, and education), subjects were assessed for internet usage patterns (PIUQ-9 and DPIU). The levels of anxiety (BAI), depression (BDI-II), and obsessive-compulsive symptoms (CBOCI) were measured. Personality traits (NEO PI-R) and interoceptive awareness (MAIA) were also assessed.

3.2.1. The Nine-Item Problematic Internet Use Questionnaire (PIUQ-9)

PIUQ-9 (Koronczai et al., 2011) is a shortened version of the Problematic Internet Usage Questionnaire (Demetrovics et al., 2008) and has been established as a reliable tool for identifying the extent of internet misuse. The PIUQ-9 consists of 9 items and retains the three-factor structure of the original 18-item questionnaire: obsession, neglect, and control disorder. Respondents score each item on a five-point Likert scale from "Never" (1) to "Always/Almost always" (5), resulting in a total score range of 9 to 45. A provisional cutoff score of 22 indicates problematic internet use, with higher scores reflecting more severe involvement (Koronczai et al., 2011).

The PIUQ-9 has been validated through factorial investigation and demonstrates strong internal consistency, with Cronbach's alpha ranging from 0.81 to 0.90 across various samples (Laconi et al., 2019), including a Lithuanian sample ($\alpha = 0.89$) (Burkauskas et al., 2020), and in the current sample, it has a Cronbach's alpha of 0.81.

3.2.2. The Dimensions of Problematic Internet Use (DPIU)

DPIU (Van Ameringen et al., 2018) is a self-report tool designed to assess problematic internet use based on DSM-IV criteria for addiction (American Psychiatric Association, 2013) and covers nine different dimensions of PIU: Entertainment and Video Streaming, Social Media, Gaming, Messaging, Dating Apps, Gambling, Sexual Content, Online Shopping, and Information Search. Every dimension starts with three initial screener questions (yes/no). For instance, in the Entertainment and Video Streaming dimension, these questions include: "Have you ever felt bad or guilty about how much you spend streaming?", "Have people ever annoyed you by criticizing how much time you spend streaming?", and "Have you ever felt you should cut down on the amount of time you spend streaming videos?". If respondents answer "yes" to two or more questions, they proceed to five additional questions on a 6-point Likert scale ranging from 0 (not at all) to 5 (a lot), assessing potential problematic usage within that dimension. Individuals with scores of 3 or greater in any of the dimensions indicate a potential risk of PIU.

The number of participants reporting problematic use in each dimension and Cronbach's alpha values were as follows: Entertainment and Video Streaming: $n=103$, $\alpha=0.8$, Social Media: $n=99$, $\alpha=0.77$, Gaming: $n=37$, $\alpha=0.86$, Messaging: $n=43$, $\alpha=0.84$, Dating Apps: $n=12$, $\alpha=0.68$, Sexual Content: $n=16$, $\alpha=0.68$, Online Shopping: $n=21$, $\alpha=0.82$, Information Search: $n=25$, $\alpha=0.74$. There was no participant reporting problematic use in Gambling, $n=0$. The Cronbach's alpha values for some DPIU subscales, although not uniformly high, are indicative of a moderate level of internal consistency, which is acceptable for exploratory research into the complex and varied patterns of problematic internet use.

3.2.3. The Beck Anxiety Inventory (BAI)

BAI developed by Beck et al. (1988), is a widely used and validated tool for measuring the severity of anxiety symptoms. The BAI comprises 21 items, each rated on a Likert-type scale from 0 (not at all) to 3 (severely) based on the individual's reported experience of anxiety symptoms over the period of the last two weeks. Total scores can range from 0 to 63 points, with higher scores indicating greater severity of anxiety. Interpretative categories are as follows: 0-7 for minimal anxiety, 8-15 for mild, 16-25 for moderate, and 26-63 for severe anxiety.

The BAI has been extensively validated and is a reliable and valuable instrument for assessing anxiety levels in both clinical and research settings. The Cronbach's alpha values, ranging from 0.91 to 0.92 across Lithuanian samples (Grigutytė et al., 2023), and a Cronbach's alpha of the scale in the current sample of α=0.86 indicate excellent internal consistency, affirming the reliability of the scale.

3.2.4. The Beck's Depression Inventory (BDI-II)

BDI-II (Beck et al., 1996) is designed to assess the severity of depression and is widely applicable for research and clinical settings (García-Batista et al., 2018; Wang & Gorenstein, 2013). The inventory includes 21 items, each scored on a scale from 0 (completely disagree) to 3 (completely agree), based on the individual's reported experience of depressive symptoms over the past two weeks, reflecting the frequency and intensity of depressive symptoms. The total score ranges from 0 to 63, with higher scores indicating greater severity of depression. In non-clinical populations, scores above 20 suggest depression, whereas in clinical settings, scores categorize the severity of depression from minimal to severe and are interpreted as follows: 0-13 minimal, 14-19 mild, 20-28 moderate, and 29-63 severe depression (Jackson-Koku, 2016).

The BDI is a reliable and valuable instrument for assessing depression levels, monitoring changes over time, and evaluating treatment response in both clinical and research settings. The internal consistency of the BDI-II in the Lithuanian sample was found to range from 0.897 to 0.94 (Grigutytė et al., 2023) and achieved a Cronbach's alpha value of 0.9 in the current study, thereby affirming its reliability for assessing depression.

3.2.5. The Clark-Beck Obsessive-Compulsive Inventory (CBOCI)

CBOCI (Clark et al., 2005) is designed to assess the frequency and severity of obsessive and compulsive symptoms. The 25-item scale consists of two subscales: obsessions (14 items) and compulsions (11 items). Each item is constructed on four response statements (0 – 3, each reflecting escalating levels of symptom frequency or severity), where the total score can range from 0 to 72, and higher scores indicate greater symptom severity.

The CBOCI is a reliable and valid instrument for screening and monitoring obsessive-compulsive disorder (OCD) symptoms in both clinical and research settings. The Cronbach's alpha values for the total scale and subscales within Lithuanian samples vary from 0.838 to 0.938 (Grigutytė et al., 2023), and the

Cronbach's alpha values for the subscales in the current study were as follows: total CBOCI score α= 0.92, obsessions subscale α= 0.88, compulsions subscale α= 0.87.

3.2.6. The NEO Personality Inventory-Revised (NEO PI-R)

NEO PI-R (Costa & McCrae, 1992) in its 240-item version, is a comprehensive self-report questionnaire designed to assess an individual's personality based on the Five-Factor Model (FFM). This model encompasses five broad domains of personality: Neuroticism, Extraversion, Openness to Experience, Agreeableness, and Conscientiousness. Each item on the NEO PI-R is rated on a five-point Likert scale ranging from "strongly disagree" to "strongly agree". Respondents are asked to indicate the extent to which they agree or disagree with various statements about their thoughts, feelings, and behaviors. The 240 items provide a detailed assessment of each of the five domains and their corresponding facets, allowing for a nuanced understanding of an individual's personality profile.

The NEO PI-R has been translated into numerous languages and is used globally to assess personality traits in diverse populations. Cronbach's alpha of the factors indicates a high degree of internal consistency, including the Lithuanian sample (Žukauskienė & Barkauskienė, 2006), as well the current sample: Neuroticism α= 0.92, Openness to Experience α= 0.9, Extraversion α= 0.89, Agreeableness α= 0.89, Conscientiousness α= 0.91.

3.2.7. The Multidimensional Assessment of Interoceptive Awareness (MAIA)

MAIA, developed by Mehling et al. (2012), is a self-report questionnaire designed to assess an individual's interoceptive awareness, which is the ability to perceive and interpret bodily sensations. The MAIA consists of 32 items, each rated on a six-point Likert scale ranging from 0 (never) to 5 (always). The MAIA is divided into eight subscales, each measuring a different dimension of interoceptive awareness: Noticing (the ability to consciously perceive uncomfortable, comfortable, or neutral bodily sensations), Not-Distracting (the tendency to remain present with discomfort rather than avoiding it through distraction), Not-Worrying (the capacity to experience bodily sensations without significant emotional distress), Attention regulation (the ability to intentionally focus on and control attention to bodily sensations), Emotional awareness (the ability to recognize the connection between physical sensations and emotions), Self-regulation (the capacity to utilize awareness of bodily sensations to regulate emotions), Body listening (the tendency to actively listen to the body for insights), and Trusting (the extent to which one views their body as safe and trustworthy).

The MAIA is a valuable tool for research and clinical practice, providing a comprehensive assessment of interoceptive awareness (Mehling et al., 2012). The scale has been validated in a Lithuanian sample (Baranauskas et al., 2016; Grabauskaitė et al., 2017). Cronbach's alpha values for the present study were as follows: whole scale ($\alpha = 0.88$), subscales: noticing ($\alpha = 0.67$), not distracting ($\alpha = 0.58$), not worrying ($\alpha = 0.55$), attention regulation ($\alpha = 0.83$), emotional awareness ($\alpha = 0.81$), self-regulation ($\alpha = 0.8$), body listening ($\alpha = 0.82$) and trust ($\alpha = 0.87$). Consistent with other authors, we found two subscales showing less optimal values; however, evidence supports its validity and discriminant ability in use (de Jong et al., 2016; Mehling et al., 2018).

Although a revised version of the instrument (MAIA-2) was developed to address these psychometric limitations, it has not yet been validated in the Lithuanian language, thus the original version was used in the present study.

3.3. EEG recording

Participants were comfortably seated in an upright position within a dimly lit, electrically shielded, and sound-attenuated chamber. EEG data were recorded using a 64-channel WaveGuard EEG cap with silver/silver chloride (Ag/AgCl) electrodes, following the International 10-10 System, and acquired using ANT Neuro (The Netherlands) equipment. Mastoid electrodes (M1 and M2) served as reference, and the ground electrode was positioned near Fz. Electrode impedances were maintained below 20 kΩ, and the data were sampled at 2048 Hz. An electro-oculogram (EOG) was recorded to monitor ocular artifacts, with vertical EOG (VEOG) electrodes placed above and below the right eye and horizontal EOG (HEOG) electrodes positioned at the outer canthi of both eyes.

3.4. Tasks paradigms

3.4.1. The equiprobable auditory Go/NoGo task

The auditory equiprobable Go/NoGo paradigm consisted of 150 auditory stimuli (50% Go and 50% NoGo), with 75 Go and 75 NoGo trials. Following Barry et al. (2007) and our previous studies (Griskova-Bulanova et al., 2016; Melynyte et al., 2017), two binaural tones (1000 Hz and 1500 Hz, 60 dBA, 50 ms duration, and 5 ms rise/fall time) were presented in a random order with a fixed stimulus onset asynchrony (SOA) of 1100 ms. The assignment of tone frequency to Go or NoGo conditions was counterbalanced across participants.

Participants were instructed to respond as quickly and accurately as possible by pressing a key for Go stimuli and withholding responses for NoGo stimuli, while maintaining fixation on a white cross (+) on a black screen. A practice block of 5 trials preceded the task. Schematic representation of the equiprobable auditory Go/NoGo task is provided in Figure 3.2.

Responses were categorized to as follows: correct Go – key pressed within 1000 ms of a Go stimulus onset; correct NoGo – no response to a NoGo stimulus; incorrect Go (omission errors) – no response within 1000 ms of Go stimulus onset; and incorrect NoGo (commission errors) – key pressed during a NoGo stimulus.

Reaction times (RT) for Go trials were measured from stimulus onset to the participant's response, while response accuracy was computed as the percentage of correct Go and NoGo responses.

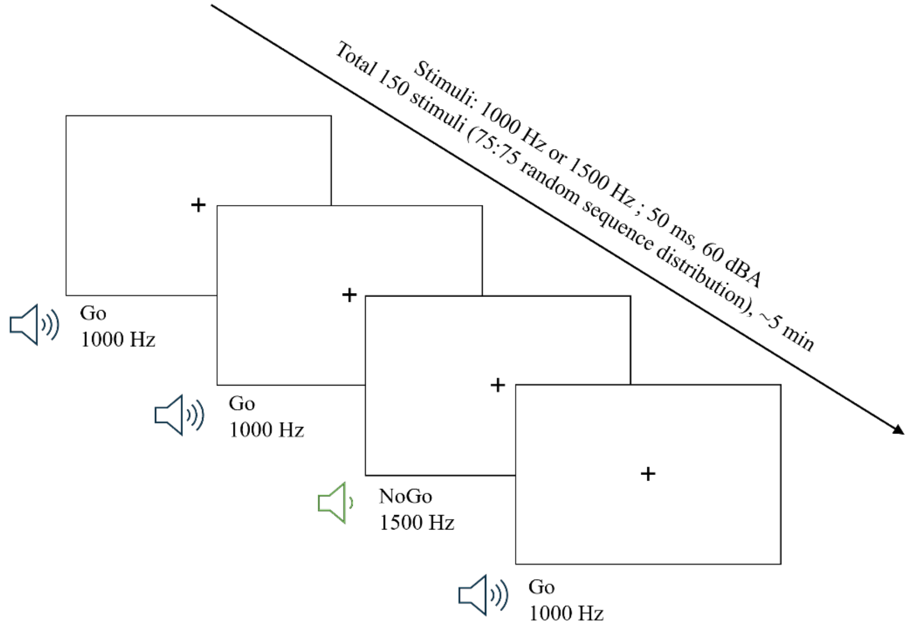

Figure 3.2. Schematic representation of the equiprobable auditory Go/NoGo task.

3.4.2. The resting-state alpha asymmetry

Participants were instructed to keep their eyes open (EO condition) for the first two minutes of the session. Following an alarm indicating a change, they were asked to close their eyes (EC condition) for the next two minutes, while resting-state EEG signals were recorded. Research indicates that a 2-minute EEG recording provides asymmetry scores with internal consistency and reliability comparable to an 8-minute recording (Allen et al., 2004).

Throughout the session, participants were instructed to avoid movement and remain still, relax, and avoid engaging in specific thoughts. In the EO condition, they were directed to fixate their gaze on a white cross against a grey background on a screen placed in front, and not to fall asleep during the eyes-closed condition. Throughout the session, EEG recordings for all participants were actively monitored to ensure compliance with instructions and to detect any indications of drowsiness.

3.4.3. The resting-state microstates

Participants were instructed to keep their eyes closed for the entire 5-minute period, as indicated by auditory cues marking the beginning and end of the recording. They were also asked to remain still, relax, avoid engaging in specific thoughts, and refrain from falling asleep. EEG recordings were continuously observed throughout the session to ensure adherence to the experimental instructions and to identify any signs of drowsiness.

3.5. EEG data processing

The offline EEG data processing was conducted using MATLAB (version R2020a, The Mathworks, Natick, MA, USA) in conjunction with the EEGLAB toolbox (Delorme & Makeig, 2004). Initial steps included the removal of power line noise utilizing the CleanLine plugin in EEGLAB, which applies Thomas F-statistics for 50 Hz noise elimination. Subsequent steps involved correcting artifacts attributable to eye movements and cardiac activity using an independent component analysis (ICA) approach ('runica' with default settings on EEGLAB). The data was then visually inspected, and channels exhibiting excessive artifacts were manually rejected, followed by reconstruction using a spherical spline interpolation method (Perrin et al., 1989).

3.5.1. The equiprobable auditory Go/NoGo task

For the Go/NoGo task dataset, the preprocessed data were further filtered between 0.1 and 25 Hz using a Butterworth filter of 2nd order. Clean data were segmented into stimulus-locked epochs from -100 ms (pre-stimulus onset) to 600 ms (post-stimulus onset) and sorted to correct Go, correct NoGo, incorrect Go, and incorrect NoGo conditions. Recomputed to an average reference, baseline-corrected (−100 to 0 ms pre-stimulus onset), artifact-free epochs were averaged to compute ERP waveforms for each participant. Only correct Go and correct NoGo trials with a minimum of 40 artifact-free epochs per condition were included in the final analysis. On average, participants had

60.43 ± 7.45 artifact-free epochs for Go trials and 58.47 ± 8.03 epochs for NoGo trials across a total of 133 participants.

Mean amplitudes (averaged over a 40 ms window centered on peak latency) and latencies (time points of peak amplitudes) were extracted within established time windows based on grand average ERP waveforms and prior research. The N1 peak was defined as the most negative peak between 80 and 190 ms post-stimulus; the N2 peak was defined as the most negative peak between 190 and 350 ms post-stimulus; the P2 peak was defined as the most positive peak between 150 and 270 ms post-stimulus; and the P3 peak was defined as the most positive peak between 240 and 600 ms post-stimuli. All components were measured at Fz, FCz, Cz, CPz, and Pz electrodes.

3.5.2. The resting-state alpha asymmetry

In the alternating resting-state dataset, data were filtered between 0.1 and 30 Hz using a second-order Butterworth filter to ensure the quality of the EEG signals for further analysis, and the datasets were recomputed to an average reference. Data were then segmented into non-overlapping, artefact-free, two-second epochs (resulting in an average of 53.86±5.13 artifact-free epochs for EO1 and 53.76±6.16 for EC datasets) that were baselined over the epoch duration. Each participant had to have at least 40 clean trials for the data to be included for further analyses.

Power spectra (μV^2) were derived from EEG data by applying MATLAB's Fast Fourier Transform (FFT) function using a Hanning window (Fieldtrip parameters mtmfft and Hanning). The mean frontal and parietal alpha power were calculated by averaging absolute power over predefined alpha frequencies (8-12 Hz) across respective electrodes (frontal: F7, F3, Fz, F4, F8, and parietal: P7, P3, Pz, P4, P8) and conditions (eyes-open (EO) and eyes-closed (EC)) for each participant.

The Alpha Asymmetry index (AAI) was computed as the log-transformed difference between right and left alpha power values (Reznik & Allen, 2018; Smith et al., 2017):

$$AAI = \ln(R) - \ln(L)$$

where L and R denote left (F3, F7, P3 or P7) and right (F4, F8, P4 or P8) electrode sites responses, respectively. The FFT-derived alpha power was analyzed at four paired electrode sites to assess middle (F3/F4 and P3/P4) and lateral (F7/F8 and P7/P8) alpha asymmetry. Alpha asymmetry scores were calculated for each condition (EO, EC), with positive scores indicating greater right alpha power (and greater relative left hemisphere activity) and negative scores indicating greater left alpha power (and relative right hemisphere dominance).

3.5.3. The resting-state microstates

For the eyes-closed resting-state dataset, preprocessing continued with downsampling to 512 Hz, followed by filtering between 1 and 40 Hz using a second-order Butterworth filter. The reference was again recomputed to the average reference prior to further analysis.

EEG microstate segmentation was performed using the Cartool toolbox (v.5.01) (Brunet et al., 2011). Each individual EEG was segmented into 20 random epochs of 6000 time frames. For each epoch, global field power (GFP) was calculated as the standard spatial deviation, and only topographies at GFP peaks were submitted to k-means clustering, ignoring its polarity and applying a minimal correlation threshold (<0.5). A spatial filter was applied to smooth out topographies (Michel & Brunet, 2019). The number of clusters for each epoch was set between 1 and 12, with 50 random initializations, and the optimal number of clusters for each epoch was based on the meta-criteria. Meta-criteria is a synthetic cluster evaluation criteria, obtained by combining outputs from 6 different criteria, such as Silhouettes, Krzanowski-Lai-Lai, Gamma, Davies-Bouldin, Dunn index, and Point Biserial (Cartool's Reference Guide: Brunet et al., 2011). For the second stage, all sets of the most dominant individual templates were concatenated and submitted to the second k-means clustering, where concatenated data was resampled into 20 random epochs of 500 time frames. The number of clusters this time ranged between 1 and 15 with 50 random initializations, once again ignoring polarity differences and applying a minimal correlation threshold. Group level topographies obtained from all subjects were backfitted to individual EEGs by winner-takes-all approach. Three temporal parameters were quantified for each subject: mean duration, occurrence rate, and time coverage.

3.6. Statistical analysis

A continuous evaluation across the entire sample was conducted using correlation analyses to assess the associations between:

- PIU scores and affective symptoms (anxiety (BAI), depression (BDI-II), obsessive-compulsive symptoms (CBOCI)) based on self-report data.
- PIU scores and interoceptive awareness (MAIA) and personality traits (NEO PI-R), based on self-report data.
- PIU scores, behavioral task performance, and ERP amplitudes and latencies (N1, N2, P2, and P3) in the Go/NoGo task dataset.

- PIU scores and frontal and parietal alpha asymmetry indices in the alternating resting-state dataset.
- PIU scores and microstates parameters (mean duration, occurrence rate, time coverage) in the eyes-closed resting-state dataset.

Normality was tested using the Shapiro–Wilk test, followed by Spearman's correlation analysis. To enhance result robustness, non-parametric bootstrapping with 5000 replicates was applied, the significance threshold was set to $\alpha = 0.05$, and p values were corrected for multiple comparisons using the False Discovery Rate (FDR) method (Benjamini & Hochberg, 1995).

In parallel, a group-based approach was applied to compare individuals at the extremes of internet use. Participants were categorized into low and high PIU groups based on PIUQ-9 scores, using a quartile-based approach with inclusive thresholds. The low PIU group included individuals with scores ranging from 10 to 16, while the high PIU group comprised individuals with scores from 23 to 36. The lower threshold for the high PIU group (a score of 23) closely aligns with the provisional cutoff score of 22 suggested in earlier research (Koronczai et al., 2011). This overlap supports the validity of using a quartile-based method in our non-clinical sample, while also capturing individuals whose PIUQ-9 scores approximate clinical relevance.

To examine differences between the high and low PIU groups, Shapiro–Wilk tests were conducted to assess bivariate normality. Levene's test was used to evaluate homogeneity of variance between groups. As violations of normality and homogeneity of variance were detected, Mann–Whitney U tests were employed for group comparisons. Non-parametric bootstrapping with 5000 replicates was applied, and the FDR method (Benjamini & Hochberg, 1995) was used to correct for multiple comparisons in cases of significant main or interaction effects. The significance threshold for all comparisons was set to $\alpha = 0.05$, and the effect size is given by the rank biserial correlation, with values of approximately 0.25, 0.40, and 0.65 representing small, medium, and large effects, respectively (Plonsky & Oswald, 2014).

Statistical analyses were conducted using MS Excel (version 2053, Microsoft Corporation, 2018), JASP 0.18.3 (JASP Team, 2024), and SPSS (version 29.0.2.0, IBM SPSS).

3.6.1. Interoceptive awareness and PIU: network analysis approach

Additionally, the interrelations between interoceptive and personality factors associated with internet use severity and various online behaviors were explored. A linear regression model was subsequently employed to evaluate the independent contribution of interoceptive awareness (MAIA) and personality traits (NEO PI-R) for the risk of problematic internet use (PIUQ-9). The normality of the standardized residuals for the linear regression model was assessed visually using a Q-Q plot, which indicated approximate normality.

To explore the dynamic interactions between interoceptive dimensions, personality factors, and internet use patterns, the EBICglasso method was employed to conduct network analysis. The extended Bayesian information criterion (EBIC), alongside a hyperparameter set at 0.5 and non-parametric bootstrapping (with 1000 bootstrap samples), was used to ensure a balance between specificity, interpretability, and sensitivity (Epskamp et al., 2018; Foygel & Drton, 2010). The common centrality measures (strength, closeness, betweenness, and expected influence) (Opsahl et al., 2010) were evaluated to assess the importance and connectivity of variables within the network. The results are visualized as a weighted network structure, where each node represents a variable, and each edge represents a correlation, with blue edges indicating positive and red edges indicating negative relationships. Edge thickness and color saturation reflect the strength of these correlations. Only links with an absolute weight above 0.10 were considered meaningful and interpreted. Data were analyzed using IBM SPSS Statistics (IBM SPSS, V29.0.2.0, Armonk, NY) for the descriptive and inferential tests and JASP 0.18.3 software (JASP Team, 2024) for the network analysis.

Statistical power was evaluated using a post hoc power analysis with G*Power (version 3.1.9.4; (Faul et al., 2007)). For the multiple linear regression analysis with nine predictors, this sample provided 94% power to detect an overall model effect size of f2=0.15. While formal sample size guidelines for the network analysis are still evolving, recommendations suggest that larger samples contribute to more accurate and stable parameter estimation (Epskamp et al., 2018).

4. RESULTS

4.1. Psychological measures

Descriptive statistics (means and standard deviations) for the internet usage patterns, psychological characteristics, interoceptive awareness, and personality traits are presented in Table 4.1.

The mean PIUQ-9 score (19.68 ± 5.43) of the whole sample falls below the provisional cutoff of 22 for problematic internet use (Koronczai et al., 2011). The DPIU total score (25.45 ± 18) reflected diverse engagement across online activities, with entertainment/video streaming (9.84 ± 4.49) and social media (9.26 ± 4.33) being the most common, while gaming (11.97 ± 5.32) and messaging (13.77 ± 5.35) showed higher variability.

Psychological measures indicated moderate group levels of anxiety (BAI: 31.83 ± 7.53), with some participants likely experiencing clinically relevant symptoms (Beck et al., 1988). The mean BDI score (10.44 ± 8.72) indicated generally low depressive symptoms in a cohort, though suggesting individual differences. The CBOCI total score (19.23 ± 11.44) highlighted variability in obsessive–compulsive traits, with obsession-related symptoms (11.68 ± 6.64) exceeding compulsions (7.59 ± 6.02).

Overall, these findings support wide-ranging internet use behaviors and different levels of experienced psychological symptoms.

Table 4.1. Descriptive statistics of internet usage patterns, psychological characteristics, interoceptive awareness, and personality traits in the sample.

Variable	Valid (n)	Mean	SD
Internet Usage Patterns (PIUQ-9, DPIU)			
PIUQ-9	161	19.68	5.43
DPIU_total	161	25.45	18
Entertainment and Video Streaming	103	9.84	4.49
Social Media	99	9.26	4.33
Gaming	37	11.97	5.32
Messaging	43	12.77	5.35
Dating Apps	12	7.75	3.98
Sexual Content	16	10.25	3.99
Online Shopping	21	9.05	4.73
Information Search	25	12.56	4.42
Psychological Characteristics			
BAI	160	31.83	7.53

Variable	Valid (n)	Mean	SD
BDI	157	10.44	8.72
CBOCI	160	19.23	11.44
CBOCI obsessions	160	11.68	6.64
CBOCI compulsions	161	7.59	6.02
Interoceptive Awareness (MAIA)			
Noticing	159	3.34	0.93
Not-Distracting	159	2.97	0.91
Not-Worrying	159	3.02	1.10
Attention Regulation	159	3.00	0.83
Emotional Awareness	151	3.28	1.05
Self-Regulation	151	2.71	1.09
Body Listening	151	2.26	1.17
Trusting	151	3.64	1.02
Personality Traits (NEO PI-R)			
Neuroticism	158	52.63	12
Extraversion	159	48.58	11.14
Openness	158	58.00	10.35
Agreeableness	159	48.98	12.15
Conscientiousness	160	49.87	10.79

BAI – Beck Anxiety Inventory, BDI – Beck's Depression Inventory, CBOCI – Clark-Beck Obsessive-Compulsive Inventory, DPIU – Dimensions of Problematic Internet Use; MAIA – Multidimensional Assessment of Interoceptive Awareness; NEO PI-R – Revised NEO Personality Inventory; PIUQ-9 – Problematic Internet Use Questionnaire.

Due to the small number of participants reporting usage of the Dating Apps (n=12), Sexual Content (n=16), and Online Shopping categories (n=21), these domains were excluded from the following analysis.

4.1.1. Relationships between problematic internet use questionnaires (PIUQ-9 and DPIU)

As expected, strong correlations were found between PIUQ-9 and DPIU scores, as well as among most DPIU subdomains, suggesting the consistency of problematic internet use measures. Full correlation results and visual representations for significant associations are shown in Table 4.2 and Figure 4.1.

4.1.2. Relationships between internet use and psychological measures

As expected, higher PIUQ-9 and DPIU scores were associated with poorer psychological states. PIUQ-9 scores positively correlated with all the measures assessed: BAI (r_s=.288, p <.001*), BDI (r_s=.285, p <.001*), obsessions (r_s=.309, p <.001*) and compulsions (r_s=.332, p <.001*), and the overall CBOCI score (r_s=.377, p <.001*). These findings suggest that greater internet use severity is linked to higher levels of anxiety, depression, and obsessive–compulsive symptoms. Detailed results are presented in Table 4.3 and correlation plots for domains showing significant correlations are provided in Figure 4.2.

Among DPIU subdomains, social media use positively correlated with anxiety (BAI, $r_s = 0.277$, $p = 0.005$), depression (BDI, $r_s = 0.333$, $p = 0.001$), total CBOCI (CBOCI, $r_s = 0.267$, $p = 0.007$) and both subscales: obsessions ($r_s = 0.23$, $p = 0.023$) and compulsions ($r_s = 0.221$, $p = 0.028$) levels. Entertainment and video streaming use was positively correlated with anxiety (BAI, $r_s = 0.3$, $p = 0.002$), total CBOCI score (CBOCI, $r_s = 0.215$, $p = 0.029$), and obsessions (CBOCI obsessions subscale, $r_s = 0.242$, $p = 0.014$). Messaging was positively correlated with total CBOCI score (CBOCI, $r_s = 0.362$, $p = 0.017$), and obsessions (CBOCI obsessions subscale, $r_s = 0.388$, $p = 0.01$). Correlations of gaming and information search dimensions did not reach significance with any of the psychological variables, suggesting that the impact of internet use on mental health varies across different online activities. Detailed results are presented in Table 4.3.

4.1.3. Group differences in psychological measures

The low PIU group (n = 45, 22 females, PIU score 13.73 ± 2.04) included individuals with scores ranging from 10 to 16, while the high PIU group (n = 46, 30 females, PIU score 26.67 ± 3.2) comprised individuals with scores from 23 to 36. The groups did not differ in age (p = 0.263) but showed significant differences across all psychological measures. Descriptive statistics for psychological measures between the two groups are presented in Table 4.4, and group comparison results are detailed in Table 4.5.

Table 4.2. Spearman's correlations between problematic internet use questionnaires (PIUQ-9 and DPIU).

Variable		PIUQ-9	Gaming	Social Media	Messaging	Entertainment and Video Streaming	Information Search
Gaming	Spearman's rho	**0.343***					
	p-value	0.038					
	n	37					
Social Media	Spearman's rho	**0.534***	0.338				
	p-value	<0.001	0.107				
	n	99	24				
Messaging	Spearman's rho	**0.49***	0.377	**0.656***			
	p-value	<0.001	0.283	<0.001			
	n	43	10	34			
Entertainment and Video Streaming	Spearman's rho	**0.598***	0.251	**0.462***	**0.743***		
	p-value	<0.001	0.198	<0.001	<0.001		
	n	103	28	66	31		
Information Search	Spearman's rho	0.342	0.1	0.295	**0.843***	0.221	
	p-value	0.095	0.950	0.183	<0.001	0.323	
	n	25	5	22	12	22	
DPIU_total	Spearman's rho	**0.556***	**0.341***	**0.55***	**0.801***	**0.618***	**0.596***
	p-value	<0.001	0.039	<0.001	<0.001	<0.001	0.002
	n	145	37	99	43	103	25

* The significance of the results survived FDR correction. DPIU—The Dimensions of Problematic Internet Use and PIUQ-9—The Nine-Item Problematic Internet Use Questionnaire. The variation in sample sizes across the subscales is attributed to the low overlap between specific dimensions, resulting in smaller sample sizes for certain subscales within the study.

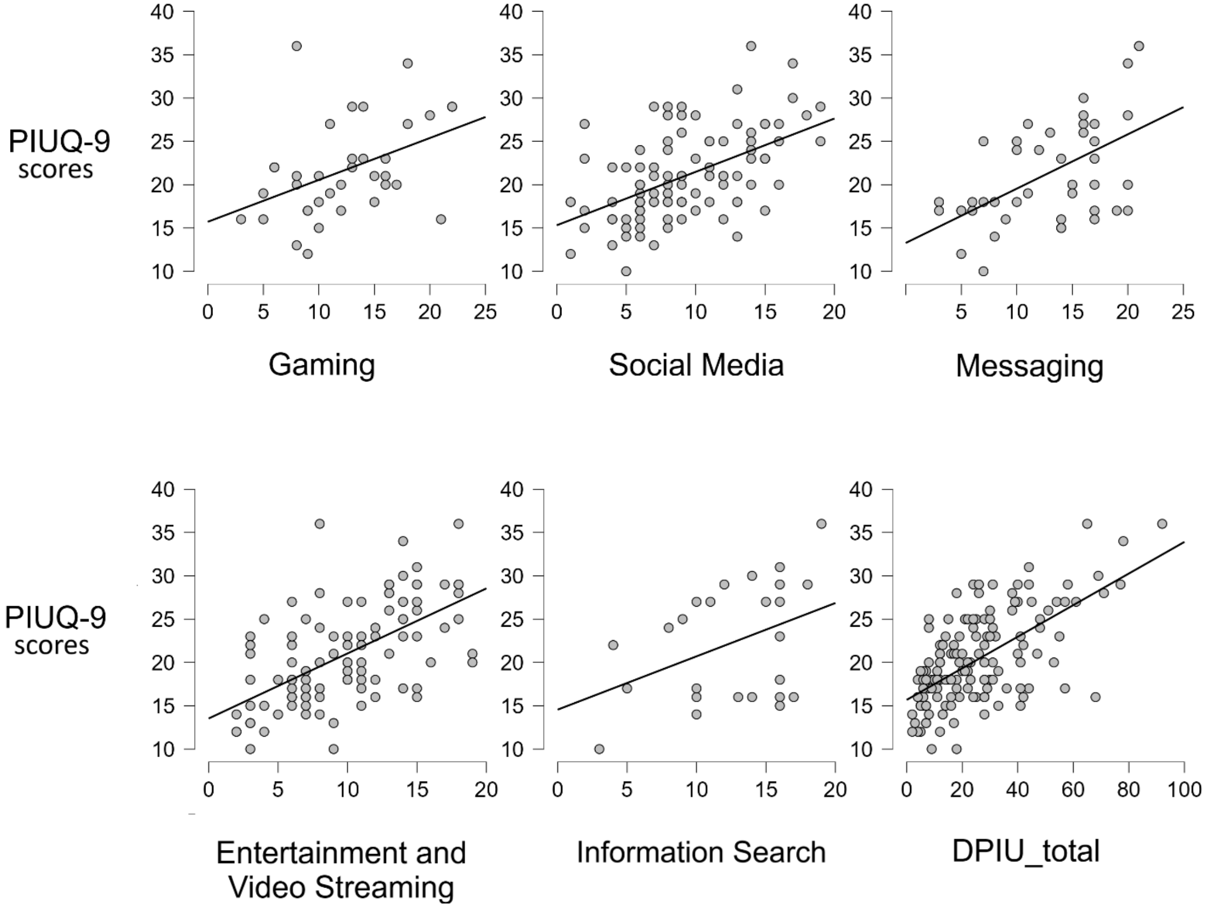

Figure 4.1. Correlation of PIUQ-9 scores with gaming, social media, messaging, entertainment and video streaming, information search, and DPIU_total scales scores.

Table 4.3. Spearman's correlations between psychological evaluation measures and internet use questionnaires (PIUQ-9 and DPIU).

Variable		BAI	BDI	CBOCI	CBOCI obsessions	CBOCI compulsions
PIUQ-9	Spearman's rho	**0.288***	**0.285***	**0.377***	**0.309***	**0.332***
	p-value	< .001	< .001	< .001	< .001	< .001
	n	160	157	160	160	161
Entertainment and Video Streaming	Spearman's rho	**0.3***	0.185	**0.215***	**0.242***	0.135
	p-value	0.002	0.067	0.029	0.014	0.174
	n	103	99	103	103	103
Gaming	Spearman's rho	0.076	0.183	0.182	0.192	0.174
	p-value	0.653	0.286	0.281	0.254	0.303
	n	37	36	37	37	37
Social Media	Spearman's rho	**0.277***	**0.33***	**0.267***	**0.23***	**0.221***
	p-value	0.005	0.001	0.007	0.023	0.028
	n	99	96	99	98	99
Messaging	Spearman's rho	0.085	**0.346**	**0.362***	**0.388***	0.256
	p-value	0.588	0.027	0.017	0.01	0.098
	n	43	41	43	43	43
Information Search	Spearman's rho	-0.258	0.317	0.246	0.319	0.08
	p-value	0.213	0.14	0.235	0.121	0.705
	n	25	23	25	25	25
DPIU_total	Spearman's rho	**0.369***	**0.315***	**0.342***	**0.347***	**0.228***
	p-value	< .001	< .001	< .001	< .001	0.006
	n	145	141	145	144	145

* the significance of the results survived FDR correction. PIUQ-9 – The Nine-Item Problematic Internet Use Questionnaire, BAI – The Beck Anxiety Inventory, BDI-II – Beck's Depression Inventory, CBOCI – The Clark-Beck Obsessive-Compulsive Inventory, DPIU – The Dimensions of Problematic Internet Use.

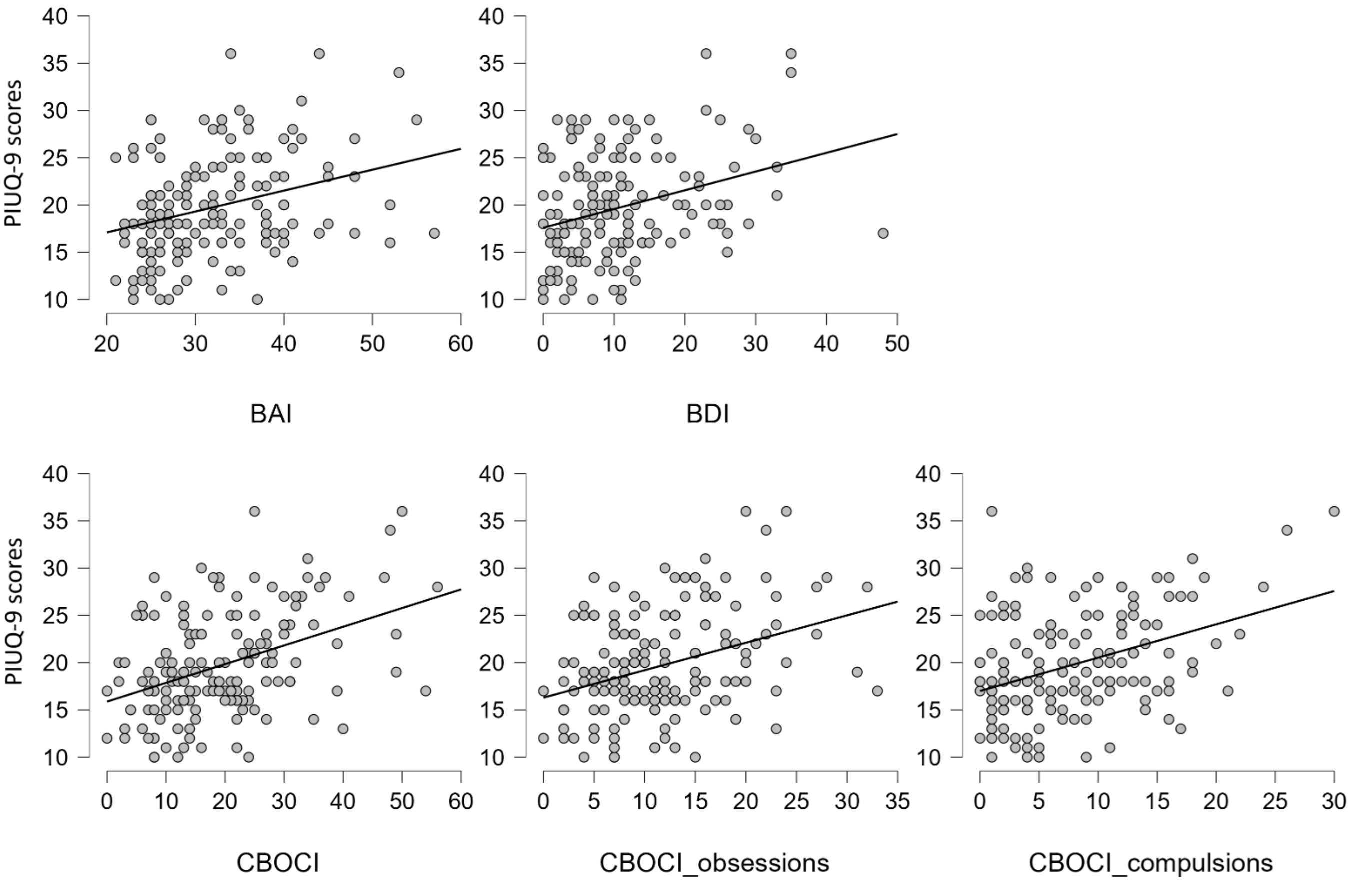

Figure 4.2. Correlation plots of PIUQ-9 scale scores with the scores of the questionnaires assessing psychological symptoms. PIUQ-9 – The Nine-Item Problematic Internet Use Questionnaire, BAI – The Beck Anxiety Inventory, BDI-II –Beck's Depression Inventory, CBOCI – The Clark-Beck Obsessive-Compulsive Inventory.

Table 4.4. Descriptive statistics for psychological measures between high and low PIUQ-9 score groups.

Variable	Group	n	Mean	SD
PIUQ-9	High PIU	46	26.67	3.22
	Low PIU	45	13.73	2.04
BAI	High PIU	46	34.96	7.98
	Low PIU	44	29.41	6.52
BDI	High PIU	45	12.82	9.73
	Low PIU	44	7.30	5.73
BOCI	High PIU	46	24.78	13.04
	Low PIU	45	14.47	8.50
CBOCI obsessions	High PIU	46	14.46	7.23
	Low PIU	45	9.60	5.28
CBOCI compulsions	High PIU	46	10.33	7.14
	Low PIU	45	4.96	4.26

BAI—Beck Anxiety Inventory; BDI—Beck Depression Inventory; CBOCI—Clark–Beck Obsessive–Compulsive Inventory; PIUQ-9—The Nine-Item Problematic Internet Use Questionnaire.

Table 4.5. Group differences between psychological evaluation measures.

Variable	U	*p*	Effect Size	SE Effect Size
PIUQ-9	1188	**< .001***	1	0.121
BAI	575.5	**< .001***	0.431	0.122
BDI	659	**0.007***	0.334	0.122
CBOCI	536	**< .001***	0.482	0.121
CBOCI obsessions	628	**.001***	0.393	0.121
CBOCI compulsions	553.5	**< .001***	0.465	0.121

* The significance of the results survived FDR correction. Mann–Whitney U test. BAI—Beck Anxiety Inventory; BDI—Beck Depression Inventory; CBOCI—Clark–Beck Obsessive–Compulsive Inventory; PIUQ-9—The Nine-Item Problematic Internet Use Questionnaire; SE effect size—standard error of effect size; and U—Mann–Whitney U test statistic.

4.1.4. Psychological findings within EEG subsamples

The associations observed between measures of PIU and scores on psychological questionnaires within the EEG subsamples closely mirrored those identified in the full sample, as detailed in Section 4.1.2. Descriptive statistics and comprehensive correlation results specific to each EEG subsample are presented in Supplementary Material 1 (Table SM 1.1 and Table SM 1.2, respectively).

Group differences in psychological measures within these EEG subsamples were also consistent with those observed in the full sample, as detailed in Section 4.1.3. Descriptive statistics and detailed results are provided in Supplementary Material 1 (Table SM 1.3 and Table SM 1.4, respectively).

4.2. Association between interoceptive awareness and PIU

4.2.1. Relationships between interoceptive awareness and internet use

Significant relationships were observed between interoceptive awareness and internet use patterns (Table 4.6). PIUQ-9 scores were negatively correlated with Not-Distracting (r_s=-.359, p<0.001). Regarding the dimensions of internet use, messaging domain demonstrated significant negative correlations with Attention Regulation (r_s=-.397, p=0.008), Emotional Awareness (r_s=-.399, p=0.011), Self-Regulation (r_s=-.456, p=0.003), and Body Listening (r_s=-.47, p=0.002). No significant correlations were observed between interoceptive domains and entertainment and video streaming, information search, social media, and gaming dimensions.

4.2.2. Association between interoceptive awareness and personality traits

Significant relationships were observed between interoceptive awareness and personality traits across all traits, except for Agreeableness (Table 4.6). However, after applying FDR correction, personality traits significantly correlated with interoceptive awareness were Openness and Neuroticism. Specifically, Openness was positively correlated with Body Listening (r_s=.275, p<0.001) and Emotional Awareness (r_s=.284, p<0.001), while Neuroticism was negatively correlated with Self-Regulation (r_s=-.39, p<0.001), Attention Regulation (r_s=-.37, p<0.001), Not-Worrying (r_s=-.388, p<0.001) and Trusting (r_s=-.446, p<0.001).

4.2.3. Contribution of different interoceptive variables and neuroticism to internet use

In the linear regression analysis, three variables – Neuroticism (p = 0.04), Trusting (p = 0.04), and Not-Distracting (p < 0.001) were found to be statistically significant predictors of PIU (Figure 4.3.). The model achieved an R value of 0.509, indicating a moderate positive linear relationship between the predictors and PIU, and explained 25.9% of the variability in the PIU score. Results are presented in Table 4.7.

4.2.4. Network visualization of interoception, personality traits, and internet use

To explore the interrelationships among various interoceptive states, personality traits, and PIU, a network of eight interoception state variables, five personality traits, and two PIU measures was constructed (Figure 4.4.). Out of 105 potential edge weights, 33 were non-zero, resulting in a network sparsity of 0.686. The weighted edge matrix is detailed in Supplementary Material 2, Table SM 2.1.

The network analysis showed Neuroticism as a key intermediary in the network, acting as a "bridge" between PIU and interoceptive awareness variables. As anticipated, both the PIUQ-9 and DPIU questionnaires showed connections to Neuroticism (0.053, 0.129, respectively). Within interoceptive states, Neuroticism was negatively associated with Trusting (-0.239) and Not-Worrying (-0.202) variables, along with weaker connections to Self-Regulation (-0.124).

The analysis revealed that both PIU questionnaires (PIUQ-9 and DPIU) showed connections to each other (0.421), but neither was strongly connected to most interoception dimensions, except for negative links from PIUQ-9 to Not-Distracting (-0.192).

The standardized centrality indices for betweenness, closeness, degree, and expected influence are presented in Figure 4.5. The degree index highlights Neuroticism, Body Listening, and Self-Regulation as the nodes with the most connections. In terms of betweenness, Neuroticism, Self-Regulation, and Body Listening are positioned as the nodes with the shortest pathways connecting other variables in the network. Considering closeness, the index shows Self-Regulation as having the highest inverse sum of shortest paths to all other nodes in the network. For expected influence, the nodes with the highest cumulative edge weights, considering both positive and negative relationships, are Body Listening, Self-Regulation, and Attention Regulation. The precision of these edge weights was assessed using 95% bootstrapped confidence intervals, with an illustration of the estimated edge-weight matrix and these intervals presented in Supplementary Material 2, Figure SM 2.1.

Table 4.6. Spearman's correlations between interoceptive awareness (IA) and personality traits and internet usage patterns.

IA domain / Variable	Noticing	Not-Distracting	Not-Worrying	Attention Regulation	Emotional Awareness	Self-Regulation	Body Listening	Trusting
Personality Traits (NEO PI-R)								
Neuroticism	-0.055	-0.151	**-0.388***	**-0.37***	**0.174**	**-0.39***	-0.107	**-0.446***
Extraversion	0.045	0.075	0.079	0.058	**0.187**	**0.172**	**0.189**	**0.196**
Openness	**0.202**	0.08	-0.053	0.128	**0.284***	**0.181**	**0.275***	0.046
Agreeableness	-0.029	0.097	-0.067	-0.023	0.065	0.081	0.108	0.079
Conscientiousness	0.084	0.059	-0.136	0.146	0.04	0.135	0.121	**0.213**
Internet Usage Patterns (PIUQ-9, DPIU)								
PIUQ-9	0.027	**-0.359***	-0.083	0.061	0.103	-0.036	0.063	**-0.162**
DPIU_total	0.083	**-0.202**	-0.004	-0.11	0.073	-0.08	0.008	-0.166
Entertainment and Video Streaming	0.09	-0.19	-0.079	-0.152	-0.007	-0.024	0.013	-0.157
Social Media	-0.081	-0.043	-0.066	-0.069	0.056	0.012	0.01	-0.034
Gaming	0.157	-0.085	-0.226	0.116	0.237	0.277	0.305	0.122
Messaging	-0.101	0.024	-0.078	**-0.397***	**-0.399***	**-0.456***	**-0.47***	**-0.314**
Information Search	-0.131	-0.225	**0.439**	-0.108	-0.184	-0.048	-0.343	0.081

* The significance of the results survived FDR correction. DPIU = Dimensions of Problematic Internet Use; MAIA = Multidimensional Assessment of Interoceptive Awareness; NEO PI-R = Revised NEO Personality Inventory; PIUQ-9 = Problematic Internet Use Questionnaire.

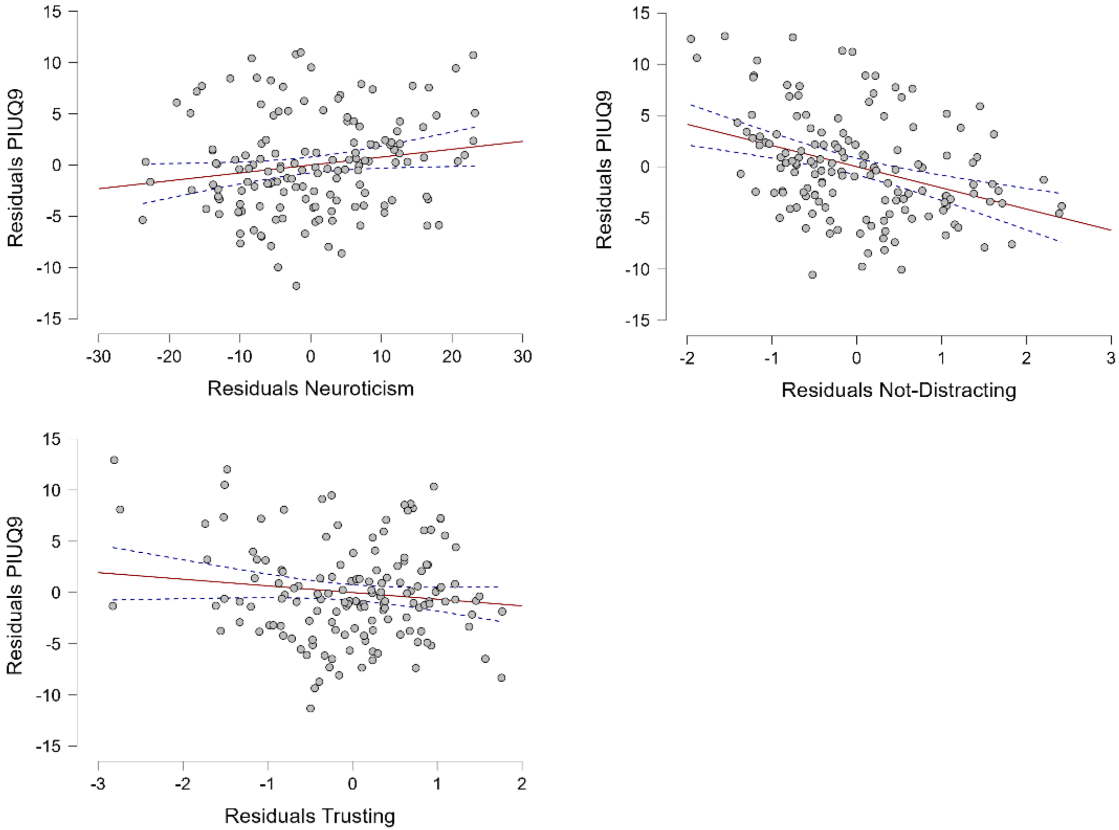

Figure 4.3. Partial regression plots of statistically significant predictors of Problematic Internet Use. Dashed lines represent the 95% confidence interval of the regression estimates.

Table 4.7. Linear regression model assessing the independent contribution of neuroticism and different interoceptive awareness variables to PIUQ-9 score.

Predictors	***B***	***SE***	***β***	***t***	***p***	***95% CI***
(Intercept)	20.631	4.279		4.822	**< .001**	12.171 to 29.092
Neuroticism	0.088	0.042	0.199	2.075	**0.04**	0.004 to 0.172
Noticing	-0.435	0.526	-0.072	-0.827	0.41	-1.474 to 0.605
Not-Distracting	-1.848	0.457	-0.318	-4.044	**< .001**	-2.752 to -0.945
Not-Worrying	0.182	0.435	0.037	0.418	0.677	-0.678 to 1.042
Attention Regulation	1.159	0.658	0.179	1.76	0.081	-0.143 to 2.460
Emotional Awareness	0.422	0.595	0.084	0.708	0.48	-0.755 to 1.598
Self-Regulation	-0.006	0.532	-0.001	-0.011	0.991	-1.057 to 1.045
Body Listening	-0.164	0.55	-0.036	-0.299	0.766	-1.252 to 0.923
Trusting	-0.993	0.478	-0.192	-2.078	**0.04**	-1.938 to -0.048

Significant values are bolded. **B** = Unstandardized regression coefficient, **SE** = Standard error of B, **β** = Standardized regression coefficient, **t** = t-value for the predictor, **p** = p-value (significance level).

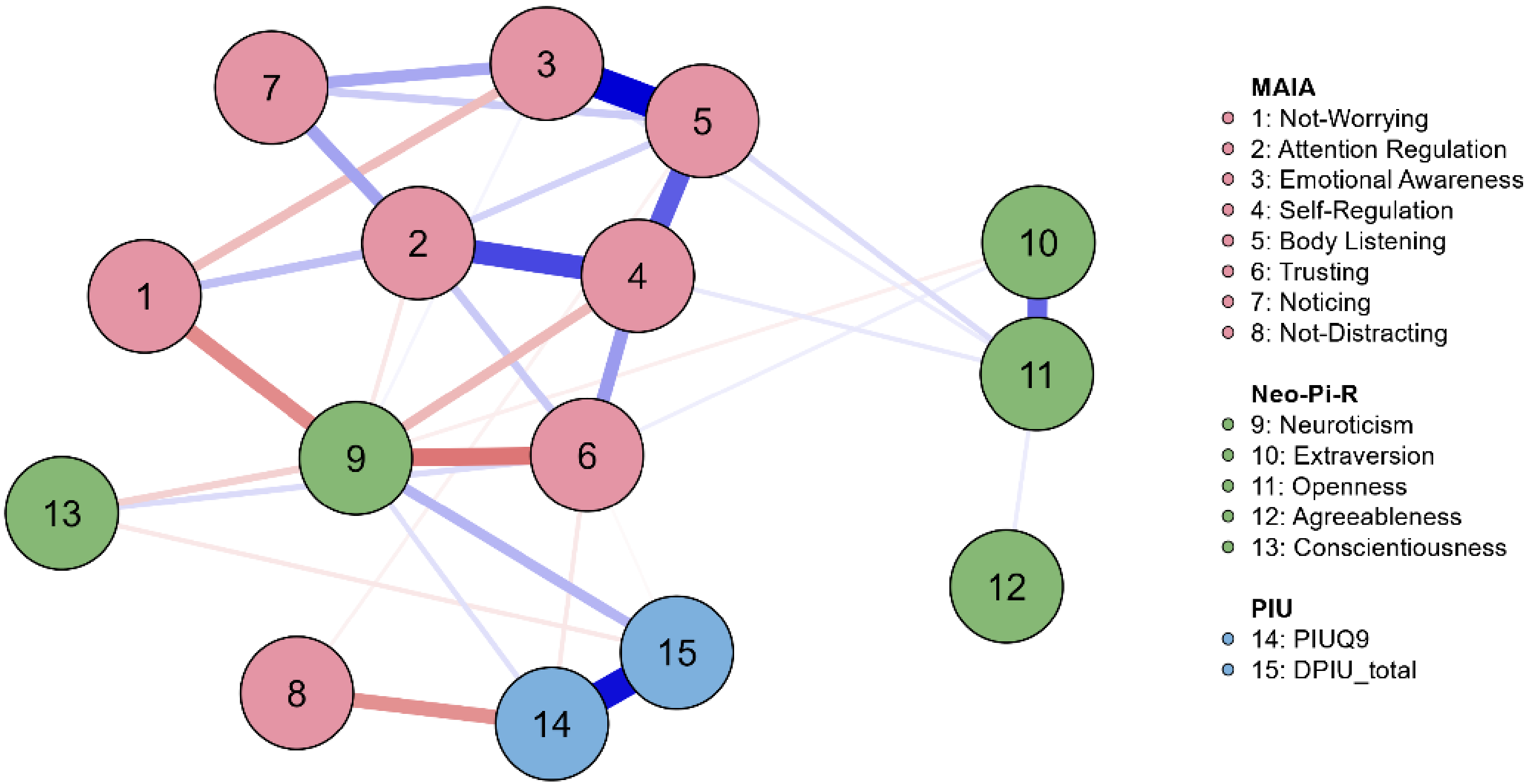

Figure 4.4. Network of Interoceptive awareness, Personality traits, and Problematic Internet Use. This diagram includes 15 distinct variables, labeled on the right, with connections depicted through EBICglasso partial correlations. Positive relationships are shown with blue edges, and negative ones with red edges. The width and saturation of these edges indicate the strength of the relationships.

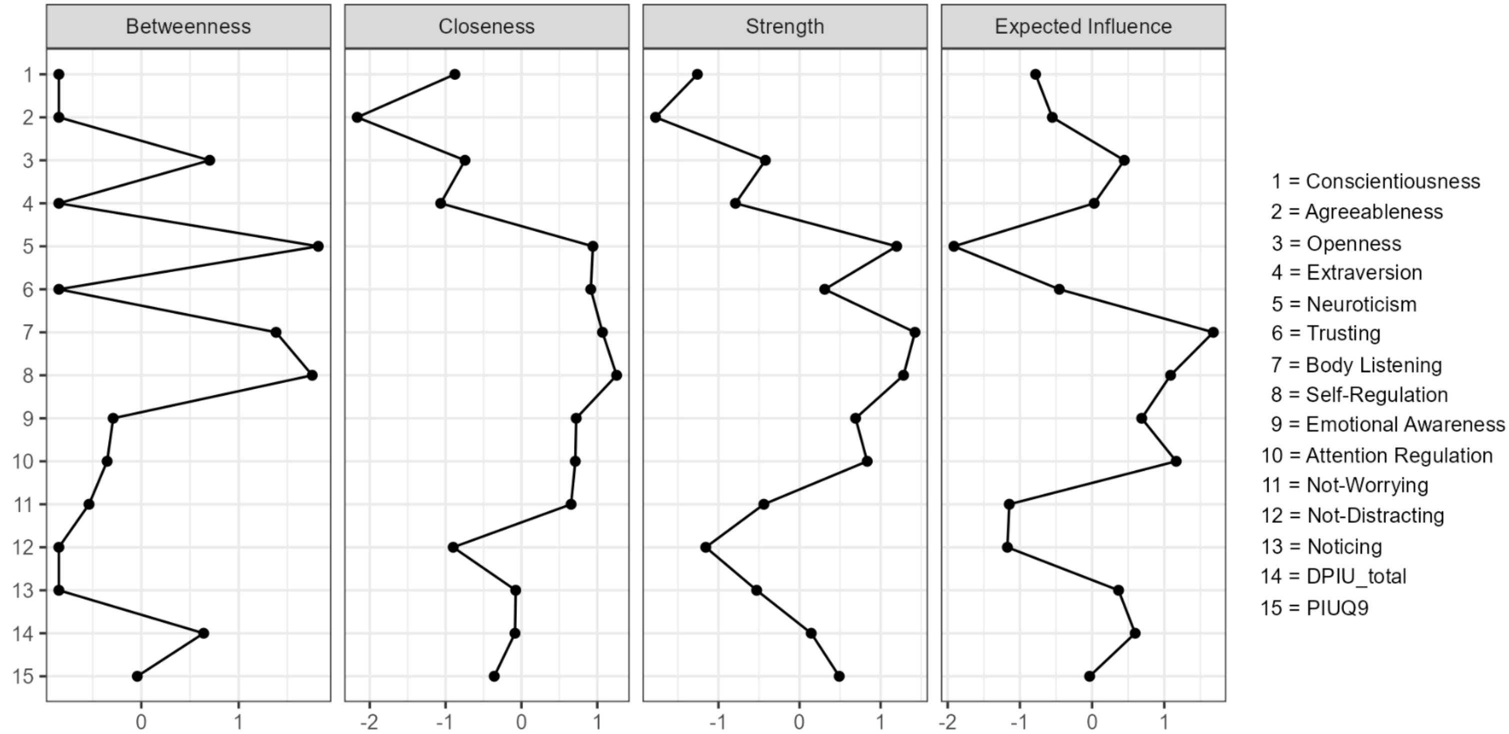

Figure 4.5. Centrality Indices for the Network of Interoceptive Awareness, Personality Traits, and Problematic Internet Use. The horizontal axis shows standardized (Z) centrality scores, while the vertical axis lists each variable in the network. Variables exhibiting higher centrality are positioned further to the right, away from the vertical axis.

4.3. The equiprobable auditory Go/NoGo task and ERPs

The final sample of 133 participants (74 females) had a mean PIUQ-9 score of 19.85 ± 5.32. The low PIU group (n = 35, 17 females) had a mean score of 13.83 ± 1.95 while the high PIU group (n = 38, 24 females) had a mean score of 26.76 ± 3. No significant age difference was observed between the low and high PIU groups (p = 0.461).

4.3.1. Behavioral Results

The average reaction time in the Go trials was 425 ± 70 ms, and the accuracy of the Go condition was 96.81%, corresponding to an average of 72.61 ± 4.82 correct responses. The mean accuracy of the NoGo trials was 96.97%, equivalent to 72.73 ± 2.53 successful inhibitions.

4.3.2. Association between PIU questionnaires and behavioral responses

No significant correlations were observed between overall PIU scores and behavioral performance measures, except for a positive correlation between gaming scores and Go reaction times ($r_s = 0.32$, $p = 0.003$), suggesting that higher levels of gaming-related internet use may be associated with slower response execution. The absence of significant correlations between general PIU severity and behavioral outcomes indicates that internet use within regular internet users does not appear to directly affect basic cognitive performance. Full correlation results are provided in Supplementary Material 3, Table SM 3.1.

Furthermore, no significant behavioral differences were found between the Low and High PIU groups (Table 4.8). Descriptive statistics for behavioral measures across these groups are presented in Supplementary Material 3, Table SM 3.2.

Table 4.8. Group differences between behavioral measures.

Variable	U	*p*	Effect Size	SE Effect Size
Correct_Go	617	0.571	0.072	0.135
Correct_NoGo	734	0.436	−0.104	0.135
Go_RT	766	0.267	−0.152	0.135

Mann–Whitney U test. Go_RT—average Go reaction time; SE effect size—standard error of effect size; and U—Mann–Whitney U test statistic.

4.3.3. ERP Results

Descriptive statistics for ERP amplitudes and latencies in Go and NoGo conditions are presented in Table 4.9. As expected, Go-P3 exhibited a more parietal distribution, while NoGo-P3 was more centrally distributed, aligning with previous studies using the equiprobable Go/NoGo task (Barry et al., 2016; Melynyte et al., 2017). The averaged topographic maps illustrating the spatial distribution of each ERP component for both conditions are shown in Figure 4.6.

4.3.3.1. Relationship between internet use and ERP components in Go condition

A negative correlation was observed between N1 amplitude at Cz and the gaming domain ($r_s = -0.467$, $p = 0.009$), indicating that higher gaming-related internet use is associated with reduced N1 amplitude. A significant negative correlation was found between N1 latency at CPz and the total DPIU score ($r_s = -0.24$, $p = 0.009$), suggesting a potential link between increased internet use and faster N1 responses. Detailed statistical results are available in Supplementary Material 3, Table SM 3.3 for Go amplitudes and Table SM 3.4 for Go latencies.

Table 4.9. Descriptive statistics for the amplitudes and latencies of ERP components during Go and NoGo conditions.

	Go Condition				NoGo Condition			
Electrode	N1	N2	P2	P3	N1	N2	P2	P3
				Amplitudes				
Fz	−2.49 ± 1.4	−2.86 ± 2.3	0.25 ± 1.7	−1.1 ± 2.2	−2.62 ± 1.5	−1.53 ± 1.9	0.28 ± 1.8	1.55 ± 2
FCz	−2.48 ± 1.3	−1.78 ± 2.1	1.1 ± 1.8	0.17 ± 2.5	−2.57 ± 1.4	−0.66 ± 1.8	1.08 ± 1.8	3.06 ± 2.4
Cz	−1.7 ± 1.1	−0.38 ± 1.7	1.64 ± 1.6	1.79 ± 2.5	−1.75 ± 1.1	0.22 ± 1.4	1.5 ± 1.4	3.48 ± 2.2
CPz	−0.85 ± 0.9	0.64 ± 1.5	1.76 ± 1.3	3.33 ± 2.4	−0.85 ± 0.9	0.6 ± 1.2	1.68 ± 1.2	2.95 ± 1.7
Pz	−0.51 ± 0.9	0.67 ± 1.5	1.64 ± 1.3	4.03 ± 2.3	−0.54 ± 0.9	0.15 ± 1.4	0.15 ± 1.4	2.19 ± 1.5
				Latencies				
Fz	127.12 ± 12.2	280.39 ± 43.1	191.13 ± 20	366.25 ± 68.7	128.44 ± 15.4	248.54 ± 34.9	189.74 ± 28.3	339.57 ± 41.2
FCz	125.25 ± 9.4	263.71 ± 33.4	188.13 ± 17.5	340.19 ± 42.8	126.03 ± 10.5	240.08 ± 31.2	188.32 ± 23	332.07 ± 40.7
Cz	123.37 ± 11.6	259.44 ± 35.4	189.8 ± 21.8	352.71 ± 53.4	124.24 ± 8.3	235 ± 32	184.79 ± 17.7	328.24 ± 43.3
CPz	115.07 ± 18.7	242.3 ± 37.3	189.14 ± 24.5	362.07 ± 61.5	117.18 ± 16.6	237.34 ± 38.4	189.9 ± 29.8	334.85 ± 53.6
Pz	97.12 ± 23.7	224.05 ± 35.9	173.57 ± 28.8	362.52 ± 60.3	99.81 ± 27.3	239.94 ± 42.9	182.9 ± 31	350.18 ± 63

Amplitudes are reported in microvolts (μV) and latencies are reported in milliseconds (ms); means ± SDs provided.

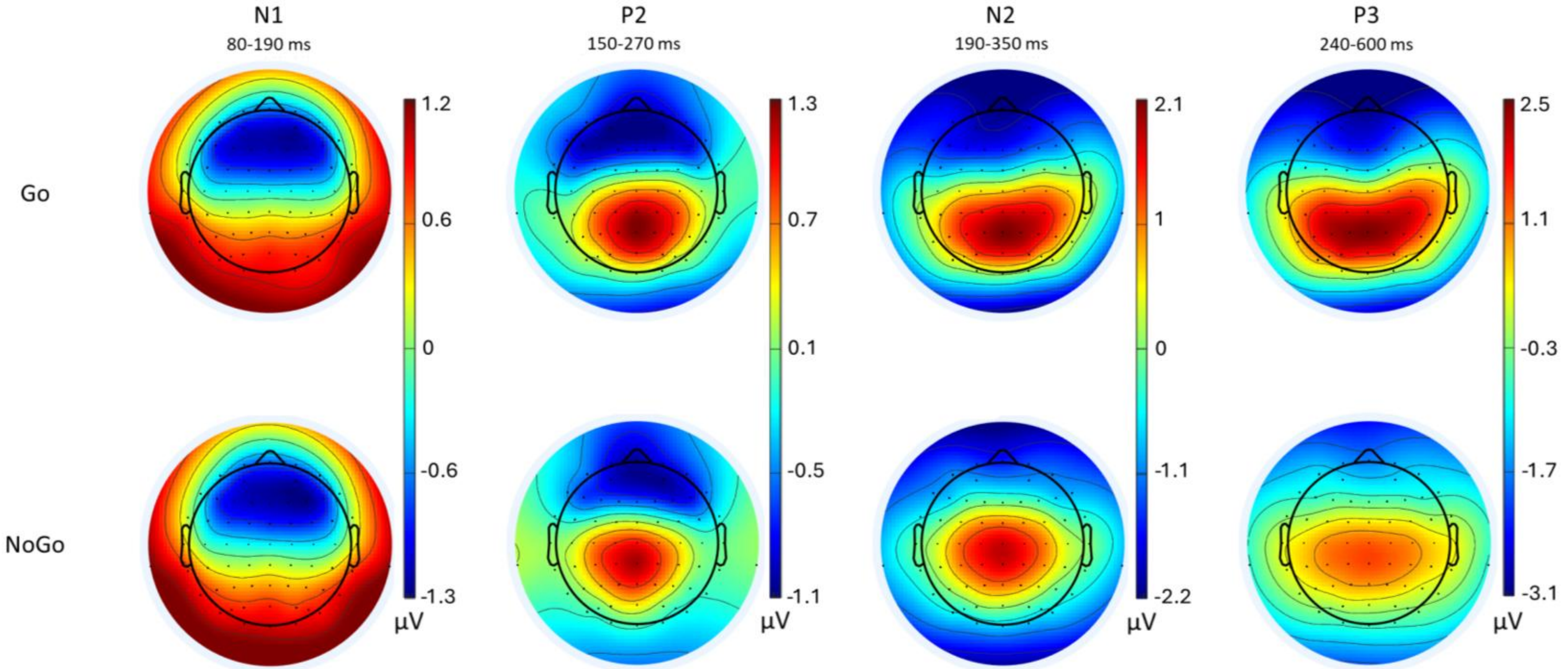

Figure 4.6. Topographical maps for Go and NoGo stimuli. Topographical representation of the N1, P2, N2, and P3 components in response to Go (top row) and NoGo (bottom row) stimuli.

4.3.3.2. Relationship between internet use and ERP components in NoGo condition

A negative correlation was observed between N1 amplitudes and the gaming domain at Cz ($r_s = -0.486$, $p = 0.006$), suggesting that greater engagement in gaming is linked to reduced early sensory processing during inhibitory control.

Analysis of ERP latencies in NoGo trials revealed a significant association between P3 latency and information search domain. Positive correlations observed within three electrode sites (Fz: $r_s = 0.503$, $p = 0.017$; Cz: $r_s = 0.443$, $p = 0.039$; and Pz: $r_s = 0.466$, $p = 0.029$). This finding suggests that greater engagement in information-seeking activities is associated with delayed P3 responses, potentially reflecting increased cognitive demand or reduced efficiency in response inhibition. Detailed statistical results are provided in Supplementary Material 3, Table SM 3.5 for NoGo amplitudes and Table SM 3.6 for NoGo latencies.

4.3.3.3. Comparison between Low vs. high PIU groups

No significant differences between the groups were detected at the neurophysiological level of Go/NoGo tasks (Table 4.10). The averaged ERP waveforms for Go and NoGo conditions are displayed in Figure 4.7. and topographical representation of the components in response to Go and NoGo stimuli between the groups is presented in Supplementary Material 3, Figure SM 3.1. Descriptive statistics for ERP amplitudes and latencies between the groups are presented in Supplementary Material 3, Table SM 3.7.

Table 4.10. Group differences between the amplitudes and latencies of ERP components during the Go condition.

		Amplitudes				Latencies			
Electrode Site	Component	U	*p*	Effect Size	SE Effect Size	U	*p*	Effect Size	SE Effect Size
Go_Fz	N1	709	0.633	0.066	0.135	676.5	0.903	0.017	0.135
	N2	634	0.738	−0.047	0.135	574.5	0.32	−0.136	0.135
	P2	625	0.665	−0.06	0.135	604	0.504	−0.092	0.135
	P3	580	0.353	−0.128	0.135	467	0.029	−0.298	0.135
Go_FCz	N1	652	0.891	−0.02	0.135	616.5	0.596	−0.073	0.135
	N2	622	0.641	−0.065	0.135	727.5	0.494	0.094	0.135
	P2	626	0.673	−0.059	0.135	635.5	0.749	−0.044	0.135
	P3	634	0.738	−0.047	0.135	556.5	0.233	−0.163	0.135
Go_Cz	N1	551	0.211	−0.171	0.135	560.5	0.251	−0.157	0.135
	N2	652	0.891	−0.02	0.135	730.5	0.473	0.098	0.135
	P2	586	0.388	−0.119	0.135	734	0.449	0.104	0.135
	P3	682	0.856	0.026	0.135	738.5	0.42	0.111	0.135
Go_CPz	N1	515	0.099	−0.226	0.135	551.5	0.212	−0.171	0.135
	N2	713	0.602	0.072	0.135	624	0.655	−0.062	0.135
	P2	542	0.177	−0.185	0.135	678	0.89	0.02	0.135
	P3	753	0.336	0.132	0.135	707.5	0.643	0.064	0.135
Go_Pz	N1	440	0.013	−0.338	0.135	587.5	0.395	−0.117	0.135
	N2	665	1	0	0.135	498	0.066	−0.251	0.135
	P2	578	0.342	−0.131	0.135	623.5	0.65	−0.062	0.135
	P3	741	0.407	0.114	0.135	706	0.655	0.062	0.135
NoGo_Fz	N1	644	0.822	−0.032	0.135	689	0.795	0.036	0.135

		Amplitudes				Latencies			
Electrode Site	Component	U	*p*	Effect Size	SE Effect Size	U	*p*	Effect Size	SE Effect Size
	N2	709	0.633	0.066	0.135	685.5	0.825	0.031	0.135
	P2	659	0.952	−0.009	0.135	720.5	0.544	0.083	0.135
	P3	708	0.641	0.065	0.135	742	0.398	0.116	0.135
NoGo_FCz	N1	649	0.865	−0.024	0.135	626.5	0.675	−0.058	0.135
	N2	716	0.579	0.077	0.135	709.5	0.627	0.067	0.135
	P2	719	0.557	0.081	0.135	720.5	0.544	0.083	0.135
	P3	669	0.969	0.006	0.135	692.5	0.766	0.041	0.135
NoGo_Cz	N1	646	0.839	−0.029	0.135	594	0.436	−0.107	0.135
	N2	664	0.996	−0.002	0.135	664	0.996	−0.002	0.135
	P2	659	0.952	−0.009	0.135	680	0.873	0.023	0.135
	P3	697	0.73	0.048	0.135	673	0.934	0.012	0.135
NoGo_CPz	N1	619	0.617	−0.069	0.135	672.5	0.938	0.011	0.135
	N2	575	0.325	−0.135	0.135	683	0.847	0.027	0.135
	P2	622	0.641	−0.065	0.135	675.5	0.912	0.016	0.135
	P3	662	0.978	−0.005	0.135	813	0.103	0.223	0.135
NoGo_Pz	N1	632	0.721	−0.05	0.135	773.5	0.231	0.163	0.135
	N2	578	0.342	−0.131	0.135	794	0.156	0.194	0.135
	P2	588	0.401	−0.116	0.135	654.5	0.912	−0.016	0.135
	P3	603	0.499	−0.093	0.135	752.5	0.337	0.132	0.135

No results survived FDR correction. Note. Mann−Whitney U test. SE effect size—standard error of effect size; and U—Mann−Whitney U test statistics.

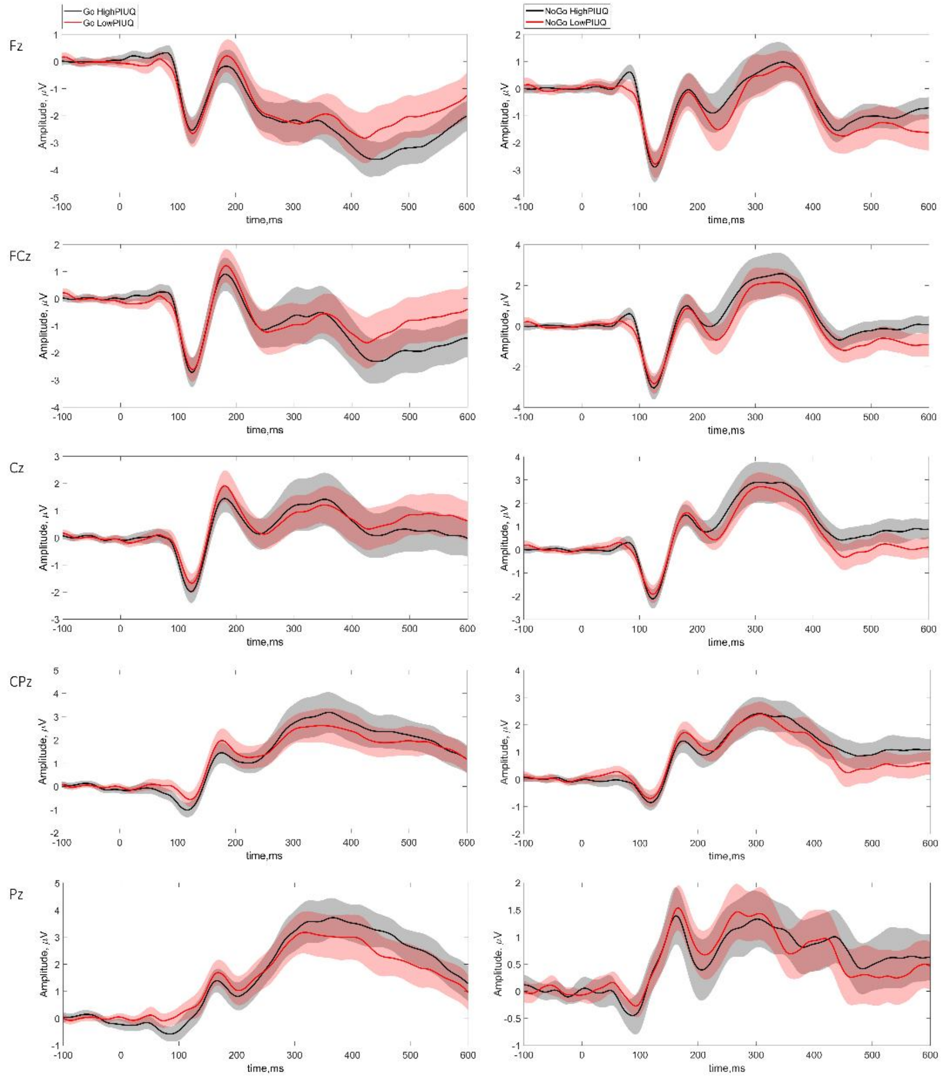

Figure 4.7. Grand average ERP waveforms for Go and NoGo stimuli across high and low internet use groups. Grand average ERP waveforms to Go (left column) and NoGo (right column) stimuli at midline electrode sites (Fz, FCz, Cz, CPz, and Pz) between high PIUQ-9 scores (black line) and low PIUQ-9 scores (red line) groups. The shaded areas around each waveform signify the 1.96×standard error (mean ± 1.96*SE).

4.4. Alternating resting-state EEG: Alpha asymmetry

The final sample of 129 participants (80 females) had a mean PIUQ-9 score of 19.39 ± 5.2. The low PIU group (n = 36, 22 females) had a mean score of 13.72 ± 2.07 while the high PIU group (n = 33, 24 females) had a mean score of 26.49 ± 3.1. No significant age difference was observed between the low and high PIU groups ($p = 0.329$).

4.4.1. Spectral analysis

The absolute power grand-averages across all participants during eyes-open (EO) and eyes-closed (EC) conditions are presented in Figure 4.8A. Descriptive statistics for absolute alpha power averaged within frontal and parietal regions during both conditions across the full sample are provided in Table 4.11.

Weak but significant negative correlations were observed between PIUQ-9 scores and alpha power at frontal ($r_s = -0.248$, $p = 0.005$) and parietal ($r_s = -0.209$, $p = 0.018$) regions during EO, and frontal ($r_s = -0.241$, $p = 0.006$) and parietal ($r_s = -0.183$, $p = 0.038$) regions during EC, but not with psychological variables. Correlation table and corresponding plots are provided in Supplementary Material 4, Table SM 4.1 and Figure SM 4.1, respectively.

As expected, comparisons of alpha power between high and low PIU groups also revealed significant differences across both conditions (EO, EC) in both frontal and parietal regions. Detailed results are displayed in Table 4.12, averaged absolute power grand-averages between the groups are visualized in Figure 4.8B, and descriptive statistics provided in Supplementary Material 4, Table SM 4.2.

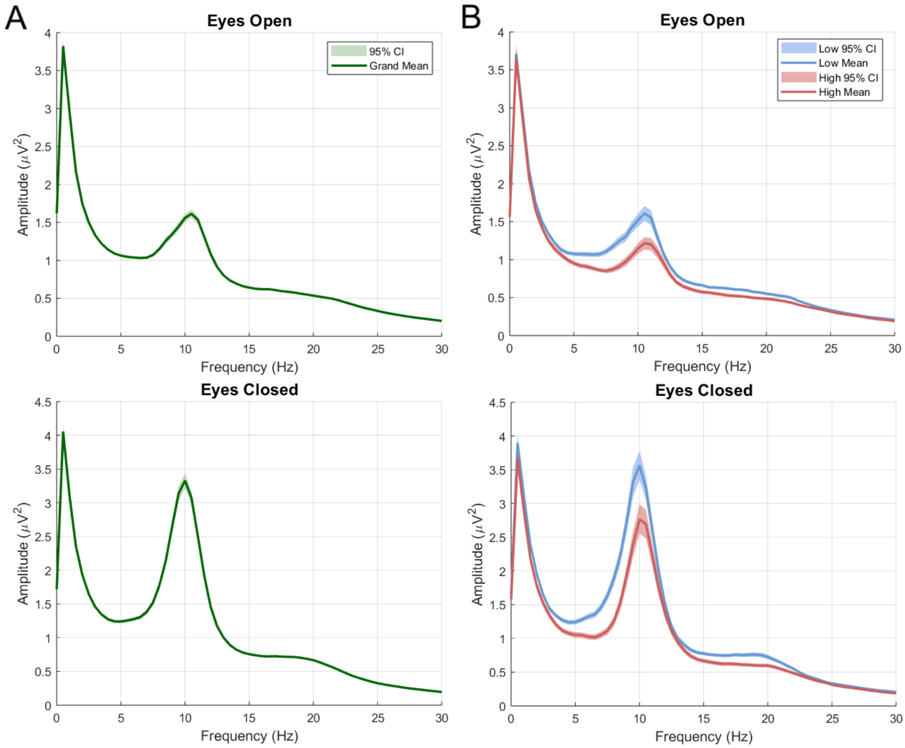

Figure 4.8. Absolute power grand-average across the full sample (n=129) (A) and between the high (n=33) and low (n=36) PIU groups (B). The shaded areas represent the 95% confidence intervals around the mean amplitude.

Table 4.11. Descriptive statistics for averaged alpha power (µV) and alpha asymmetry scores within frontal and parietal regions during eyes-open (EO) and eyes-closed (EC) conditions within the full sample.

Variable	n	Mean ± SD	Variable	n	Mean ± SD	Variable	n	Mean ± SD
Alpha frequency (µV)			Alpha asymmetry (EO)			Alpha asymmetry (EC)		
EO1_frontal	128	0.52±0.39	F3/F4	125	-0.03±0.24	F3/F4	128	-0.05±0.19
EO1_parietal	128	0.72±0.58	F7/F8	124	-0.05±0.50	F7/F8	128	-0.06±0.43
EC_frontal	129	1.71±1.30	P3/P4	122	0.19±0.40	P3/P4	123	0.33±0.48
EC_parietal	129	3.05±2.34	P7/P8	120	0.13±0.41	P7/P8	121	0.33±0.55

Table 4.12. Differences between high and low PIU groups for alpha frequency range at frontal and parietal regions during eyes-open (EO) and eyes-closed (EC) conditions.

Variable	U	*p*	Effect Size	SE Effect Size
EO_frontal	376	**0.008***	-0.367	0.139
EO_parietal	428	**0.046***	-0.279	0.139
EC_frontal	373	**0.008***	-0.372	0.139
EC_parietal	430	**0.049***	-0.276	0.139

* The significance of the results survived FDR correction. Mann–Whitney U test.

4.4.2. Relationship between internet use and alpha asymmetry index

Descriptive statistics for alpha asymmetry scores during EO and EC conditions are presented in Table 4.11. A significant positive correlation was observed between PIUQ-9 scores and alpha asymmetry score at P3/P4 during the EO condition (r_s=0.317, p<0.001) (Figure 4.9.), indicating greater right parietal alpha power – and thus increased left hemisphere activity, with higher levels of internet use. Detailed statistical results are presented in Table 4.13.

Initially, several additional associations were observed: positive correlation between PIUQ-9 and P7/P8 during EO (r_s=0.190, p=0.038), and regarding psychological variables, a negative correlation between depression (BDI) and alpha asymmetry at P7/P8 during EO (r_s=-0.199, p=0.032). However, none of these associations remained significant after FDR correction.

Consistent with the correlational analysis, the high PIU group demonstrated significantly higher alpha asymmetry values at P3/P4 during the EO condition compared to low PIU group (p=0.002; 0.28±0.46 vs 0.02±0.29, respectively) (Figure 4.10). Detailed results are presented in Table 4.14, with descriptive statistics provided in Supplementary Material 4, Table SM 4.2.

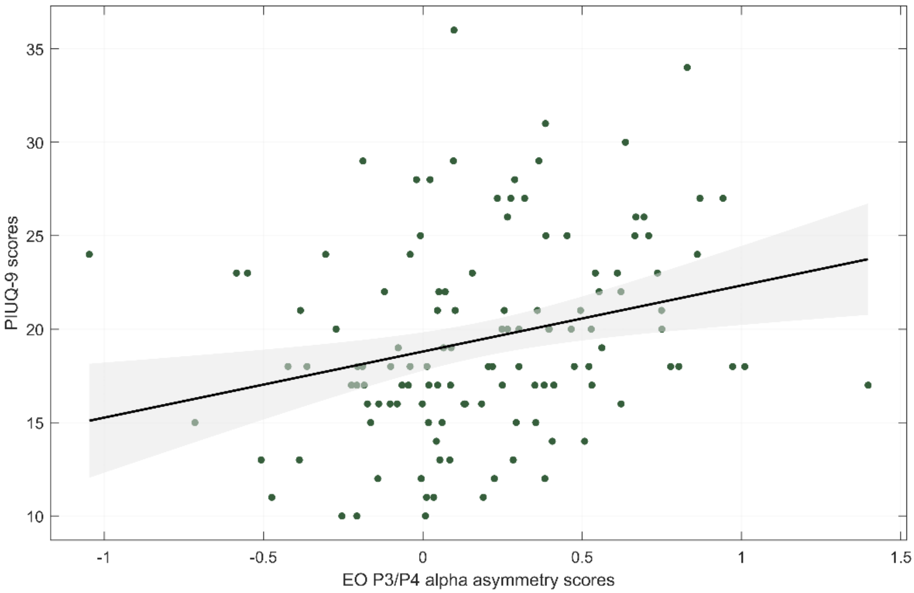

Figure 4.9. Correlation plot of PIU severity (PIUQ-9 scores) with alpha asymmetry scores at location site that reached significance. EO – eyes-open condition. Shaded areas represent the 95% confidence interval of the regression estimates.

Table 4.13. Spearman's Correlations between internet use (PIUQ-9 scores) and alpha asymmetry for all electrode pairs (F3/F4, F7/F8, P3/P4, P7/P8) during eyes-open (EO) and eyes-closed (EC) conditions.

Variable		EO	EC
F3/F4	Spearman's rho	0.096	-0.038
	p-value	0.286	0.668
	n	125	128
F7/F8	Spearman's rho	0.019	-0.022
	p-value	0.834	0.805
	n	124	128
P3/P4	Spearman's rho	**0.317***	0.128
	p-value	**< .001**	0.159
	n	122	123
P7/P8	Spearman's rho	**0.19**	0.176
	p-value	**0.038**	0.053
	n	120	121

* The significance of the results survived FDR correction.

Table 4.14. Group differences between alpha asymmetry scores for all electrode pairs (F3/F4, F7/F8, P3/P4, P7/P8).

Variable	U	*p*	Effect Size	SE Effect Size
EO				
F3/F4	674	0.241	0.167	0.14
F7/F8	534	0.6	-0.075	0.14
P3/P4	801	**0.002***	0.428	0.141
P7/P8	704	**0.021**	0.333	0.143
EC				
F3/F4	575	0.825	-0.032	0.139
F7/F8	524	0.406	-0.118	0.139
P3/P4	644	0.409	0.118	0.14
P7/P8	640	0.144	0.212	0.143

* The significance of the results survived FDR correction. EO—eyes-open, EC—eyes-closed; SE effect size—standard error of effect size; and U—Mann–Whitney U test statistic.

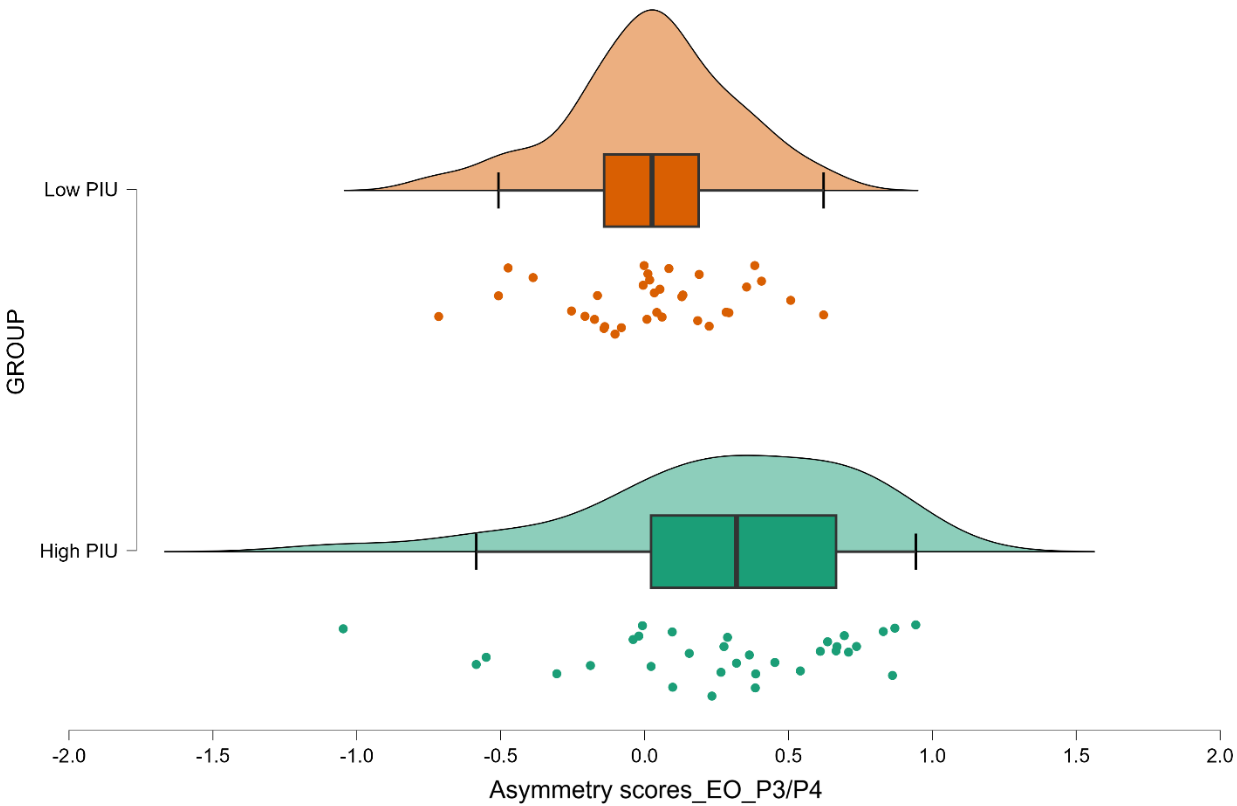

Figure 4.10. Raincloud plot (kernel density estimates, boxplots, and individual data points (Allen et al., 2021)) of parietal asymmetry scores during eyes-open (EO) condition at P3/P4 site for individuals classified as high PIU and low PIU. Individual dots represent the asymmetry scores for each participant.

4.5. Eyes-closed resting-state EEG: Microstates

The final sample of 156 participants (86 females) had a mean PIUQ-9 score of 19.65 ± 5.29. The low PIU group (n = 43, 21 females) had a mean score of 13.77 ± 2.01, while the high PIU group (n = 44, 28 females) had a mean score of 26.54 ± 2.9. No significant age difference was observed between the low and high PIU groups (p = 0.233).

4.5.1. EEG microstate maps

Based on established meta-criteria, the optimal number of microstate topographies was determined to be five for both the low and high PIU groups, as well as for the whole sample. Shared spatial variance indicated that corresponding maps between the high and low PIU groups are spatially equivalent (>95%) (Figure 4.11.). The extracted group-level maps displayed prototypical configurations and aligned closely with the most frequently reported microstate classes in the literature, as well as with the meta-microstates described in previous studies (Koenig et al., 2024). Accordingly, microstates were labeled following the updated microstate classification system (Tarailis et al., 2024).

4.5.2. Relationship between internet use and temporal parameters of microstates

The temporal parameters – duration, occurrence, and time coverage – fell within the normative 95% prediction intervals, as estimated from 93 studies (Zanesco, 2024). Descriptive statistics for the extracted spatiotemporal parameters of each microstate within the full sample are presented in Table 4.15, while group-specific statistics are provided in Supplementary Material 5, Table SM 5.1.

Table 4.15. Descriptive statistics of microstates' spatiotemporal parameters.

Electrode	Duration (ms)	Occurrence rate	Coverage (%)
MS A	51.87 ± 3.75	2.95 ± 0.61	18.1 ± 4.69
MS B	54.14 ± 4.47	3.25 ± 0.55	21.22 ± 5.4
MS C	68.91 ± 9.57	4.33 ± 0.39	38.79 ± 8.73
MS D	46.6 ± 2.92	2.05 ± 0.53	10.9 ± 3.4
MS E	46.79 ± 3.42	2.04 ± 0.67	11 ± 4.46

Means ± SDs provided.

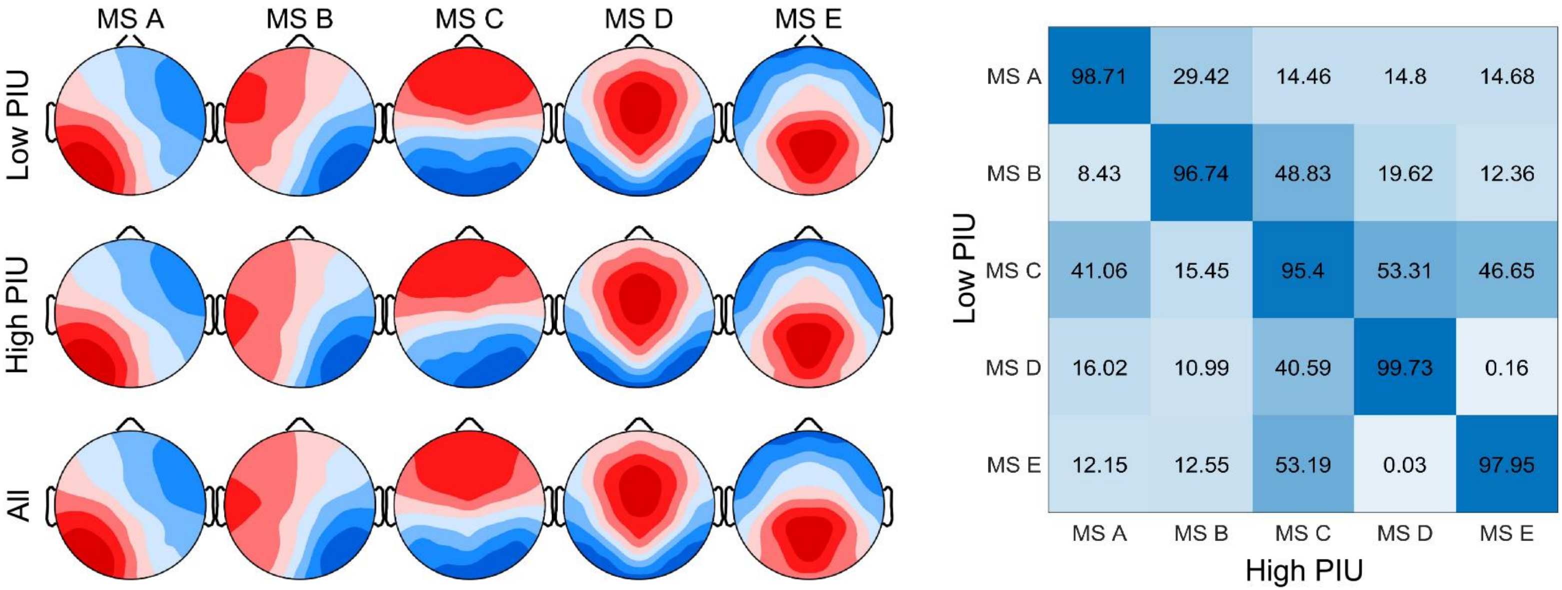

Figure 4.11. Left: spatial configuration of the five microstate classes (MS A-E): globally clustered maps for low PIU (n=43), high PIU (n=44), and all participants (n=156). Color scale represents relative polarity (normalized units) with red indicating positive and blue indicating negative values. Right: shared spatial variance (%) matrix between low and high PIU group topographies.

Following correction for multiple comparisons, several temporal parameters demonstrated significant associations within the full sample. The occurrence rate of MS E showed a positive correlation with the PIUQ-9 score (r_s = 0.235, p = 0.003), also MS E coverage was positively correlated with PIUQ-9 scores (r_s = 0.241, p = 0.002) (Figure 4.12.). Detailed correlation results are available in Supplementary Material 5, Table SM 5.2.

In terms of group comparisons, the same two temporal parameters showed significant differences between the high and low PIU groups. Specifically, the high PIU group exhibited a significantly higher occurrence rate of MS E compared to the low PIU group (p=0.006; 2.23±0.76 vs 1.78±0.61, respectively). Similarly, MS E coverage was significantly greater in the high PIU group (p = 0.004; 12.36 ± 5.31% vs. 9.29 ± 3.76%, respectively). No other temporal parameters differed significantly between the groups. Detailed results are presented in Table 4.16. Individual data points, along with group means and standard deviations, are visualized in Figure 4.13.

Table 4.16. Group differences in the spatiotemporal parameters of microstates.

Variable	U	*p*	Effect Size	SE Effect Size
Duration (ms)				
MS A	984	0.751	0.04	0.124
MS B	927	0.876	-0.02	0.124
MS C	841	0.377	-0.111	0.124
MS D	764	0.124	-0.192	0.124
MS E	1190	**0.038**	0.258	0.124
Occurrence rate				
MS A	957	0.929	0.012	0.124
MS B	920	0.829	-0.027	0.124
MS C	898	0.688	-0.051	0.124
MS D	712	**0.047**	-0.247	0.124
MS E	1270	**0.006***	0.342	0.124
Coverage (%)				
MS A	965	0.876	0.02	0.124
MS B	938	0.949	-0.008	0.124
MS C	842	0.381	-0.11	0.124
MS D	686	**0.027**	-0.275	0.124
MS E	1281	**0.004***	0.354	0.124

* The significance of the results survived FDR correction. SE effect size—standard error of effect size; and U—Mann–Whitney U test statistic.

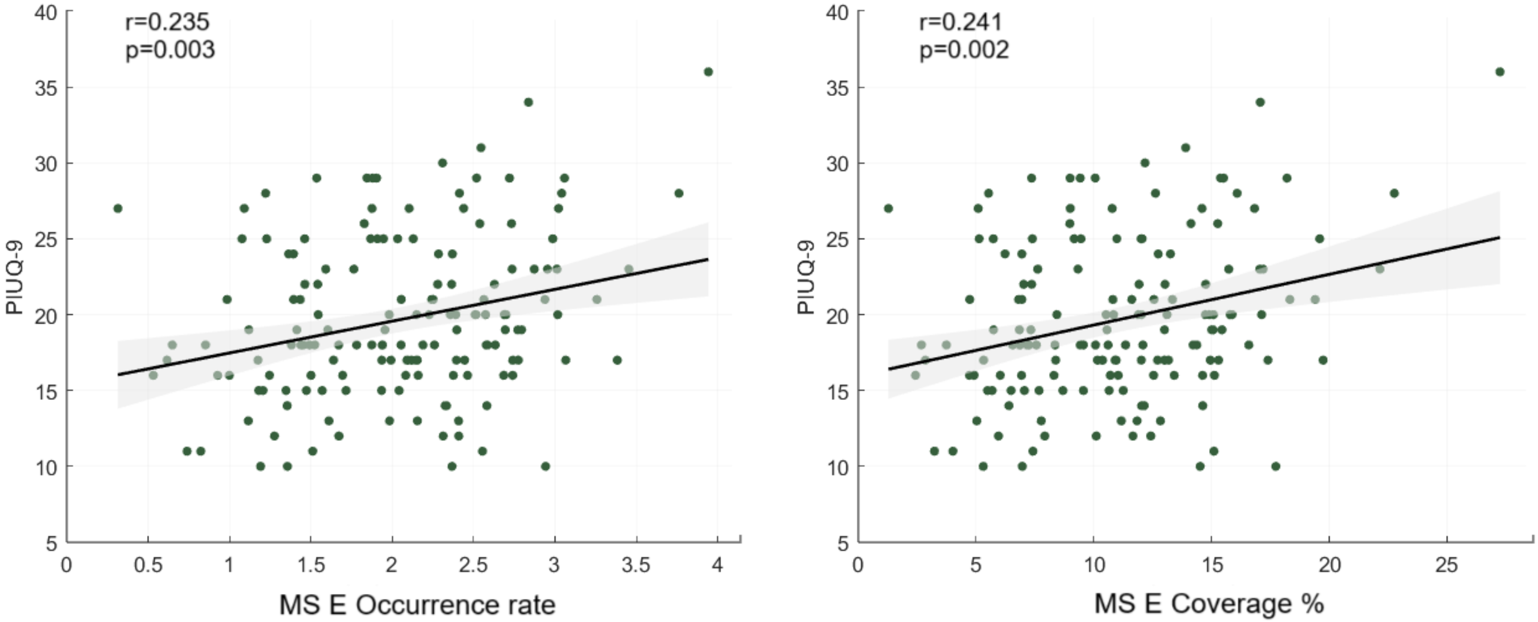

Figure 4.12. Correlation plots of PIUQ-9 scores with microstates parameters that reached significance. Shaded areas represent the 95% confidence interval of the regression estimates.

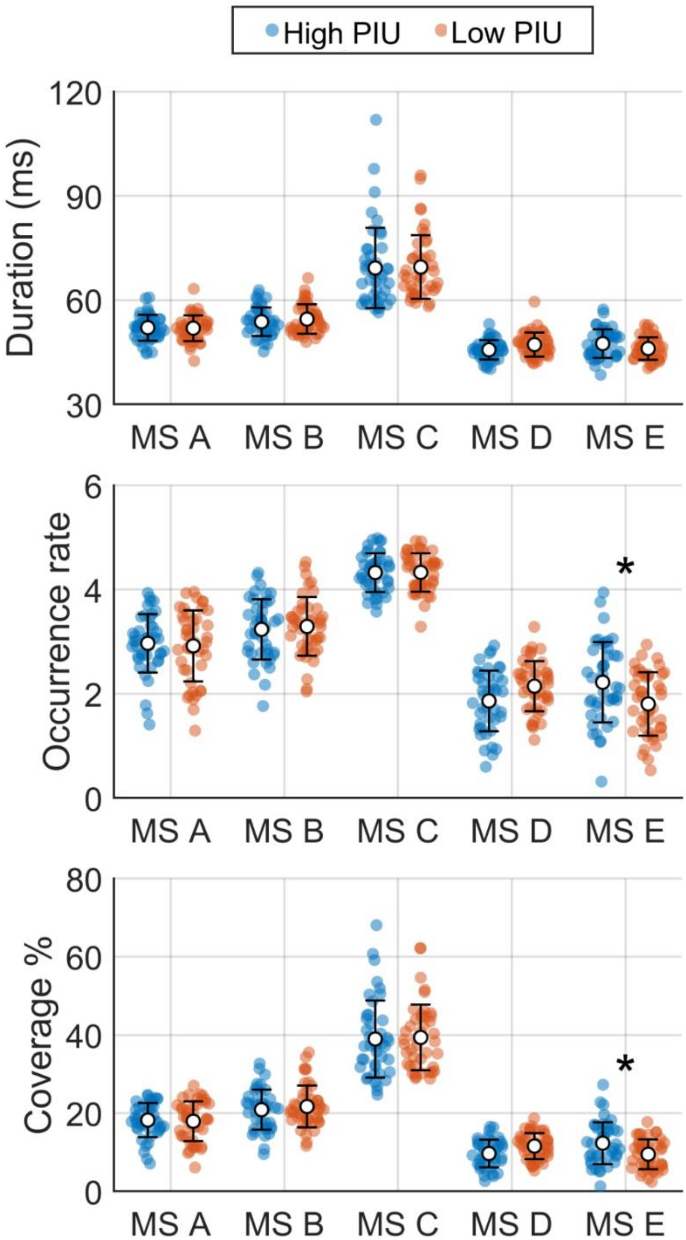

Figure 4.13. Individual microstate values for extracted parameters, white dots indicate mean values, and error bars indicate standard deviations. Asterisks (*) indicate FDR corrected statistically significant ($p<0.05$) differences between means.

Additionally, significant associations were observed between microstate temporal parameters and psychological symptoms, particularly anxiety (BAI) and obsessive–compulsive (CBOCI) traits. The total score on the CBOCI scale was negatively associated with the duration of MS D ($r_s = -0.215$, $p = 0.007$). Anxiety symptoms demonstrated broader relationships, showing negative correlations with the duration of MS D ($r_s = -0.263$, $p < 0.001$), the occurrence rate of MS B ($r_s = -0.216$, $p = 0.007$) and MS D ($r_s = -0.205$, $p = 0.010$), as well as the coverage of MS B ($r_s = -0.198$, $p = 0.014$) and MS D ($r_s = -0.237$, $p = 0.003$). In contrast, anxiety was positively associated with the coverage of MS C ($r_s = 0.189$, $p = 0.019$). Detailed results are presented in Supplementary Material 5, Table SM 5.3 and significant correlations are visualized in Supplementary Material 5, Figure SM 5.1.

5. DISCUSSION

5.1. Psychological level

Consistent with previous meta-analyses and systematic reviews (Carli et al., 2013; Ho et al., 2014; Kuss & Lopez-Fernandez, 2016; Noroozi et al., 2021), current findings in a healthy young adult sample confirm firm associations between internet use severity and symptoms of anxiety, depression, and obsessive–compulsive behaviors. The significant psychological differences between high and low PIU score groups further reinforce the well-established mental health impact of problematic internet behaviors.

Moreover, specific PIU subdomains varied in their associations with levels of experienced depression, anxiety, and obsessive–compulsive symptoms. While social media was linked to all investigated indices (anxiety, depression, obsessions, and compulsions), the entertainment/video streaming domain was linked to anxiety and obsessive symptoms, and the messaging domain to obsessions only. In contrast, the gaming and information search domains showed no significant associations with psychological measures. Such results reinforce the idea that despite common underlying factors (Andreassen et al., 2013; Robbins & Clark, 2015), different forms of PIU may be differentially associated with mental health factors, possibly indicating distinct patterns of psychological vulnerability or divergent mental health consequences.

Current findings align with theoretical models suggesting that PIU is not a uniform disorder but rather a spectrum of behaviors with distinct motivational and psychological underpinnings (Al-Menayes, 2015;Griffiths, 2014; Király et al., 2014; Lee et al., 2017; Schou Andreassen et al., 2016).

5.2. Interoceptive awareness, personality traits, and internet use

Interoceptive awareness – the capacity to accurately perceive internal bodily signals – has been shown to influence cognitive-affective responses to reward-related behaviors (including substance use disorders) and to shape subjective bodily feedback, facilitating flexible and rapid responses (Forkmann et al., 2016; Khalsa et al., 2018; Sönmez et al., 2016; Verdejo-Garcia et al., 2012). Individuals with altered interoceptive awareness are more likely to experience intense craving states and face an increased risk of addiction relapse in response to stress or negative effects (Herman, 2023; Khalsa et al., 2018; Paulus & Stewart, 2014). It has been suggested that poor interoceptive awareness limits the effective use of internal bodily cues, causing individuals to rely more on external sources for decision-making, which under conditions of uncertainty may increase susceptibility to maladaptive choices (Pollatos et al., 2023).

Within the context of PIU, the present findings revealed a significant negative association between PIU scores and the Not-Distracting dimension of interoceptive awareness. Specifically, individuals with a lower tendency to refrain from avoiding or distracting themselves from bodily discomfort (Mehling et al., 2012) exhibited a higher internet use. These results suggest that diminished interoceptive awareness may impair self-regulatory capacity and risk evaluation efficiency, thereby potentially explaining susceptibility to problematic patterns of internet use as an escape from discomfort.

Furthermore, neuroticism emerged as a central factor in the network of personality traits, interoceptive states, and internet use patterns, strongly linked to either problematic internet use or impaired interoceptive awareness. A substantial body of evidence, including meta-analyses and systematic reviews, has identified neuroticism as a key personality trait associated with PIU (Jeronimus et al., 2016; Kayiş et al., 2016; Koronczai et al., 2019; Marciano et al., 2020; Müller et al., 2023). Furthermore, Marciano et al. (2020) emphasized neuroticism’s interplay between personality characteristics (e.g., heightened sensitivity to negative emotions, emotional instability, poor self-regulation), dysfunctional coping strategies, and environmental stimuli, rather than being a direct consequence of excessive internet use. In this view, neuroticism (not as independent trait, but as expression of underlying dysfunction) predisposes individuals to problematic online behaviors by amplifying pre-existing psychological traits and vulnerabilities (such as emotional and interpersonal difficulties) (Jeronimus et al., 2016; Kayiş et al., 2016; Marciano et al., 2020; Tian et al., 2021), creating ground for maladaptive coping (e.g., rewarding online experiences in various internet platforms) in response to environmental triggers.

In support of the above, negative connections between neuroticism and several interoceptive domains, including Not-Worrying, Self-Regulation, and Trusting, were observed in the current study. These results are in line with a previous study by Gaggero et al. (2022), which also showed that people high in neuroticism have interoceptive deficits across the same domains. The observed associations suggest that individuals with higher neuroticism may face difficulties in perceiving and responding effectively to bodily sensations. Specifically, to experience greater emotional distress in response to discomforting sensations (Not-Worrying dimension), challenges in regulating psychological distress to these states (Self-Regulation dimension), and a decreased ability to perceive one’s body as reliable or safe (Trusting dimension) (Mehling et al., 2012). These findings support the proposition that neuroticism may predispose individuals to engage in digital activities as a coping mechanism, associated with lower self-regulation abilities (Caplan, 2010; Pastor et al., 2022). In this context, neuroticism may serve both as a predisposing vulnerability and a potential therapeutic target in addressing maladaptive PIU patterns.

To date, only one study has investigated PIU within a context of interoceptive awareness (Di Carlo et al., 2024). Di Carlo et al. (2024) revealed significant differences between groups with and without PIU (as measured by the IAT), particularly in the domains of Not-Distracting, Trusting, Not-Worrying, and Emotional Awareness. The present study supports the involvement of the Not-Distracting and trusting dimensions in PIU, similar to as found by Di Carlo et al. (2024), the associations with Not-Worrying and Emotional Awareness appeared to be more domain-specific rather than general. Specifically, the messaging domain showed negative correlations with the most interoceptive variables, including Attention Regulation, Self-Regulation, Body Listening, and Emotional Awareness and Trusting. In contrast, the information search domain was specifically associated with Not-Worrying variable only. Meanwhile, the remaining domains – entertainment and video streaming, social media, and gaming – did not show associations with any of the interoceptive awareness variables at all. This contrast may be partly attributed to differences in the conceptualization and measurement of PIU: while Di Carlo et al. (2024) focused on general PIU risk using a single IAT threshold to define PIU and non-PIU groups, the current study employed a multi-dimensional approach (PIUQ-9 and DPIU), assessing PIU as a continuous construct across the full sample and aiming to capture variation across specific internet activities. Additionally, the current findings suggest that emotionally and cognitively demanding activities, such as messaging (Camerini et al., 2022; Fante et al., 2013), may interact more directly with bodily self-regulation mechanisms, indicating that certain interoceptive processes could be more sensitive to contextual internet use rather than global usage patterns. These findings suggest that distinct types of internet activities may differentially interact with interoceptive processes – engaging or bypassing specific dimensions of bodily awareness – and underscore both shared and activity-specific patterns across studies.

To sum up, this is the second attempt to investigate interoceptive awareness within the field of PIU, and the first to approach PIU within a network framework that incorporates both interoceptive dimensions and personality factors. These results contribute to the field by suggesting that interoceptive awareness may play a meaningful role in maladaptive digital behaviors.

5.3. Behavioral level: performance of equiprobable auditory Go/NoGo task

As commonly reported in addiction-related research, deficits in cognitive control, including response inhibition, are often linked to problematic and addictive behaviors (Littel et al., 2012; Pandey et al., 2016; Ramey & Regier, 2019; Yao et al., 2015; Zhou et al., 2010). However, our results challenge this assumption as we found no significant correlations between internet use severity level and behavioral performance on the equiprobable auditory Go/NoGo task in a sample of healthy regular internet users, as well as no difference was observed between individuals with high and low PIU scores.

Nevertheless, intact behavioral performance despite involvement in problematic internet use has been observed in other studies as well (Dong et al., 2010; Vargas et al., 2019; Zhang et al., 2024), indicating that individuals may not exhibit overt behavioral deficits. However, previous research has also shown that the absence of behavioral alterations in individuals with addictive disorders may be compensated by changes in neural processing, as reflected in ERP alterations (Houston & Schlienz, 2018).

Notably, when dissecting internet use into specific online activities, the gaming domain showed a positive correlation with Go reaction times, suggesting a subtle delay in response execution among individuals with higher gaming engagement. This result contrasts with findings by Littel et al. (2012) who observed shorter reaction times in excessive gamers. However, in their study, they also observed an association between reaction times and commission errors, interpreted as a speed-accuracy trade-off, whereas in the present study, associations with other measures of behavioral performance were not found. As Go reaction times are linked to cognitive efficiency and motor preparation processes (Fogarty et al., 2020a; Nakata et al., 2021), current finding may reflect increased altered motor planning rather than a generalized cognitive deficit in individuals with higher engagement in gaming.

In sum, these findings suggest that behavioral markers of response inhibition during the equiprobable auditory Go/NoGo task may not reflect problematic internet use in non-clinical populations.

5.4. Neurophysiological indices

5.4.1. Early sensory processing in equiprobable auditory Go/NoGo task: N1 and P2

In the first 250 ms following stimulus presentation in auditory tasks, early ERPs primarily reflect automatic sensory and perceptual processes like sensory gating and stimulus discrimination (Barry & De Blasio, 2013; Fogarty et al., 2020b; Pires et al., 2014). However, while these responses are largely exogenous and driven by stimulus properties (Pires et al., 2014; Sokhadze et al., 2017), early attentional mechanisms may also modulate initial sensory processing (Sokhadze et al., 2017). Additionally, early activity within a frontal network suggests the involvement of top-down control and task-relevant goal maintenance even during these initial stages of processing (Fogarty et al., 2020b).

Considering current findings, N1 amplitudes negatively correlated with Gaming scores in both Go and NoGo conditions, while N1 latencies negatively correlated with overall DPIU scores in the Go condition. Given that the N1 component reflects early sensory processing (e.g., stimulus detection) and attentional allocation (Fogarty et al., 2020a; Joos et al., 2014; Tomé et al., 2015), these findings suggest that high internet engagement, particularly in the gaming domain, may alter how sensory information is processed at an early stage. As previous findings regarding the N1 component in IGD have been mixed – reporting reduced amplitudes, increased amplitudes, or no alterations (Duven et al., 2015; Ge et al., 2011; Park et al., 2017b) – the current observation of reduced N1 amplitudes in individuals with high gaming engagement is consistent with studies such as Park et al. (2017b), which also found diminished N1 responses during an oddball task in IGD groups. Such a reduction in amplitude may reflect either diminished efficiency or, conversely, a reduced need for effort in allocating early attentional resources to external (auditory) input.

Moreover, the shorter N1 latencies associated with higher overall problematic internet use (as reflected by DPIU scores) may seem counterintuitive, as delays are typically linked to impaired processing (Joos et al., 2014). Yet, this earlier N1 peak might indicate heightened vigilance or hyper-reactivity to external stimuli in individuals with greater PIU severity; an interpretation supported by findings that individuals frequently exposed to fragmented, rapidly shifting digital content (e.g., through multiple concurrent media streams) tend to adopt a bottom-up attentional style (Firth et al., 2019; Ophir et al., 2009). Alternatively, as opposed to prolonged latencies, the earlier N1 response may indicate altered, and potentially less effortful, attention switching toward relevant stimuli during early-stage processing (Duven et al., 2015; Fogarty et al., 2020b; Joos et al., 2014).

Thus, these results support a broader view that N1 alterations may indicate differences in early stimulus-driven processing among heavy internet users rather than being a specific biomarker for IGD (Kashif et al., 2021).

Similarly to N1, P2 is considered a stimulus-related component involved in sensory and perceptual processing (Fogarty et al., 2020a) and is thought to reflect more advanced perceptual processes necessary for target identification and classification (Crowley & Colrain, 2004; Fogarty et al., 2020b; Sokhadze et al., 2017). To date, both the functional interpretation of the P2 component and research on its role within the context of PIU remain limited. Nevertheless, no associations were observed between P2 amplitudes and PIU severity or any specific internet use dimensions in the current study, findings consistent with those of Ge et al. (2011), who also reported no differences in P2 between individuals with PIU and controls during an auditory oddball task.

5.4.2. Response monitoring and inhibition in equiprobable auditory Go/NoGo task: N2 and P3

Late cognitive ERP components, particularly N2 and P3, are among the most extensively studied markers of cognitive control (Bruin & Wijers, 2002; Pires et al., 2014). The Go/NoGo tasks offer a valuable framework for investigating these late processes, as distinct neural mechanisms are engaged during Go and NoGo trials (Fogarty, 2020; Fogarty et al., 2018; Pires et al., 2014). Specifically, NoGo trials are associated with conflict monitoring and motor inhibition (Detandt et al., 2017; Huster et al., 2013) while ERPs during Go trials primarily reflect motor execution and response evaluation (Fogarty, 2020).

However, no significant associations between N2 amplitudes and PIU measures were found. While some studies have reported reduced NoGo-N2 amplitudes in individuals with PIU or IGD (Dong et al., 2010; Fathi et al., 2024; Lee & Kang, 2014; Zhou et al., 2010), others have observed increased amplitudes or inconsistent N2 responses (Chen et al., 2018; Littel et al., 2012). Additionally, previous research has shown prolonged N2 latencies in relation to PIU (Kim et al., 2017; Ge et al., 2011). The lack of significant N2 effects in the current study suggests that conflict detection and monitoring processes may remain intact in non-clinical populations (Donkers & van Boxtel, 2004; Enriquez-Geppert et al., 2010; Sokhadze et al., 2017; Wessel, 2018).

Moreover, alterations in NoGo-P3 amplitude have been broadly documented in substance use disorders (Colrain et al., 2011; Evans et al., 2009; Porjesz & Begleiter, 2003; Sokhadze et al., 2008; Yin et al., 2016) and also in IGD and PIU (Dong et al., 2010; Gao et al., 2019; Moretta & Buodo, 2021; Park et al., 2016; Park et al., 2017b). However, findings across these studies remain inconsistent, and yet, despite the inconsistency, reduced P3 amplitude has been proposed as a potential neurophysiological marker of IGD (Park et al., 2016; Yu et al., 2024). Nonetheless, no significant alterations within P3 amplitudes were observed in the current study, challenging the notion of its reliability as a marker, at least within a non-clinical sample of regular internet users.

Yet, a significant positive correlation emerged between NoGo-P3 latency and the information search domain, suggesting delayed evaluative and inhibitory processing in individuals who frequently engage in extensive online searching (Fogarty et al., 2018; Gajewski & Falkenstein, 2013). P3 latency is considered as a marker of stimulus evaluation speed, with shorter latencies reflecting more efficient cognitive functioning (Kamijo et al., 2004; Kutas et al., 1977; Polich & Criado, 2006). In contrast, the current finding of prolonged P3 latency may reflect both delayed response-related updating in working memory (Fogarty, 2020) and deficits in behavioral inhibition (Donkers & van Boxtel, 2004; Nieuwenhuis et al., 2004; Randall & Smith, 2011). However, since no significant correlations were observed between behavioral measures and the information search domain, this latency increase may represent an early neurocognitive sign rather than a developed functional deficit.

Notably, despite the observed correlational patterns in the overall sample and significant psychological differences between high and low PIU groups, no significant ERP differences emerged between the groups. This suggests that while internet use severity may influence specific neurophysiological correlates, its effects do not scale linearly across the PIU continuum in a healthy sample. Although previous studies have consistently reported distinct ERP alterations in clinical PIU or IGD samples (Chen et al., 2018; Dong et al., 2010; Ge et al., 2011; Yu et al., 2009; Zhou et al., 2010), findings across components have been mixed. Based on the current results, it is plausible that neurophysiological alterations develop gradually, becoming more pronounced only in more severe cases. As the question of causality – whether such alterations precede or result from PIU – remains unresolved in the field, this underscores the importance of longitudinal research or approaching PIU as a continuum (Anderson et al., 2017), rather than assuming categorical differences between individuals with severe PIU and healthy controls.

Taken together, current findings suggest that while PIU may influence early sensory processing (N1) and processes related to response inhibition (NoGo-P3) to some extent, its impact on response monitoring and execution (N2 and Go-P3) is not pronounced in non-clinical populations.

5.4.3. Alternating resting-state EEG: Alpha asymmetry

A general theory posits that resting-state alpha activity lateralization reflects trait-like predispositions toward affective and motivational orientations (Davidson, 1992), with greater relative left frontal activity being linked to approach motivation and positive affect, and right frontal dominance relating to withdrawal motivation and negative affect (de Vries et al., 2023; Kelley et al., 2017; Reznik & Allen, 2018; Smith et al., 2017). However, although alpha asymmetry is the most studied marker of brain lateralization, research has mainly focused on frontal regions, with parietal asymmetry remaining largely overlooked (Metzen et al., 2022; Wang et al., 2025).

In the context of PIU and internet-related disorders, research shows altered resting-state brain activity within frontal and parietal regions, with alterations significantly correlating with PIU severity (Burleigh et al., 2020; Sun et al., 2019; Wang et al., 2017). For instance, reduced frontal and parietal alpha power was observed in excessive gamers (Xu et al., 2024), and PIU with comorbid depression (Lee et al., 2014), however the latter finding implies that a decrease in global alpha power, even though commonly observed, is not specific to PIU. Review by Burleigh et al. (2020) summarized increased alpha coherence within the right hemisphere (including parietal regions) in gamers, probably associated with consistent activation of visuospatial working memory and executive function in frequent gaming. In support, individuals with PIU exhibit reduced functional connectivity in the left parietal lobe of the right frontoparietal network (Sun et al., 2019), suggesting impaired cross-hemispheric network communication. In line with this, greater right frontal hemisphere activity has been observed in Problematic Social Media users (Tsilosani et al., 2023) and the IA group (Yan et al., 2022). Notably, this right-dominant frontal pattern was also associated with poorer emotion regulation choices in the IA group. To date, no studies have directly investigated parietal alpha asymmetry within the PIU field. Furthermore, the greater relative left hemisphere activity at parietal sites among healthy individuals with more severe internet engagement observed in the present study might align with aforementioned findings, albeit speculatively, considering evidence that parietal asymmetry often exhibits patterns opposite to those observed in frontal regions (Baik et al., 2019; Blackhart et al., 2006; Metzen et al., 2022;

Schiltz et al., 2018). Moreover, the current findings generally do not contradict but rather extend the results of the pilot study on recreational internet users by Wang & Griskova-Bulanova (2018). The authors did not find associations between internet use and frontal alpha asymmetry; similarly, no such associations were observed in the present larger sample, instead, a significant correlation emerged at parietal sites.

Importantly, internet use severity was associated with greater left parietal activity only during the eyes-open (EO) condition, but not during eyes-closed (EC). This discrepancy may be attributed to the distinct temporal neurophysiological characteristics of each condition. Although both EO and EC are often treated as resting-state baselines, research has shown that they differ meaningfully in terms of arousal and activation levels, and thus do not provide equivalent baseline measures (Barry, Clarke, et al., 2007). The EC condition, marked by reduced sensory input and thalamo-cortical rhythmicity, represents a low-arousal state that may be less sensitive to individual differences in attention or motivation traits. In contrast, the EO condition – even under minimal visual stimulation – elicits alpha desynchronization and widespread cortical activation, including frontoparietal networks involved in attention control (Barry et al., 2007). Moreover, brain regions associated with unconstrained mental activities – such as self-reflective thought, environmental monitoring, and mind wandering – may be differentially engaged under different resting-state conditions, and as shown by Yan et al. (2009), regions within the default mode network (DMN), particularly those implicated in sensory monitoring and salience evaluation, exhibit higher functional connectivity during EO conditions compared to EC. In line, as reviewed by Chang & Lee (2024), IA induces widespread neural alterations rather than changes restricted to isolated brain regions and highlights significant disruptions within large-scale brain networks, including DMN, pointing to shifts in reward valuation, impulsivity, salience attribution, and cue reactivity.

Furthermore, as a neurophysiological index, alpha asymmetry has been proposed to reflect both psychological traits and underlying regulatory mechanisms (Smith et al., 2017). Specifically, parietal alpha asymmetry has been associated with behavioral approach and inhibition systems, with greater left-sided parietal activity linked to higher behavioral activation (Schiltz et al., 2018), which may characterize individuals with more compulsive internet engagement. Additionally, both frontal and parietal asymmetries have been linked to attentional bias independent of subclinical levels of mood or anxiety symptoms (Grimshaw et al., 2014), supporting the idea that such asymmetries reflect underlying top-down attentional control mechanisms and index trait-like attentional biases rather than psychological issues per se. As shown by Ophir et al. (2009), heavy media multitaskers are more susceptible to interference from irrelevant environmental stimuli, easily distracted by multiple concurrent media streams, less effective at filtering out distractions, and tend to rely on a bottom-up attentional control style, favoring exploratory over focused top-down information processing compared to light media multitaskers. In this context, heightened responsivity to external stimuli may manifest more strongly in the EO condition, when attentional systems are in a more reactive, externally focused state. Together with findings of reduced global alpha power in higher internet users – which corresponds to increased cortical excitability and lower perceptual thresholds (Foxe & Snyder, 2011) – this interpretation aligns with theoretical models of PIU emphasizing compulsive engagement with external stimuli and impaired top-down attentional regulation among deficits in attentional inhibition (D'Hondt et al., 2015; Firth et al., 2019; Ioannidis et al., 2019).

Moreover, the current results did not reveal the association between depressive symptoms and alpha asymmetry. Alpha asymmetry has been extensively studied in the context of depression; however, due to inconsistencies across studies, the directionality of the effect remains inconclusive (Marcu et al., 2023). Notably, although PIU and depression were correlated in the current sample ($r_s = 0.285$, $p = 0.001$), the initially observed negative association between depression symptoms and parietal asymmetry did not survive FDR correction, and only PIU showed a significant association with parietal alpha asymmetry. Nevertheless, this might suggest a possible divergence in lateralization patterns: in line with prior research (Mitchell & Pössel, 2012; Pössel et al., 2008; Reznik & Allen, 2018; Wang & Griskova-Bulanova, 2018) – a trend towards greater right parietal activity in association with depression, and greater left parietal activity in relation to PIU, potentially reflecting distinct lateralized neural processes underlying PIU and depressive symptoms, despite their overlapping psychological features within a sample of regular internet users.

Taken together, current findings advance the field of PIU research by identifying parietal alpha asymmetry as a potential specific correlate for internet use severity and highlight EO resting-state condition as a more sensitive context for detecting PIU-related asymmetry patterns, particularly in association with attentional dysregulation in regular internet users.

5.4.4. Eyes-closed resting-state EEG: Microstates

EEG microstate analysis is frequently used to assess the state of the underlying networks in the brain. Temporal parameters of microstates reflect synchronous activity of intracortical generators and the tendency of those sources to be activated with quasi-zero phase relations (i.e., simultaneously) (Khanna et al., 2015; Seeber & Michel, 2021; Tarailis et al., 2024). Decreased parameters can indicate the lack of stability or co-activation of functionally incompatible networks, as well as disturbed information flow and processing. Meanwhile, increased activity might not only reflect more stable connections and information sharing between network hubs, but also hypervigilance and physical and emotional hyperactivity (as reported in patients with ADHD) (Férat, Arns, et al., 2022), or higher sustained alertness and an exacerbated response to salience processing (as in patients with borderline personality disorder (Deiber et al., 2024)).

However, the microstates approach has been minimally employed in studies on behavioral addiction so far (Ding et al., 2023; Li et al., 2022; Qi et al., 2023). Qi et al. (2023) reported reduced duration and coverage of MS C in the IA group as compared to controls. Furthermore, the duration of MS C in the IAD group was inversely related to reaction times on Go trials in the Go/NoGo task. Additionally, decreased MS D parameters (duration, occurrence, and coverage) were recently reported in constant media (e.g., messages, emails, social media, video games, online games) users (Zhang et al., 2024). In line, MS D occurrence showed a negative correlation with mobile phone addiction tendency and withdrawal symptoms (Li et al., 2021). Comparable results were obtained in behavioral and fMRI studies, where alterations in the brain activity and functional connectivity were associated with a failure to optimize task-related attentional resources and worsened executive functions (Dong et al., 2012, 2015) and comorbidity with symptoms of depression, anxiety, and substance abuse (Cheng & Liu, 2020; Xie et al., 2023). In contrast, these findings were not replicated in the current study, as parameters of MS C or MS D were not associated with internet use severity in a sample of healthy regular internet users, suggesting that alterations in these microstates may be more pronounced in more severely expressed or clinically diagnosed cases and are not detectable in non-clinical or subclinical populations.

Furthermore, positive correlations with overall PIUQ-9 scores and an increase in time coverage and occurrence rate of MS E in high PIU group emerged. Increased activity of MS E was also reported in individuals who constantly use any form of media (Zhang et al., 2024). This microstate class is known to be related to interoceptive and emotional information processing (Pipinis et al., 2017; Tarailis et al., 2021; Tomescu et al., 2022; Tomescu, Van der Donck, et al., 2024) and certain cognitive functions (Jabès et al., 2021; Zanesco et al., 2021) and is thought to be generated by brain areas that overlap with salience and cingulo-opercular networks (Britz et al., 2010; Custo et al., 2017). A recent study suggested a potential link between increased activity of MS E and traits such as emotional instability and impulsivity (Deiber et al., 2024), yet no significant correlations between MS E parameters and any of the assessed psychological variables were observed in the present study.

Additionally, significant associations were found between parameters of MS D, MS C, and MS B and symptoms of anxiety and obsessive-compulsive tendencies. Individuals with PIU frequently exhibit comorbid depression and anxiety (Burleigh et al., 2020; Lee et al., 2014; Zhou et al., 2011), and a recent meta-analysis reported decreased activity in MS D among individuals with mood and anxiety disorders (Chivu et al., 2024). Consistent with these findings, significant negative correlations were observed between anxiety scores and all MS D parameters: duration, coverage, and occurrence. Although PIUQ-9 scores showed significant and positive correlations with all psychological measures (anxiety, depression, and obsessive–compulsive symptoms), the specific association between MS E hyperactivity and internet use severity – but not psychological factors – suggests that MS E may serve as a distinct marker of neurophysiological processes underlying PIU. In contrast, alterations in MS C, MS B, and especially MS D may reflect broader psychological traits within a healthy, non-clinical sample.

Overall, the current study was the first attempt to approach microstate analysis in a non-clinical sample of regular internet users and the abovementioned findings suggest that EEG microstates are distinct and potentially sensitive biomarkers that can be utilized not only to differentiate neurological and psychological conditions, but also potentially problematic internet use.

5.5 Limitations

This study has several limitations. As far as can be determined from the existing literature, DPIU, which was constructed based on DSM-5 diagnostic criteria for addictive disorders (Van Ameringen et al., 2018), has not been validated in previous studies. However, both PIUQ-9 and DPIU were selected for this study because of their complementary strengths in assessing PIU. The validated and widely used PIUQ-9 offers a quick and comprehensive assessment of general PIU, capturing individuals' overall internet use patterns, while DPIU provides a deeper look into the specific aspects of internet use, categorizing PIU into specific domains like social networking, gaming, or messaging, among others. Together, these tools address both broad and specific dimensions of PIU, providing a comprehensive framework for understanding and addressing problematic internet behaviors. However, due to the lack of DPIU validation, these results should be interpreted cautiously.

Moreover, the sample of 161 participants allowed for a broad correlational analysis; however, certain internet use domains were underrepresented, and as a result, subscales with particularly small samples (e.g., gambling, dating apps, online shopping, and sexual content) were excluded. Furthermore, limited sample sizes render the data unsuitable for broader network analysis, reducing statistical power and limiting the reliability of findings in these areas, and caution should be exercised even when interpreting some correlations. Future research should aim for more balanced recruitment to improve representation across all domains.

The current findings indicate a potential psychoneurophysiological pattern that corresponds to the severity of digital engagement among healthy regular internet users.

First, the expected association between higher internet use and increased psychological distress aligns with previous findings, showing that excessive internet engagement may exacerbate (or be exacerbated by) vulnerabilities in emotional regulation (Fineberg et al., 2025; Kuss & Lopez-Fernandez, 2016). The observed link between lower interoceptive awareness and increased internet use, especially when mediated by neuroticism, points to a potential disconnection from embodied self-regulation mechanisms (Caplan, 2010; Jeronimus et al., 2016; Kayiş et al., 2016; Marciano et al., 2020; Mehling et al., 2012; Pastor et al., 2022; Tian et al., 2021). Notably, the association with the Not-Distracting dimension specifically highlights impaired attentional allocation to internal states (Mehling et al., 2012) and aligns with models proposing that internet use can serve as a coping strategy to escape real-life distress (Brand et al., 2019; Feher et al., 2023; Fineberg et al., 2025; Hussain & Griffiths, 2009; Mehroof & Griffiths, 2010). In short, this co-occurrence of distress and diminished interoceptive awareness may reflect a feedback loop in which emotionally reactive individuals with limited bodily insight turn to digital environments, reinforcing maladaptive usage patterns.

Over time, such engagement could drive neuroplastic changes, particularly within systems governing attention and self-referential processing. The observed electrophysiological alterations within a healthy non-clinical sample may thus represent early adaptations to sustained exposure to highly stimulating, immersive, rewarding, and fast-paced digital contexts (Fineberg et al., 2025; Liu, 2005; Nicholas et al., 2009; Robbins & Clark, 2015). The combined profile emerging from the present electrophysiological findings – comprising modulation of the N1 component, parietal alpha asymmetry, and prevalence of microstate E – suggests a unified pattern of dysregulation in attentional control and self-regulatory processes associated with higher internet use, aligning with theoretical accounts and empirical findings, showing that frequent media multitaskers exhibit increased distractibility, reduced filtering of irrelevant stimuli, and a bias toward stimulus-driven attention (Firth et al., 2019; Ophir et al., 2009).

Specifically, the N1 component reflects early-stage auditory processing and attentional orientation, typically enhanced when attention is directed toward task-relevant stimuli (Fogarty et al., 2020b; Joos et al., 2014; Pires et al., 2014; Sokhadze et al., 2017; Tomé et al., 2015). It engages both bottom-up sensory and top-down predictive mechanisms, with contributions from regions (e.g., vlPFC) involved in attention switching and goal maintenance (Fogarty et al., 2020b; Joos et al., 2014). In individuals with higher internet use, especially within the gaming domain, N1 modulation might indicate altered attentional gating, with earlier N1 peak latencies possibly reflecting either hyper-reactivity to external stimuli or less effortful, habitual attention switching, indicative of bottom-up attentional automation (Duven et al., 2015; Fogarty et al., 2020b; Joos et al., 2014), likely shaped by chronic exposure to stimulus-rich digital environments.

Alpha-band measures further reflect the possible attentional imbalance within higher internet involvement. Greater left parietal hemisphere activity has been associated with approach-related behavioral tendencies and externally focused attention (Schiltz et al., 2018). Reduced global alpha power, indicative of increased cortical excitability and lowered perceptual thresholds (Foxe & Snyder, 2011) reinforces this interpretation. These findings, particularly in eyes-open condition, may further suggest a persistent neural readiness for engagement with external environmental stimuli and support prior work implicating attentional dysregulation and compulsive responsiveness in problematic internet use (D'Hondt et al., 2015; Firth et al., 2019; Ioannidis et al., 2019).

Furthermore, microstate E, characterized by centro-parietal topography and associated with the salience network, has been linked to both emotional and interoceptive processing, showing a negative link between microstate E temporal parameters and somatic awareness (Pipinis et al., 2017; Tarailis et al., 2021). Current findings – increased MS E occurrence and temporal coverage in individuals with higher internet usage scores suggest the opposite pattern – a predominance of externally focused cognitive states, once again echoing findings of persistent engagement with bottom-up-driven or stimulus-salient information.

Although temporally and spatially distinct, these measures converge on a broader neurocognitive shift: from internally regulated, interoceptively attuned top-down control toward externally driven, reactive bottom-up attentional processing. This shift may underlie core features of problematic internet use – psychological distress, diminished bodily awareness, and compulsive engagement with digital content – by disrupting the balance between internal and external attentional modes.

CONCLUSIONS

1. Greater internet use is associated with higher self-reported psychological distress (symptoms of anxiety, depression, obsessions-compulsions) in a non-clinical sample of regular internet users.
2. Greater internet use is associated with lower interoceptive awareness (the Not-Distracting and Trusting dimensions), with neuroticism linking reduced bodily awareness to excessive digital behavior patterns.
3. Behavioral performance measures from the auditory equiprobable Go/NoGo task do not differentiate between levels of internet use severity.
4. EEG ERPs obtained during the auditory equiprobable Go/NoGo task show domain-specific associations with internet use: N1 amplitude is negatively associated with the Gaming domain, Go-N1 latency is negatively associated with the total DPIU score, and NoGo-P3 latency is positively associated with the Information-Search domain; however, no ERP component differentiate between levels of internet use severity.
5. EEG parietal alpha asymmetry correlates with internet use, indicating an association between greater left parietal hemisphere activity and higher levels of internet use.
6. EEG MS E parameters (occurrence rate and coverage) correlate with higher internet use, indicating an association between greater MS E activity and higher levels of internet use.

CONTRIBUTIONS

The project was conceptualized, methodologically designed, and supervised by Dr. Inga Griškova-Bulanova, who also secured the funding and provided overarching guidance throughout all stages of the research.

Data collection was carried out by Dovilė Šimkutė and Dr. Povilas Tarailis.

Regarding the set of psychological questionnaires, data handling, analysis, interpretation, and manuscript preparation were conducted by D. Šimkutė. For the Go/NoGo ERP analysis, EEG preprocessing, statistical analysis, visualization, interpretation, and manuscript writing were performed by D. Šimkutė. The alternating resting-state alpha asymmetry study was likewise fully conducted and reported by D. Šimkutė. In the eyes-closed resting-state microstate study, EEG preprocessing was conducted by P. Tarailis, statistical analysis by D. Šimkutė, while visualization, interpretation, and manuscript preparation were carried out jointly.

REFERENCES

1. A Clark, D., Antony, M., T Beck, A., Swinson, R., & A Steer, R. (2005). Screening for Obsessive and Compulsive Symptoms: Validation of the Clark-Beck Obsessive-Compulsive Inventory. *Psychological Assessment*, *17*, 132–143. https://doi.org/10.1037/1040-3590.17.2.132
2. Aarseth, E., Bean, A. M., Boonen, H., Colder Carras, M., Coulson, M., Das, D., Deleuze, J., Dunkels, … Van Rooij, A. J. (2017). Scholars' open debate paper on the World Health Organization ICD-11 Gaming Disorder proposal. *Journal of Behavioral Addictions*, *6*(3), 267–270. https://doi.org/10.1556/2006.5.2016.088
3. Akil, A. M., Cserjési, R., Nagy, T., Demetrovics, Z., Németh, D., & Logemann, H. N. A. (2024). The relationship between frontal alpha asymmetry and behavioral and brain activity indices of reactive inhibitory control. *Journal of Neurophysiology*, *132*(2), 362–374. https://doi.org/10.1152/jn.00046.2024
4. Allen, J. J. B., Coan, J. A., & Nazarian, M. (2004). Issues and assumptions on the road from raw signals to metrics of frontal EEG asymmetry in emotion. *Biological Psychology*, *67*(1–2), 183–218. https://doi.org/10.1016/j.biopsycho.2004.03.007
5. Allen, M., Poggiali, D., Whitaker, K., Marshall, T., van Langen, J., & Kievit, R. (2021). Raincloud plots: A multi-platform tool for robust data visualization. *Wellcome Open Research*, *4*(63). https://doi.org/10.12688/wellcomeopenres.15191.2
6. Al-Menayes, J. (2015). Motivations for Using Social Media: An Exploratory Factor Analysis. *International Journal of Psychological Studies*, *7*. https://doi.org/10.5539/ijps.v7n1p43
7. Alonzo, R., Hussain, J., Stranges, S., & Anderson, K. K. (2021). Interplay between social media use, sleep quality, and mental health in youth: A systematic review. *Sleep Medicine Reviews*, *56*, 101414. https://doi.org/10.1016/j.smrv.2020.101414
8. Al-Sanaa, B. (2009). Intimate strangers and estranged intimates: An investigation of the impact of instant messaging and short message service on the size and strength of social networks in Kuwait. Ph.D. thesis, The University of Southern Mississippi.
9. American Psychiatric Association. (2013). *Diagnostic and Statistical Manual of Mental Disorders* (5th ed.). American Psychiatric Association. https://doi.org/10.1176/appi.books.9780890425596
10. Ames, S. L., Wong, S. W., Bechara, A., Cappelli, C., Dust, M., Grenard, J. L., & Stacy, A. W. (2014). Neural correlates of a Go/NoGo task with alcohol stimuli in light and heavy young drinkers. *Behavioural Brain Research*, *274*, 382–389. https://doi.org/10.1016/j.bbr.2014.08.039
11. Anderson, A. J., & Perone, S. (2018). Developmental change in the resting state electroencephalogram: Insights into cognition and the brain. *Brain and Cognition*, *126*, 40–52. https://doi.org/10.1016/j.bandc.2018.08.001

12. Anderson, E. L., Steen, E., & Stavropoulos, V. (2017). Internet use and Problematic Internet Use: A systematic review of longitudinal research trends in adolescence and emergent adulthood. *International Journal of Adolescence and Youth*, *22*(4), 430–454. https://doi.org/10.1080/02673843.2016.1227716
13. Andreassen, C. S., Griffiths, M. D., Gjertsen, S. R., Krossbakken, E., Kvam, S., & Pallesen, S. (2013). The relationships between behavioral addictions and the five-factor model of personality. *Journal of Behavioral Addictions*, *2*(2), 90–99. https://doi.org/10.1556/JBA.2.2013.003
14. Anguera, J. A., Boccanfuso, J., Rintoul, J. L., Al-Hashimi, O., Faraji, F., Janowich, J., Kong, E., Larraburo, Y., Rolle, C., Johnston, E., & Gazzaley, A. (2013). Video game training enhances cognitive control in older adults. *Nature*, *501*(7465), 97–101. https://doi.org/10.1038/nature12486
15. Antons, S., & Matthias, B. (2020). Inhibitory control and problematic Internet-pornography use – The important balancing role of the insula. *Journal of Behavioral Addictions*, *9*(1), 58–70. https://doi.org/10.1556/2006.2020.00010
16. Antons, S., Mueller, S. M., Wegmann, E., Trotzke, P., Schulte, M. M., & Brand, M. (2019). Facets of impulsivity and related aspects differentiate among recreational and unregulated use of Internet pornography. *Journal of Behavioral Addictions*, *8*(2), 223–233. https://doi.org/10.1556/2006.8.2019.22
17. Argyriou, E., Davison, C. B., & Lee, T. T. C. (2017). Response Inhibition and Internet Gaming Disorder: A Meta-analysis. *Addictive Behaviors*, *71*, 54–60. https://doi.org/10.1016/j.addbeh.2017.02.026
18. Arjoonsingh, A., Jamal, B. C., & Ganti, L. (2024). History and Evolution of the Electroencephalogram. *Cureus*, *16*(8), e66385. https://doi.org/10.7759/cureus.66385
19. Aron, A. R. (2007). The neural basis of inhibition in cognitive control. *The Neuroscientist* *13*(3), 214–228. https://doi.org/10.1177/1073858407299288
20. Artoni, F., Maillard, J., Britz, J., Seeber, M., Lysakowski, C., Bréchet, L., Tramèr, M. R., & Michel, C. M. (2022). EEG microstate dynamics indicate a U-shaped path to propofol-induced loss of consciousness. *NeuroImage*, *256*, 119156. https://doi.org/10.1016/j.neuroimage.2022.119156
21. Auxier, B., Anderson, M., Perrin, A., & Turner, E. (2020). *Parenting Children in the Age of Screens*. Pew Research Center. https://www.pewresearch.org/internet/2020/07/28/parenting-children-in-the-age-of-screens/
22. Babiloni, C., Arakaki, X., Azami, H., Bennys, K., Blinowska, K., Bonanni, L., Bujan, A., Carrillo, M. C., Cichocki, A., de Frutos-Lucas, J., Del Percio, C., Dubois, B., Edelmayer, R., Egan, G., Epelbaum, S., Escudero, J., Evans, A., Farina, F., Fargo, K., … Guntekin, B. (2021). Measures of Resting State EEG Rhythms for Clinical Trials in

Alzheimer's Disease. *Alzheimer's & Dementia : The Journal of the Alzheimer's Association*, *17*(9), 1528–1553. https://doi.org/10.1002/alz.12311
23. Bäcklund, C., Elbe, P., Gavelin, H. M., Sörman, D. E., & Ljungberg, J. K. (2022). Gaming motivations and gaming disorder symptoms: A systematic review and meta-analysis. *Journal of Behavioral Addictions*, *11*(3), 667–688. https://doi.org/10.1556/2006.2022.00053
24. Baggio, S., Starcevic, V., Billieux, J., King, D. L., Gainsbury, S. M., Eslick, G. D., & Berle, D. (2022). Testing the spectrum hypothesis of problematic online behaviors: A network analysis approach. *Addictive Behaviors*, *135*, 107451. https://doi.org/10.1016/j.addbeh.2022.107451
25. Baik, S. Y., Kim, C., Kim, S., Yook, D.-W., Kim, H. S., Chang, H., & Lee, S.-H. (2019). The moderating effect of heart rate variability on the relationship between alpha asymmetry and depressive symptoms. *Heliyon*, *5*(3), e01290. https://doi.org/10.1016/j.heliyon.2019.e01290
26. Balconi, M., & Angioletti, L. (2021). Neurophysiology of Gambling Behavior and Internet Use Vulnerability: A Comparison Between Behavioral and EEG Measures. *Clin EEG Neurosci.* Doi: 10.1177/15500594211038469. PMID: 34382432
27. Ballester-Arnal, R., García-Barba, M., Castro-Calvo, J., Giménez-García, C., & Gil-Llario, M. D. (2023). Pornography Consumption in People of Different Age Groups: An Analysis Based on Gender, Contents, and Consequences. *Sexuality Research and Social Policy*, *20*(2), 766–779. https://doi.org/10.1007/s13178-022-00720-z
28. Balodis, I. M., & Potenza, M. N. (2020). Common neurobiological and psychological underpinnings of gambling and substance-use disorders. *Progress in Neuro-Psychopharmacology and Biological Psychiatry*, *99*, 109847. https://doi.org/10.1016/j.pnpbp.2019.109847
29. Baranauskas, M., Grabauskaite, A., & Griskova-Bulanova, I. (2016). Psychometric characteristics of Lithuanian version of multidimensional assessment of interoceptive awareness. *Neurologijos Seminarai, 20(4)*.
30. Bari, A., & Robbins, T. W. (2013). Inhibition and impulsivity: Behavioral and neural basis of response control. *Progress in Neurobiology*, *108*, 44–79. https://doi.org/10.1016/j.pneurobio.2013.06.005
31. Barratt, E. S. (1959). Anxiety and Impulsiveness Related to Psychomotor Efficiency. *Perceptual and Motor Skills*, *9*(3), 191–198. https://doi.org/10.2466/pms.1959.9.3.191
32. Barratt, E. S. (1985). Impulsiveness subtraits: Arousal and information processing. *Motivation, Emotion and Personality,* New York: Elsevier Science Publishers; p. 137–46.
33. Barrett, L. F., & Simmons, W. K. (2015). Interoceptive predictions in the brain. *Nature Reviews Neuroscience*, *16*(7), 419–429. https://doi.org/10.1038/nrn3950
34. Barry, R. J., Clarke, A. R., Johnstone, S. J., Magee, C. A., & Rushby, J. A. (2007). EEG differences between eyes-closed and eyes-open resting

conditions. *Clinical Neurophysiology: Official Journal of the International Federation of Clinical Neurophysiology*, *118*(12), 2765–2773. https://doi.org/10.1016/j.clinph.2007.07.028

35. Barry, R. J., & De Blasio, F. M. (2013). Sequential processing in the equiprobable auditory Go/NoGo task: A temporal PCA study. *International Journal of Psychophysiology: Official Journal of the International Organization of Psychophysiology*, *89*(1), 123–127. https://doi.org/10.1016/j.ijpsycho.2013.06.012
36. Barry, R. J., & De Blasio, F. M. (2017). EEG differences between eyes-closed and eyes-open resting remain in healthy ageing. *Biological Psychology*, *129*, 293–304. https://doi.org/10.1016/j.biopsycho.2017.09.010
37. Barry, R. J., De Blasio, F. M., & Borchard, J. P. (2014). Sequential processing in the equiprobable auditory Go/NoGo task: Children vs. adults. *Clinical Neurophysiology*, *125*(10), 1995–2006. https://doi.org/10.1016/j.clinph.2014.02.018
38. Barry, R. J., De Blasio, F. M., & Cave, A. E. (2016). Sequential processing in young and older adults in the equiprobable auditory Go/NoGo task. *Clinical Neurophysiology*, *127*(5), 2273–2285. https://doi.org/10.1016/j.clinph.2016.02.010
39. Barry, R. J., Johnstone, S. J., Clarke, A. R., Rushby, J. A., Brown, C. R., & McKenzie, D. N. (2007). Caffeine effects on ERPs and performance in an auditory Go/NoGo task. *Clinical Neurophysiology*, *118*(12), 2692–2699. https://doi.org/10.1016/j.clinph.2007.08.023
40. Barry, R., Steiner, G., De Blasio, F., Fogarty, J., Karamacoska, D., & Macdonald, B. (2019). Components in the P300: Don't forget the Novelty P3! *Psychophysiology*, *57*. https://doi.org/10.1111/psyp.13371
41. Başar, E., Başar-Eroglu, C., Karakaş, S., & Schürmann, M. (2001). Gamma, alpha, delta, and theta oscillations govern cognitive processes. *International Journal of Psychophysiology*, *39*(2), 241–248. https://doi.org/10.1016/S0167-8760(00)00145-8
42. Bechara, A. (2005). Decision making, impulse control and loss of willpower to resist drugs: A neurocognitive perspective. *Nature Neuroscience*, *8*(11), 1458–1463. https://doi.org/10.1038/nn1584
43. Beck, A. T., Epstein, N., Brown, G., & Steer, R. A. (1988). An inventory for measuring clinical anxiety: Psychometric properties. *Journal of Consulting and Clinical Psychology*, *56*(6), 893–897.
44. Beck, A. T., Steer, R. A., & Brown, G. K. (1996). *BDI-II: Beck Depression Inventory Manual (2nd ed.)* San Antonio: Psychological Corporation.
45. Benjamini, Y., & Hochberg, Y. (1995). Controlling the False Discovery Rate: A Practical and Powerful Approach to Multiple Testing. *Journal of the Royal Statistical Society. Series B (Methodological)*, *57*(1), 289–300.
46. Beppi, C., Violante, I. R., Hampshire, A., Grossman, N., & Sandrone, S. (2020). Patterns of Focal- and Large-Scale Synchronization in Cognitive

Control and Inhibition: A Review. *Frontiers in Human Neuroscience*, *14*. https://www.frontiersin.org/article/10.3389/fnhum.2020.00196

47. Berger, M. N., Taba, M., Marino, J. L., Lim, M. S. C., & Skinner, S. R. (2022). Social Media Use and Health and Well-being of Lesbian, Gay, Bisexual, Transgender, and Queer Youth: Systematic Review. *Journal of Medical Internet Research*, *24*(9), e38449. https://doi.org/10.2196/38449
48. Billieux, J., Flayelle, M., Rumpf, H.-J., & Stein, D. J. (2019). High Involvement Versus Pathological Involvement in Video Games: A Crucial Distinction for Ensuring the Validity and Utility of Gaming Disorder. *Current Addiction Reports*, *6*(3), 323–330. https://doi.org/10.1007/s40429-019-00259-x
49. Billieux, J., King, D. L., Higuchi, S., Achab, S., Bowden-Jones, H., Hao, W., Long, J., Lee, H. K., Potenza, M. N., Saunders, J. B., & Poznyak, V. (2017). Functional impairment matters in the screening and diagnosis of gaming disorder. *Journal of Behavioral Addictions*, *6*(3), 285–289. https://doi.org/10.1556/2006.6.2017.036
50. Billieux, J., Schimmenti, A., Khazaal, Y., Maurage, P., & Heeren, A. (2015). Are we overpathologizing everyday life? A tenable blueprint for behavioral addiction research. *Journal of Behavioral Addictions*, *4*(3), 119–123. https://doi.org/10.1556/2006.4.2015.009
51. Blackhart, G. C., Minnix, J. A., & Kline, J. P. (2006). Can EEG asymmetry patterns predict future development of anxiety and depression? A preliminary study. *Biological Psychology*, *72*(1), 46–50. https://doi.org/10.1016/j.biopsycho.2005.06.010
52. Bonnard, M., Chen, S., Gaychet, J., Carrere, M., Woodman, M., Giusiano, B., & Jirsa, V. (2016). Resting state brain dynamics and its transients: A combined TMS-EEG study. *Scientific Reports*, *6*(1), 31220. https://doi.org/10.1038/srep31220
53. Borgomaneri, S., Serio, G., & Battaglia, S. (2020). Please, don't do it! Fifteen years of progress of non-invasive brain stimulation in action inhibition. *Cortex,* *132*, 404–422. https://doi.org/10.1016/j.cortex.2020.09.002
54. Bőthe, B., Nagy, L., Koós, M., Demetrovics, Z., Potenza, M. N., International Sex Survey Consortium, & Kraus, S. W. (2024). Problematic pornography use across countries, genders, and sexual orientations: Insights from the International Sex Survey and comparison of different assessment tools. *Addiction*, *119*(5), 928–950. https://doi.org/10.1111/add.16431
55. Brand, M. (2022). Can internet use become addictive? *Science*, *376*(6595), 798–799. https://doi.org/10.1126/science.abn4189
56. Brand, M., Wegmann, E., Stark, R., Müller, A., Wölfling, K., Robbins, T. W., & Potenza, M. N. (2019). The Interaction of Person-Affect-Cognition-Execution (I-PACE) model for addictive behaviors: Update, generalization to addictive behaviors beyond internet-use disorders, and specification of the process character of addictive behaviors.

Neuroscience & Biobehavioral Reviews, *104*, 1–10. https://doi.org/10.1016/j.neubiorev.2019.06.032
57. Brand, M., Young, K. S., & Laier, C. (2014). Prefrontal Control and Internet Addiction: A Theoretical Model and Review of Neuropsychological and Neuroimaging Findings. *Frontiers in Human Neuroscience*, *8*. https://doi.org/10.3389/fnhum.2014.00375
58. Brand, M., Young, K. S., Laier, C., Wölfling, K., & Potenza, M. N. (2016). Integrating psychological and neurobiological considerations regarding the development and maintenance of specific Internet-use disorders: An Interaction of Person-Affect-Cognition-Execution (I-PACE) model. *Neuroscience & Biobehavioral Reviews*, *71*, 252–266. https://doi.org/10.1016/j.neubiorev.2016.08.033
59. Braver, T. S. (2012). The variable nature of cognitive control: A dual mechanisms framework. *Trends in Cognitive Sciences*, *16*(2), 106–113. https://doi.org/10.1016/j.tics.2011.12.010
60. Bréchet, L., Brunet, D., Perogamvros, L., Tononi, G., & Michel, C. M. (2020). EEG microstates of dreams. *Scientific Reports*, *10*(1), 17069. https://doi.org/10.1038/s41598-020-74075-z
61. Brevers, D., Baeken, C., Bechara, A., He, Q., Maurage, P., Sescousse, G., Vögele, C., & Billieux, J. (2024). Increased ventral anterior insular connectivity to sports betting availability indexes problem gambling. *Addiction Biology*, *29*(3), e13389. https://doi.org/10.1111/adb.13389
62. Brevers, D., & Noël, X. (2013). Pathological gambling and the loss of willpower: A neurocognitive perspective. *Socioaffect Neurosci Psychol.*, *3*. https://doi.org/10.3402/snp.v3i0.21592
63. Britz, J., Van De Ville, D., & Michel, C. (2010). BOLD correlates of EEG topography reveal rapid resting-state network dynamics. *NeuroImage*, *52*, 1162–1170. https://doi.org/10.1016/j.neuroimage.2010.02.052
64. Bruin, K. J., & Wijers, A. A. (2002). Inhibition, response mode, and stimulus probability: A comparative event-related potential study. *Clinical Neurophysiology*, *113*(7), 1172–1182. https://doi.org/10.1016/S1388-2457(02)00141-4
65. Bruin, K. J., Wijers, A. A., & van Staveren, A. S. (2001). Response priming in a go/nogo task: Do we have to explain the go/nogo N2 effect in terms of response activation instead of inhibition? *Clinical Neurophysiology*, *112*(9), 1660–1671. https://doi.org/10.1016/s1388-2457(01)00601-0
66. Brunet, D., Murray, M. M., & Michel, C. M. (2011). Spatiotemporal analysis of multichannel EEG: CARTOOL. *Computational Intelligence and Neuroscience*, *2011*, 813870. https://doi.org/10.1155/2011/813870
67. Bunge, S., & Kahn, I. (2009). Cognition: An Overview of Neuroimaging Techniques. *Encyclopedia of Neuroscience* (Vol. 2, pp. 1063–1067). Elsevier. https://doi.org/10.1016/B978-008045046-9.00298-9
68. Burkauskas, J., Király, O., Demetrovics, Z., Podlipskyte, A., & Steibliene, V. (2020). Psychometric Properties of the Nine-Item Problematic Internet

Use Questionnaire (PIUQ-9) in a Lithuanian Sample of Students. *Frontiers in Psychiatry*, *11*. https://doi.org/10.3389/fpsyt.2020.565769

69. Burkauskas, J., Pellegrini, L., Mozuraityte, K., Gecaite-Stonciene, J., Hidvégi, D., Demetrovics, Z., & Fineberg, N. A. (2023). Problematic internet use during the COVID-19 pandemic: A systematic review and meta-analysis of prevalence data. *Neuropsychopharmacologia Hungarica: A Magyar Pszichofarmakologiai Egyesulet Lapja = Official Journal of the Hungarian Association of Psychopharmacology*, *25*(3), 131–141.
70. Burleigh, T. L., Griffiths, M. D., Sumich, A., Wang, G. Y., & Kuss, D. J. (2020). Gaming disorder and internet addiction: A systematic review of resting-state EEG studies. *Addictive Behaviors*, *107*, 106429. https://doi.org/10.1016/j.addbeh.2020.106429
71. Burnette, E. M., Grodin, E. N., Lim, A. C., MacKillop, J., Karno, M. P., & Ray, L. A. (2019). Association between impulsivity and neural activation to alcohol cues in heavy drinkers. *Psychiatry Research. Neuroimaging*, *293*, 110986. https://doi.org/10.1016/j.pscychresns.2019.110986
72. Bush, G. (2011). Cingulate, Frontal and Parietal Cortical Dysfunction in Attention-Deficit/Hyperactivity Disorder. *Biological Psychiatry*, *69*(12), 1160–1167. https://doi.org/10.1016/j.biopsych.2011.01.022
73. Cai, W., Ryali, S., Chen, T., Li, C.-S. R., & Menon, V. (2014). Dissociable roles of right inferior frontal cortex and anterior insula in inhibitory control: Evidence from intrinsic and task-related functional parcellation, connectivity, and response profile analyses across multiple datasets. *The Journal of Neuroscience, 34* (44), 14652–14667. https://doi.org/10.1523/JNEUROSCI.3048-14.2014
74. Camerini, A.-L., Marciano, L., Annoni, A. M., Ort, A., & Petrocchi, S. (2022). Exploring the Emotional Experience During Instant Messaging Among Young Adults: An Experimental Study Incorporating Physiological Correlates of Arousal. *Frontiers in Psychology*, *13,* 840845. https://doi.org/10.3389/fpsyg.2022
75. Campanella, S., Pogarell, O., & Boutros, N. (2014). Event-related potentials in substance use disorders: A narrative review based on articles from 1984 to 2012. *Clinical EEG and Neuroscience*, *45*(2), 67–76. https://doi.org/10.1177/1550059413495533
76. Cantero, J. L., Atienza, M., & Salas, R. M. (2002). Human alpha oscillations in wakefulness, drowsiness period, and REM sleep: Different electroencephalographic phenomena within the alpha band. *Neurophysiol Clin, 32*(1), 54–71. https://doi.org/10.1016/s0987-7053(01)00289-1
77. Cao, F., Su, L., Liu, T., & Gao, X. (2007). The relationship between impulsivity and Internet addiction in a sample of Chinese adolescents. *European Psychiatry*, *22*(7), 466–471. https://doi.org/10.1016/j.eurpsy.2007.05.004

78. Caplan, S. E. (2010). Theory and measurement of generalized problematic Internet use: A two-step approach. *Computers in Human Behavior*, *26*(5), 1089–1097. https://doi.org/10.1016/j.chb.2010.03.012
79. Carli, M., Robbins, T. W., Evenden, J. L., & Everitt, B. J. (1983). Effects of lesions to ascending noradrenergic neurones on performance of a 5-choice serial reaction task in rats; implications for theories of dorsal noradrenergic bundle function based on selective attention and arousal. *Behavioural Brain Research*, *9*(3), 361–380. https://doi.org/10.1016/0166-4328(83)90138-9
80. Carli, V., Durkee, T., Wasserman, D., Hadlaczky, G., Despalins, R., Kramarz, E., Wasserman, C., Sarchiapone, M., Hoven, C. W., Brunner, R., & Kaess, M. (2013). The association between pathological internet use and comorbid psychopathology: A systematic review. *Psychopathology*, *46*(1), 1–13. https://doi.org/10.1159/000337971
81. Cataldo, I., Billieux, J., Esposito, G., & Corazza, O. (2022). Assessing problematic use of social media: Where do we stand and what can be improved? *Current Opinion in Behavioral Sciences*, *45*, 101145. https://doi.org/10.1016/j.cobeha.2022.101145
82. Chamberlain, S. R., Redden, S., Leppink, E., & Grant, J. E. (2017). Problematic internet use in gamblers: Impact on clinical and cognitive measures. *CNS Spectrums*, *22*(6), 495–503. https://doi.org/10.1017/S1092852917000037
83. Chambers, R. A., Taylor, J. R., & Potenza, M. N. (2003). Developmental neurocircuitry of motivation in adolescence: A critical period of addiction vulnerability. *The American Journal of Psychiatry*, *160*(6), 1041–1052. https://doi.org/10.1176/appi.ajp.160.6.1041
84. Chang, M. L. Y., & Lee, I. O. (2024). Functional connectivity changes in the brain of adolescents with internet addiction: A systematic literature review of imaging studies. *PLOS Mental Health*, *1*(1), e0000022. https://doi.org/10.1371/journal.pmen.0000022
85. Chang, Y. H., Chang, K. C., Hou, W. L., Lin, C. Y., & Griffiths, M. D. (2020). Internet gaming as a coping method among schizophrenic patients facing psychological distress. *Journal of Behavioral Addictions*, *9*(4), 1022–1031. https://doi.org/10.1556/2006.2020.00081
86. Chen, C.-C., & Lin, Y.-C. (2018). What drives live-stream usage intention? The perspectives of flow, entertainment, social interaction, and endorsement. *Telematics and Informatics*, *35*(1), 293–303. https://doi.org/10.1016/j.tele.2017.12.003
87. Chen, C.-Y., Yen, J.-Y., Wang, P.-W., Liu, G.-C., Yen, C.-F., & Ko, C.-H. (2016). Altered Functional Connectivity of the Insula and Nucleus Accumbens in Internet Gaming Disorder: A Resting State fMRI Study. *European Addiction Research*, *22*(4), 192–200. https://doi.org/10.1159/000440716
88. Chen, J., Li, X., Zhang, Q., Zhou, Y., Wang, R., Tian, C., & Xiang, H. (2020). Impulsivity and Response Inhibition Related Brain Networks in

Adolescents With Internet Gaming Disorder: A Preliminary Study Utilizing Resting-State fMRI. *Frontiers in Psychiatry*, *11*, 618319. https://doi.org/10.3389/fpsyt.2020.618319
89. Chen, J., Liang, Y., Mai, C., Zhong, X., & Qu, C. (2016). General Deficit in Inhibitory Control of Excessive Smartphone Users: Evidence from an Event-Related Potential Study. *Frontiers in Psychology*, *7*, 511. https://doi.org/10.3389/fpsyg.2016.00511
90. Chen, L., Zhou, H., Gu, Y., Wang, S., Wang, J., Tian, L., Zhu, H., & Zhou, Z. (2018). The Neural Correlates of Implicit Cognitive Bias Toward Internet-Related Cues in Internet Addiction: An ERP Study. *Frontiers in Psychiatry*, *9*, 421. https://doi.org/10.3389/fpsyt.2018.00421
91. Chen, S.-K., Lo, M.-T., & Lin, S. S. J. (2017). Impulsivity as a precedent factor for problematic Internet use: How can we be sure? *International Journal of Psychology: Journal International De Psychologie*, *52*(5), 389–397. https://doi.org/10.1002/ijop.12231
92. Cheng, C., Lau, Y.-C., Chan, L., & Luk, J. W. (2021). Prevalence of social media addiction across 32 nations: Meta-analysis with subgroup analysis of classification schemes and cultural values. *Addictive Behaviors*, *117*, 106845. https://doi.org/10.1016/j.addbeh.2021.106845
93. Cheng, C., & Li, A. Y. (2014). Internet Addiction Prevalence and Quality of (Real) Life: A Meta-Analysis of 31 Nations Across Seven World Regions. *Cyberpsychology, Behavior and Social Networking*, *17*(12), 755–760. https://doi.org/10.1089/cyber.2014.0317
94. Cheng, C.-H., Tsai, H.-Y., & Cheng, H.-N. (2019). The effect of age on N2 and P3 components: A meta-analysis of Go/Nogo tasks. *Brain and Cognition*, *135*, 103574. https://doi.org/10.1016/j.bandc.2019.05.012
95. Cheng, H., & Liu, J. (2020). Alterations in Amygdala Connectivity in Internet Addiction Disorder. *Scientific Reports*, *10*(1), 2370. https://doi.org/10.1038/s41598-020-59195-w
96. Chivu, A., Pascal, S. A., Damborská, A., & Tomescu, M. I. (2024). EEG Microstates in Mood and Anxiety Disorders: A Meta-analysis. *Brain Topography*, *37*(3), 357–368. https://doi.org/10.1007/s10548-023-00999-0
97. Choi, J.-S., Park, S. M., Lee, J., Hwang, J. Y., Jung, H. Y., Choi, S.-W., Kim, D. J., Oh, S., & Lee, J.-Y. (2013). Resting-state beta and gamma activity in Internet addiction. *International Journal of Psychophysiology*, *89*(3), 328–333. https://doi.org/10.1016/j.ijpsycho.2013.06.007
98. Christensen, E., Albertella, L., Chamberlain, S. R., Suo, C., Brydevall, M., Grant, J. E., Yücel, M., & Lee, R. S. C. (2024). A comprehensive evaluation of the neurocognitive predictors of problematic alcohol use, eating, pornography, and internet use: A 6-month longitudinal study. *Journal of Behavioral Addictions*, *13*(3), 823–840. https://doi.org/10.1556/2006.2024.00041
99. Clark, L., Studer, B., Bruss, J., Tranel, D., & Bechara, A. (2014). Damage to insula abolishes cognitive distortions during simulated gambling.

Proceedings of the National Academy of Sciences, *111*(16), 6098–6103. https://doi.org/10.1073/pnas.1322295111
100. Clarke, A. T., Fineberg, N. A., Pellegrini, L., & Laws, K. R. (2024). The relationship between cognitive phenotypes of compulsivity and impulsivity and clinical variables in obsessive-compulsive disorder: A systematic review and Meta-analysis. *Comprehensive Psychiatry*, *133*, 152491. https://doi.org/10.1016/j.comppsych.2024.152491
101. Clement, J. (2024). Gaming – statistics & facts. Video gaming worldwide. *Statista*. https://www.statista.com/topics/1680/gaming/
102. Colrain, I. M., Sullivan, E. V., Ford, J. M., Mathalon, D. H., McPherson, S.-L., Roach, B. J., Crowley, K. E., & Pfefferbaum, A. (2011). Frontally mediated inhibitory processing and white matter microstructure: Age and alcoholism effects. *Psychopharmacology*, *213*(4), 669–679. https://doi.org/10.1007/s00213-010-2073-7
103. Costa, P., & McCrae, R. (2008). The revised NEO personality inventory (NEO-PI-R). *The SAGE Handbook of Personality Theory and Assessment* (Vol. *2*, pp. 179–198). SAGE. https://doi.org/10.4135/9781849200479.n9
104. Costa, P. T., & McCrae, R. R. (1992). Professional manual: Revised NEO Personality Inventory (NEO–PI–R) and NEO Five-Factor Inventory (NEO–FFI).*Odessa, FL: Psychological Assessment Resources.*
105. Craig, A. D. (2002). How do you feel? Interoception: the sense of the physiological condition of the body. *Nature Reviews Neuroscience*, *3*(8), 655–666. https://doi.org/10.1038/nrn894
106. Crowley, K. E., & Colrain, I. M. (2004). A review of the evidence for P2 being an independent component process: Age, sleep and modality. *Clin Neurophysiol.* *115*(4), 732–744. https://doi.org/10.1016/j.clinph.2003.11.021
107. Cui, R., Jiang, J., Zeng, L., Jiang, L., Xia, Z., Dong, L., Gong, D., Yan, G., Ma, W., & Yao, D. (2021). Action Video Gaming Experience Related to Altered Resting-State EEG Temporal and Spatial Complexity. *Frontiers in Human Neuroscience*, *15*, 640329. https://doi.org/10.3389/fnhum.2021.640329
108. Custo, A., Van De Ville, D., Wells, W. M., Tomescu, M. I., Brunet, D., & Michel, C. M. (2017). Electroencephalographic Resting-State Networks: Source Localization of Microstates. *Brain Connectivity*, *7*(10), 671–682. https://doi.org/10.1089/brain.2016.0476
109. Cyders, M. A., Smith, G. T., Spillane, N. S., Fischer, S., Annus, A. M., & Peterson, C. (2007). Integration of impulsivity and positive mood to predict risky behavior: Development and validation of a measure of positive urgency. *Psychological Assessment*, *19*(1), 107–118. https://doi.org/10.1037/1040-3590.19.1.107
110. D Griffiths, M. (2014). Internet Addiction Disorder and Internet Gaming Disorder are Not the Same. *Journal of Addiction Research & Therapy*, *05*(4). https://doi.org/10.4172/2155-6105.1000e124

111. Dahl, D., & Bergmark, K. H. (2020). Problematic internet use: A scoping review - longitudinal research on a contemporary social problem, 2006-2017. *Nordisk Alkohol- & Narkotikatidskrift: NAT*, *37*(6), 497–525. https://doi.org/10.1177/1455072520941997
112. Dalbudak, E., Evren, C., Aldemir, S., Taymur, I., Evren, B., & Topcu, M. (2015). The impact of sensation seeking on the relationship between attention deficit/hyperactivity symptoms and severity of Internet addiction risk. *Psychiatry Research*, *228*(1), 156–161. https://doi.org/10.1016/j.psychres.2015.04.035
113. Dalley, J. W., Everitt, B. J., & Robbins, T. W. (2011). Impulsivity, compulsivity, and top-down cognitive control. *Neuron*, *69*(4), 680–694. https://doi.org/10.1016/j.neuron.2011.01.020
114. Damoiseaux, J. S., Rombouts, S. a. R. B., Barkhof, F., Scheltens, P., Stam, C. J., Smith, S. M., & Beckmann, C. F. (2006). Consistent resting-state networks across healthy subjects. *Proceedings of the National Academy of Sciences of the United States of America*, *103*(37), 13848–13853. https://doi.org/10.1073/pnas.0601417103
115. Darvesh, N., Radhakrishnan, A., Lachance, C. C., Nincic, V., Sharpe, J. P., Ghassemi, M., Straus, S. E., & Tricco, A. C. (2020). Exploring the prevalence of gaming disorder and Internet gaming disorder: A rapid scoping review. *Systematic Reviews*, *9*(1), 68. https://doi.org/10.1186/s13643-020-01329-2
116. Das, S., Zomorrodi, R., Enticott, P. G., Kirkovski, M., Blumberger, D. M., Rajji, T. K., & Desarkar, P. (2022). Resting state electroencephalography microstates in autism spectrum disorder: A mini-review. *Frontiers in Psychiatry*, *13*, 988939. https://doi.org/10.3389/fpsyt.2022.988939
117. Davidson, R. J. (1992). Anterior cerebral asymmetry and the nature of emotion. *Brain and Cognition*, *20*(1), 125–151. https://doi.org/10.1016/0278-2626(92)90065-t
118. Davis, R. A. (2001). A cognitive-behavioral model of pathological Internet use. *Computers in Human Behavior*, *17*(2), 187–195. https://doi.org/10.1016/S0747-5632(00)00041-8
119. de Jong, M., Lazar, S. W., Hug, K., Mehling, W. E., Hölzel, B. K., Sack, A. T., Peeters, F., Ashih, H., Mischoulon, D., & Gard, T. (2016). Effects of Mindfulness-Based Cognitive Therapy on Body Awareness in Patients with Chronic Pain and Comorbid Depression. *Frontiers in Psychology*, *7*. https://doi.org/10.3389/fpsyg.2016.00967
120. de Vries, L. P., van de Weijer, M. P., & Bartels, M. (2023). A systematic review of the neural correlates of well-being reveals no consistent associations. *Neuroscience and Biobehavioral Reviews*, *145*, 105036. https://doi.org/10.1016/j.neubiorev.2023.105036
121. Deco, G., Jirsa, V. K., & McIntosh, A. R. (2011). Emerging concepts for the dynamical organization of resting-state activity in the brain. *Nature Reviews Neuroscience*, *12*(1), 43–56. https://doi.org/10.1038/nrn2961

122. Deiber, M.-P., Piguet, C., Berchio, C., Michel, C. M., Perroud, N., & Ros, T. (2024). Resting-State EEG Microstates and Power Spectrum in Borderline Personality Disorder: A High-Density EEG Study. *Brain Topography*, *37*(3), 397–409. https://doi.org/10.1007/s10548-023-01005-3
123. Deleuze, J., Nuyens, F., Rochat, L., Rothen, S., Maurage, P., & Billieux, J. (2017). Established risk factors for addiction fail to discriminate between healthy gamers and gamers endorsing DSM-5 Internet gaming disorder. *Journal of Behavioral Addictions*, *6*(4), 516–524. https://doi.org/10.1556/2006.6.2017.074
124. Delorme, A., & Makeig, S. (2004). EEGLAB: An open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *Journal of Neuroscience Methods*, *134*(1), 9–21. https://doi.org/10.1016/j.jneumeth.2003.10.009
125. Demetrovics, Z., Szeredi, B., & Rózsa, S. (2008). The three-factor model of Internet addiction: The development of the Problematic Internet Use Questionnaire. *Behavior Research Methods*, *40*(2), 563–574. https://doi.org/10.3758/brm.40.2.563
126. Deolindo, C. S., Ribeiro, M. W., de Aratanha, M. A. A., Scarpari, J. R. S., Forster, C. H. Q., da Silva, R. G. A., Machado, B. S., Amaro Junior, E., König, T., & Kozasa, E. H. (2021). Microstates in complex and dynamical environments: Unraveling situational awareness in critical helicopter landing maneuvers. *Human Brain Mapping*, *42*(10), 3168–3181. https://doi.org/10.1002/hbm.25426
127. Detandt, S., Bazan, A., Schröder, E., Olyff, G., Kajosch, H., Verbanck, P., & Campanella, S. (2017). A smoking-related background helps moderate smokers to focus: An event-related potential study using a Go-NoGo task. *Clinical Neurophysiology, 128*(10), 1872–1885. https://doi.org/10.1016/j.clinph.2017.07.416
128. D'Hondt, F., Billieux, J., Maurage, P. (2015). Electrophysiological correlates of problematic Internet use: Critical review and perspectives for future research. *Neuroscience And Biobehavioral Reviews*, *59*, 64–82. https://doi.org/10.1016/j.neubiorev.2015.10.005.
129. D'Hondt, F., & Maurage, P. (2017). Electrophysiological studies in Internet addiction: A review within the dual-process framework. *Addictive Behaviors*, *64*, 321–327. https://doi.org/10.1016/j.addbeh.2015.10.012
130. Di Carlo, F., Vicinelli, M. C., Pettorruso, M., De Risio, L., Migliara, G., Baccolini, V., Trioni, J., Grant, J. E., Dell'Osso, B., & Martinotti, G. (2024). Connected minds in disconnected bodies: Exploring the role of interoceptive sensibility and alexithymia in problematic use of the internet. *Comprehensive Psychiatry*, *129*, 152446. https://doi.org/10.1016/j.comppsych.2023.152446
131. Diezig, S., Denzer, S., Achermann, P., Mast, F. W., & Koenig, T. (2024). EEG Microstate Dynamics Associated with Dream-Like Experiences

During the Transition to Sleep. *Brain Topography*, *37*(2), 343–355. https://doi.org/10.1007/s10548-022-00923-y

132. Ding, X., Li, X., Xu, M., He, Z., & Jiang, H. (2023). The effect of repetitive transcranial magnetic stimulation on electroencephalography microstates of patients with heroin-addiction. *Psychiatry Research. Neuroimaging*, *329*, 111594. https://doi.org/10.1016/j.pscychresns.2023.111594
133. Dixon, S. (2024). *Number of social network users worldwide from 2017 to 2028*. Statista. https://www.statista.com/statistics/278414/number-of-worldwide-social-network-users/
134. Domino, E. F., Ni, L., Thompson, M., Zhang, H., Shikata, H., Fukai, H., Sakaki, T., & Ohya, I. (2009). Tobacco Smoking Produces Widespread Dominant Brain Wave Alpha Frequency Increases. *International Journal of Psychophysiology,* *74*(3), 192–198. https://doi.org/10.1016/j.ijpsycho.2009.08.011
135. Dong, G., Devito, E. E., Du, X., & Cui, Z. (2012). Impaired inhibitory control in "internet addiction disorder": A functional magnetic resonance imaging study. *Psychiatry Research*, *203*(2–3), 153–158. https://doi.org/10.1016/j.pscychresns.2012.02.001
136. Dong, G., Li, H., & Potenza, M. N. (2017). Short-Term Internet-Search Training Is Associated with Increased Fractional Anisotropy in the Superior Longitudinal Fasciculus in the Parietal Lobe. *Frontiers in Neuroscience*, *11*, 372. https://doi.org/10.3389/fnins.2017.00372
137. Dong, G., Lin, X., & Potenza, M. N. (2015). Decreased functional connectivity in an executive control network is related to impaired executive function in Internet gaming disorder. *Progress in Neuro-Psychopharmacology & Biological Psychiatry*, *57*, 76–85. https://doi.org/10.1016/j.pnpbp.2014.10.012
138. Dong, G., Lu, Q., Zhou, H., & Zhao, X. (2010). Impulse inhibition in people with Internet addiction disorder: Electrophysiological evidence from a Go/NoGo study. *Neuroscience Letters*, *485*(2), 138–142. https://doi.org/10.1016/j.neulet.2010.09.002
139. Dong, G., & Potenza, M. N. (2014). A cognitive-behavioral model of Internet gaming disorder: Theoretical underpinnings and clinical implications. *Journal of Psychiatric Research*, *58*, 7–11. https://doi.org/10.1016/j.jpsychires.2014.07.005
140. Dong, G., & Potenza, M. N. (2016). Short-term Internet-search practicing modulates brain activity during recollection. *Neuroscience*, *335*, 82–90. https://doi.org/10.1016/j.neuroscience.2016.08.028
141. Donkers, F. C. L., & van Boxtel, G. J. M. (2004). The N2 in go/no-go tasks reflects conflict monitoring not response inhibition. *Brain and Cognition*, *56*(2), 165–176. https://doi.org/10.1016/j.bandc.2004.04.005
142. Donoghue, T., Schaworonkow, N., & Voytek, B. (2022). Methodological Considerations for Studying Neural Oscillations. *European Journal of Neuroscience*, *55*(11–12), 3502–3527. https://doi.org/10.1111/ejn.15361

143. Draganski, B., Gaser, C., Busch, V., Schuierer, G., Bogdahn, U., & May, A. (2004). Neuroplasticity: Changes in grey matter induced by training. *Nature*, *427*(6972), 311–312. https://doi.org/10.1038/427311a
144. Droutman, V., Bechara, A., & Read, S. J. (2015). Roles of the Different Sub-Regions of the Insular Cortex in Various Phases of the Decision-Making Process. *Frontiers in Behavioral Neuroscience*, *9*, 309. https://doi.org/10.3389/fnbeh.2015.00309
145. Droutman, V., Read, S. J., & Bechara, A. (2015). Revisiting the role of the insula in addiction. *Trends in Cognitive Sciences*, *19*(7), 414–420. https://doi.org/10.1016/j.tics.2015.05.005
146. Duong, X.-L., Liaw, S.-Y., & Augustin, J.-L. P. M. (2020). How has Internet Addiction been Tracked Over the Last Decade? A Literature Review and 3C Paradigm for Future Research. *International Journal of Preventive Medicine*, *11*, 175. https://doi.org/10.4103/ijpvm.IJPVM_212_20
147. Durkee, T., Kaess, M., Carli, V., Parzer, P., Wasserman, C., Floderus, B., Apter, A., Balazs, J., Barzilay, S., Bobes, J., Brunner, R., Corcoran, P., Cosman, D., Cotter, P., Despalins, R., Graber, N., Guillemin, F., Haring, C., Kahn, J.-P., … Wasserman, D. (2012). Prevalence of pathological internet use among adolescents in Europe: Demographic and social factors. *Addiction*, *107*(12), 2210–2222. https://doi.org/10.1111/j.1360-0443.2012.03946.x
148. Duven, E. C. P., Müller, K. W., Beutel, M. E., & Wölfling, K. (2015). Altered reward processing in pathological computer gamers—ERP-results from a semi-natural gaming-design. *Brain and Behavior*, *5*(1), 13–23. https://doi.org/10.1002/brb3.293
149. Dye, M. W. G., Green, C. S., & Bavelier, D. (2009). Increasing Speed of Processing With Action Video Games. *Current Directions in Psychological Science*, *18*(6), 321–326. https://doi.org/10.1111/j.1467-8721.2009.01660.x
150. Ehlers, C. L., & Phillips, E. (2007). Association of EEG alpha variants and alpha power with alcohol dependence in Mexican American Young Adults. *Alcohol,* *41*(1), 13–20. https://doi.org/10.1016/j.alcohol.2007.02.001
151. Ekinci, Ö., Çelik, T., Savaş, N., & Toros, F. (2014). Association Between Internet Use and Sleep Problems in Adolescents. *Nöro Psikiyatri Arşivi*, *51*(2), 122-128. https://doi.org/10.4274/npa.y6751
152. Enriquez-Geppert, S., Konrad, C., Pantev, C., & Huster, R. J. (2010). Conflict and inhibition differentially affect the N200/P300 complex in a combined go/nogo and stop-signal task. *NeuroImage*, *51*(2), 877–887. https://doi.org/10.1016/j.neuroimage.2010.02.043
153. Epskamp, S., Borsboom, D., & Fried, E. I. (2018). Estimating psychological networks and their accuracy: A tutorial paper. *Behavior Research Methods*, *50*(1), 195–212. https://doi.org/10.3758/s13428-017-0862-1

154. Erika-Florence, M., Leech, R., & Hampshire, A. (2014). A functional network perspective on response inhibition and attentional control. *Nature Communications*, *5*, 4073. https://doi.org/10.1038/ncomms5073
155. Evans, D. E., Park, J. Y., Maxfield, N., & Drobes, D. J. (2009). Neurocognitive variation in smoking behavior and withdrawal: Genetic and affective moderators. *Genes, Brain, and Behavior*, *8*(1), 86–96. https://doi.org/10.1111/j.1601-183X.2008.00445.x
156. Exelmans, L., & Van den Bulck, J. (2015). Sleep quality is negatively related to video gaming volume in adults. *Journal of Sleep Research*, *24*(2), 189–196. https://doi.org/10.1111/jsr.12255
157. Eysenck, H. J. (1991). Dimensions of personality: 16, 5 or 3?—Criteria for a taxonomic paradigm. *Personality and Individual Differences*, *12*(8), 773–790. https://doi.org/10.1016/0191-8869(91)90144-Z
158. Falkenstein, M., Hoormann, J., & Hohnsbein, J. (1999). ERP components in Go/Nogo tasks and their relation to inhibition. *Acta Psychologica*, *101*(2–3), 267–291. https://doi.org/10.1016/s0001-6918(99)00008-6
159. Falkenstein, M., Hoormann, J., & Hohnsbein, J. (2002). Inhibition-related ERP components: Variation with modality, age, and time-on-task. *Journal of Psychophysiology*, *16*(3), 167–175. https://doi.org/10.1027/0269-8803.16.3.167
160. Falkenstein, M., Koshlykova, N. A., Kiroj, V. N., Hoormann, J., & Hohnsbein, J. (1995). Late ERP components in visual and auditory Go/Nogo tasks. *Electroencephalography and Clinical Neurophysiology*, *96*(1), 36–43. https://doi.org/10.1016/0013-4694(94)00182-k
161. Fante, R., Jacobi, L. L., & Sexton, V. D. (2013). The effects of instant messaging and task difficulty on reading comprehension. *North American Journal of Psychology*, *15*(2), 287–298.
162. Fathi, M., Pourrahimi, A. M., Poormohammad, A., Sardari, S., Rajizadeh, M. A., Mazhari, S., & Pourkand, D. (2024). Video game addiction is associated with early stage of inhibitory control problems: An event-related potential study using cued Go/NoGo task. *Addiction Biology*, *29*(4), e13391. https://doi.org/10.1111/adb.13391
163. Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, *39*(2), 175–191. https://doi.org/10.3758/BF03193146
164. Feher, A., Fejes, E., Kapus, K., Jancsak, C., Nagy, G. D., Horvath, L., Tibold, A., & Feher, G. (2023). The association of problematic usage of the internet with burnout, depression, insomnia, and quality of life among Hungarian high school students. *Frontiers in Public Health*, *11*, 1167308. https://doi.org/10.3389/fpubh.2023.1167308
165. Férat, V., Arns, M., Deiber, M.-P., Hasler, R., Perroud, N., Michel, C. M., & Ros, T. (2022). Electroencephalographic Microstates as Novel Functional Biomarkers for Adult Attention-Deficit/Hyperactivity

Disorder. *Biological Psychiatry. Cognitive Neuroscience and Neuroimaging*, *7*(8), 814–823. https://doi.org/10.1016/j.bpsc.2021.11.006
166. Férat, V., Seeber, M., Michel, C. M., & Ros, T. (2022). Beyond broadband: Towards a spectral decomposition of electroencephalography microstates. *Human Brain Mapping*, *43*(10), 3047–3061. https://doi.org/10.1002/hbm.25834
167. Fillmore, M. T., & Rush, C. R. (2002). Impaired inhibitory control of behavior in chronic cocaine users. *Drug and Alcohol Dependence*, *66*(3), 265–273. https://doi.org/10.1016/s0376-8716(01)00206-x
168. Fineberg, N. A., Menchón, J. M., Hall, N., Dell'Osso, B., Brand, M., Potenza, M. N., Chamberlain, S. R., Cirnigliaro, G., Lochner, C., Billieux, J., Demetrovics, Z., Rumpf, H. J., Müller, A., Castro-Calvo, J., Hollander, E., Burkauskas, J., Grünblatt, E., Walitza, S., Corazza, O., … Zohar, J. (2022). Advances in problematic usage of the internet research – A narrative review by experts from the European network for problematic usage of the internet. *Comprehensive Psychiatry*, *118*, 152346. https://doi.org/10.1016/j.comppsych.2022.152346
169. Fineberg, N., Demetrovics, Z., Stein, D., Ioannidis, K., Potenza, M., Grünblatt, E., Brand, M., Billieux, J., Carmi, L., King, D., Grant, J., Yücel, M., Dell'Osso, B., Rumpf, H., Hall, N., Hollander, E., Goudriaan, A., Menchon, J., Zohar, J., … Chamberlain, S. (2018). Manifesto for a European research network into Problematic Usage of the Internet. *European Neuropsychopharmacology*, *28*(11), 1232–1246. https://doi.org/10.1016/j.euroneuro.2018.08.004
170. Fineberg, N., Grant, D., Demetrovics, Z., Brand, M., Burkauskas, J., Corazza, O., Gansner, M., Gentile, D., Gjoneska, B., Griffiths, M., Király, O., Potenza, M., & Weinstein, A. (2025). *P*roblematic Internet Use: A General Perspective (pp. 179–185). In: Christakis, D.A., Hale, L. (eds) *Handbook of Children and Screens.* Springer, Cham. https://doi.org/10.1007/978-3-031-69362-5_25
171. Firth, J., Torous, J., Stubbs, B., Firth, J. A., Steiner, G. Z., Smith, L., Alvarez-Jimenez, M., Gleeson, J., Vancampfort, D., Armitage, C. J., & Sarris, J. (2019). The "online brain": How the Internet may be changing our cognition. *World Psychiatry*, *18*(2), 119–129. https://doi.org/10.1002/wps.20617
172. Floros, G., & Siomos, K. (2014). Excessive Internet Use and Personality Traits. *Current Behavioral Neuroscience Reports*, *1*(1), 19–26. https://doi.org/10.1007/s40473-014-0006-1
173. Fogarty, J. (2020). ERP Markers of Auditory Go/NoGo Processing. *University of Wollongong Thesis Collection 2017*. https://ro.uow.edu.au/theses1/1010
174. Fogarty, J. S., Barry, R. J., De Blasio, F. M., & Steiner, G. Z. (2018). Manipulating the focus of attention in working memorygo/no-go task:

Inhibition in young adults. *Psychophysiology*, *55*(7), e13065. https://doi.org/10.1111/psyp.13065

175. Fogarty, J. S., Barry, R. J., & Steiner, G. Z. (2019). Sequential processing in the classic oddball task: ERP components, probability, and behavior. *Psychophysiology*, *56*(3), e13300. https://doi.org/10.1111/psyp.13300
176. Fogarty, J. S., Barry, R. J., & Steiner, G. Z. (2020a). Auditory stimulus- and response-locked ERP components and behavior. *Psychophysiology*, *57*(5), e13538. https://doi.org/10.1111/psyp.13538
177. Fogarty, J. S., Barry, R. J., & Steiner, G. Z. (2020b). The First 250 ms of Auditory Processing: No Evidence of Early Processing Negativity in the Go/NoGo Task. *Scientific Reports*, *10*, 4041. https://doi.org/10.1038/s41598-020-61060-9
178. Folstein, J. R., & Van Petten, C. (2008). Influence of cognitive control and mismatch on the N2 component of the ERP: A review. *Psychophysiology*, *45*(1), 152–170. https://doi.org/10.1111/j.1469-8986.2007.00602.x
179. Forkmann, T., Scherer, A., Meessen, J., Michal, M., Schächinger, H., Vögele, C., & Schulz, A. (2016). Making sense of what you sense: Disentangling interoceptive awareness, sensibility and accuracy. *International Journal of Psychophysiology*, *109*, 71–80. https://doi.org/10.1016/j.ijpsycho.2016.09.019
180. Fournier, L., Schimmenti, A., Musetti, A., Boursier, V., Flayelle, M., Cataldo, I., Starcevic, V., & Billieux, J. (2023). Deconstructing the components model of addiction: An illustration through "addictive" use of social media. *Addictive Behaviors*, *143*, 107694. https://doi.org/10.1016/j.addbeh.2023.107694
181. Foxe, J. J., & Snyder, A. C. (2011). The Role of Alpha-Band Brain Oscillations as a Sensory Suppression Mechanism during Selective Attention. *Frontiers in Psychology*, *2*. https://doi.org/10.3389/fpsyg.2011.00154
182. Foygel, R., & Drton, M. (2010). Extended Bayesian Information Criteria for Gaussian Graphical Models. *Advances in Neural Information Processing Systems, 23, 604–612. Retrieved from https://api.semanticscholar.org/CorpusID:6311495*
183. Gaggero, G., Dellantonio, S., Pastore, L., Sng, K. H. L., & Esposito, G. (2022). Shared and unique interoceptive deficits in high alexithymia and neuroticism. *PLoS ONE*, *17*(8), e0273922. https://doi.org/10.1371/journal.pone.0273922
184. Gajewski, P. D., & Falkenstein, M. (2013). Effects of task complexity on ERP components in Go/Nogo tasks. *International Journal of Psychophysiology,* *87*(3), 273–278. https://doi.org/10.1016/j.ijpsycho.2012.08.007
185. Gao, Q., Jia, G., Zhao, J., & Zhang, D. (2019). Inhibitory Control in Excessive Social Networking Users: Evidence From an Event-Related

Potential-Based Go-Nogo Task. *Frontiers in Psychology*, *10*, 1810. https://doi.org/10.3389/fpsyg.2019.01810
186. García-Batista, Z. E., Guerra-Peña, K., Cano-Vindel, A., Herrera-Martínez, S. X., & Medrano, L. A. (2018). Validity and reliability of the Beck Depression Inventory (BDI-II) in general and hospital population of Dominican Republic. *PLoS ONE*, *13*(6), e0199750. https://doi.org/10.1371/journal.pone.0199750
187. Garfinkel, S. N., Seth, A. K., Barrett, A. B., Suzuki, K., & Critchley, H. D. (2015). Knowing your own heart: Distinguishing interoceptive accuracy from interoceptive awareness. *Biological Psychology*, *104*, 65–74. https://doi.org/10.1016/j.biopsycho.2014.11.004
188. Ge, L., Ge, X., & Xu, Y. (2011). P300 change and cognitive behavioral therapy in subjects with Internet addiction disorder: A 3-month follow-up study. *Neural Regeneration Research, 6(26), 2037-2041*. https://doi.org/10.3969/j.issn.1673-5374.2011.26.007
189. Gega, L., Jankovic, D., Saramago, P., Marshall, D., Dawson, S., Brabyn, S., Nikolaidis, G. F., Melton, H., Churchill, R., & Bojke, L. (2022). Digital interventions in mental health: Evidence syntheses and economic modelling. *Health Technology Assessment (Winchester, England)*, *26*(1), 1–182. https://doi.org/10.3310/RCTI6942
190. Gelles-Watnick, R. , & Vogels E.A. (2023, April 24). Teens and social media: Key findings from Pew Research Center surveys. *Pew Research Center*. https://www.pewresearch.org/short-reads/2023/04/24/teens-and-social-media-key-findings-from-pew-research-center-surveys/
191. Gentile, D. A., Choo, H., Liau, A., Sim, T., Li, D., Fung, D., & Khoo, A. (2011). Pathological video game use among youths: A two-year longitudinal study. *Pediatrics*, *127*(2), e319-329. https://doi.org/10.1542/peds.2010-1353
192. Gervasi, A. M., La Marca, L., Costanzo, A., Pace, U., Guglielmucci, F., & Schimmenti, A. (2017). Personality and Internet Gaming Disorder: A Systematic Review of Recent Literature. *Current Addiction Reports*, *4*(3), 293–307. https://doi.org/10.1007/s40429-017-0159-6
193. Gindrat, A.-D., Chytiris, M., Balerna, M., Rouiller, E. M., & Ghosh, A. (2015). Use-dependent cortical processing from fingertips in touchscreen phone users. *Current Biology*, *25*(1), 109–116. https://doi.org/10.1016/j.cub.2014.11.026
194. *Global: Internet users 2014-2029*. (n.d.). Statista. Retrieved March 13, 2024, from https://www.statista.com/forecasts/1146844/internet-users-in-the-world
195. Goldstone, A., Javitz, H. S., Claudatos, S. A., Buysse, D. J., Hasler, B. P., de Zambotti, M., Clark, D. B., Franzen, P. L., Prouty, D. E., Colrain, I. M., & Baker, F. C. (2020). Sleep Disturbance Predicts Depression Symptoms in Early Adolescence: Initial Findings From the Adolescent Brain Cognitive Development Study. *Journal of Adolescent Health*, *66*(5), 567–574. https://doi.org/10.1016/j.jadohealth.2019.12.005

196. Grabauskaitė, A., Baranauskas, M., & Griškova-Bulanova, I. (2017). Interoception and gender: What aspects should we pay attention to? *Consciousness and Cognition*, *48*, 129–137. https://doi.org/10.1016/j.concog.2016.11.002
197. Grandy, T. H., Werkle-Bergner, M., Chicherio, C., Schmiedek, F., Lövdén, M., & Lindenberger, U. (2013). Peak individual alpha frequency qualifies as a stable neurophysiological trait marker in healthy younger and older adults. *Psychophysiology*, *50*(6), 570–582. https://doi.org/10.1111/psyp.12043
198. Green, C. S., & Bavelier, D. (2003). Action video game modifies visual selective attention. *Nature*, *423*(6939), 534–537. https://doi.org/10.1038/nature01647
199. Green, R., Meredith, L. R., Mewton, L., & Squeglia, L. M. (2023). Adolescent Neurodevelopment Within the Context of Impulsivity and Substance Use. *Current Addiction Reports*, *10*(2), 166–177. https://doi.org/10.1007/s40429-023-00485-4
200. Griffiths, M. (2005). A 'components' model of addiction within a biopsychosocial framework. *Journal of Substance Use*, *10*(4), 191–197. https://doi.org/10.1080/14659890500114359
201. Griffiths, M. (2019). The evolution of the "components model of addiction" and the need for a confirmatory approach in conceptualizing behavioral addictions. *Dusunen Adam*, *32*, 179–184. https://doi.org/10.14744/DAJPNS.2019.00027
202. Griffiths, M. D. (2013). Is "Loss of Control" Always a Consequence of Addiction? *Frontiers in Psychiatry*, *4*, 36. https://doi.org/10.3389/fpsyt.2013.00036
203. Griffiths, M. D., Kuss, D. J., & King, D. L. (2012). Video game addiction: Past, present and future. *Current Psychiatry Reviews*, *8*(4), 308–318. https://doi.org/10.2174/157340012803520414
204. Griffiths, M. D., & Szabo, A. (2014). Is excessive online usage a function of medium or activity? An empirical pilot study. *Journal of Behavioral Addictions*, *3*(1), 74–77. https://doi.org/10.1556/JBA.2.2013.016
205. Grimshaw, G. M., Foster, J. J., & Corballis, P. M. (2014). Frontal and parietal EEG asymmetries interact to predict attentional bias to threat. *Brain and Cognition*, *90*, 76–86. https://doi.org/10.1016/j.bandc.2014.06.008
206. Griskova-Bulanova, I., Griksiene, R., Voicikas, A., & Ruksenas, O. (2016). Go and NoGo: Modulation of electrophysiological correlates by female sex steroid hormones. *Psychopharmacology*, *233*(13), 2607–2615. https://doi.org/10.1007/s00213-016-4311-0
207. Gullo, M. J., Wood, A. P., & Saunders, J. B. (2022). Criteria for the establishment of a new behavioural addiction: Commentary to the debate: "Behavioral addictions in the ICD-11. *Journal of Behavioral Addictions*, *11*(2), 191–198. https://doi.org/10.1556/2006.2022.00031

208. Hampel, H., Mesulam, M.-M., Cuello, A. C., Farlow, M. R., Giacobini, E., Grossberg, G. T., Khachaturian, A. S., Vergallo, A., Cavedo, E., Snyder, P. J., & Khachaturian, Z. S. (2018). The cholinergic system in the pathophysiology and treatment of Alzheimer's disease. *Brain*, *141*(7), 1917–1933. https://doi.org/10.1093/brain/awy132
209. Hartmann, M., Pelzl, M. A., Kann, P. H., Koehler, U., Betz, M., Hildebrandt, O., & Cassel, W. (2019). The effects of prolonged single night session of videogaming on sleep and declarative memory. *PloS One*, *14*(11), e0224893. https://doi.org/10.1371/journal.pone.0224893
210. Helfrich, R. F., & Knight, R. T. (2019). Chapter 36 - Cognitive neurophysiology: Event-related potentials. In K. H. Levin & P. Chauvel (Eds.), *Handbook of Clinical Neurology* (Vol. 160, pp. 543–558). Elsevier. https://doi.org/10.1016/B978-0-444-64032-1.00036-9
211. Heller, W., Nitschke, J. B., Etienne, M. A., & Miller, G. A. (1997). Patterns of regional brain activity differentiate types of anxiety. *Journal of Abnormal Psychology*, *106*(3), 376–385. https://doi.org/10.1037//0021-843x.106.3.376
212. Herman, A. M. (2023). Interoception Within the Context of Impulsivity and Addiction. *Current Addiction Reports*, *10*(2), 97–106. https://doi.org/10.1007/s40429-023-00482-7
213. Herman, A. M., Critchley, H. D., & Duka, T. (2018). The role of emotions and physiological arousal in modulating impulsive behaviour. *Biological Psychology*, *133*, 30–43. https://doi.org/10.1016/j.biopsycho.2018.01.014
214. Ho, R. C., Zhang, M. W. B., Tsang, T. Y., Toh, A. H., Pan, F., Lu, Y., Cheng, C., Yip, P. S., Lam, L. T., Lai, C.-M., Watanabe, H., & Mak, K.-K. (2014). The association between internet addiction and psychiatric co-morbidity: A meta-analysis. *BMC Psychiatry*, *14*, 183. https://doi.org/10.1186/1471-244X-14-183
215. Hofmann, W., Schmeichel, B. J., & Baddeley, A. D. (2012). Executive functions and self-regulation. *Trends in Cognitive Sciences*, *16*(3), 174–180. https://doi.org/10.1016/j.tics.2012.01.006
216. Hong, D. H., Lee, J.-Y., Oh, D.-Y., Park, S.-Y., Yoo, S. Y., & Choi, J.-S. (2022). Differential resting-state neurophysiological activity associated with game usage patterns and genres in Internet gaming disorder. *Addiction Biology*, *27*(5). https://doi.org/10.1111/adb.13213
217. Hoptman, M. J., Girgis, R. R., & Javitt, D. C. (2024). Biomarkers for Cognitive Control, Response Inhibition, Aggressivity, Impulsivity, and Violence. In D. C. Javitt & J. C. McPartland (Eds.), *Neurophysiologic Biomarkers in Neuropsychiatric Disorders: Etiologic and Treatment Considerations* (pp. 725–756). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-69491-2_24
218. Houston, R. J., & Schlienz, N. J. (2018). Event-Related Potentials as Biomarkers of Behavior Change Mechanisms in Substance Use Disorder

Treatment. *Biological Psychiatry. Cognitive Neuroscience and Neuroimaging*, *3*(1), 30–40. https://doi.org/10.1016/j.bpsc.2017.09.006

219. Hoyniak, C. P., & Petersen, I. T. (2019). A meta-analytic evaluation of the N2 component as an endophenotype of response inhibition and externalizing psychopathology in childhood. *Neuroscience and Biobehavioral Reviews*, *103*, 200–215. https://doi.org/10.1016/j.neubiorev.2019.06.011
220. Huang, Q., Chen, X., Huang, S., Shao, T., Liao, Z., Lin, S., Li, Y., Qi, J., Cai, Y., & Shen, H. (2021). Substance and Internet use during the COVID-19 pandemic in China. *Translational Psychiatry*, *11*(1), 491. https://doi.org/10.1038/s41398-021-01614-1
221. Hung, Y., Gaillard, S. L., Yarmak, P., & Arsalidou, M. (2018). Dissociations of cognitive inhibition, response inhibition, and emotional interference: Voxelwise ALE meta-analyses of fMRI studies. *Human Brain Mapping*, *39*(10), 4065–4082. https://doi.org/10.1002/hbm.24232
222. Huot-Lavoie, M., Gabriel-Courval, M., Béchard, L., Corbeil, O., Brodeur, S., Massé, C., Fournier, É., Essiambre, A. M., Anderson, E., Cayouette, A., Giroux, I., Khazaal, Y., Demers, M.-F., & Roy, M.-A. (2023). Gaming Disorder and Psychotic Disorders: A Scoping Review. *Psychopathology*, *56*(4), 315–323. https://doi.org/10.1159/000527143
223. Hussain, Z., & Griffiths, M. D. (2009). The attitudes, feelings, and experiences of online gamers: A qualitative analysis. *Cyberpsychology & Behavior: The Impact of the Internet, Multimedia and Virtual Reality on Behavior and Society*, *12*(6), 747–753. https://doi.org/10.1089/cpb.2009.0059
224. Huster, R. J., Enriquez-Geppert, S., Lavallee, C. F., Falkenstein, M., & Herrmann, C. S. (2013). Electroencephalography of response inhibition tasks: Functional networks and cognitive contributions. *International Journal of Psychophysiology: Official Journal of the International Organization of Psychophysiology*, *87*(3), 217–233. https://doi.org/10.1016/j.ijpsycho.2012.08.001
225. *IBM SPSS,v29.0.2.0 Armonk, NY*. (n.d.). [Computer software].
226. İnce, R., Adanır, S. S., & Sevmez, F. (2021). The inventor of electroencephalography (EEG): Hans Berger (1873–1941). *Child's Nervous System*, *37*(9), 2723–2724. https://doi.org/10.1007/s00381-020-04564-z
227. Insel, T., Cuthbert, B., Garvey, M., Heinssen, R., Pine, D. S., Quinn, K., Sanislow, C., & Wang, P. (2010). Research domain criteria (RDoC): Toward a new classification framework for research on mental disorders. *The American Journal of Psychiatry*, *167*(7), 748–751. https://doi.org/10.1176/appi.ajp.2010.09091379
228. *Internet Live Stats: Internet Users*. (n.d.). Retrieved March 24, 2025, from https://www.internetlivestats.com/internet-users/
229. Ioannidis, K., Chamberlain, S. R., Treder, M. S., Kiraly, F., Leppink, E. W., Redden, S. A., Stein, D. J., Lochner, C., & Grant, J. E. (2016).

Problematic internet use (PIU): Associations with the impulsive-compulsive spectrum. An application of machine learning in psychiatry. *Journal of Psychiatric Research*, *83*, 94–102. https://doi.org/10.1016/j.jpsychires.2016.08.010
230. Ioannidis, K., Hook, R., Goudriaan, A. E., Vlies, S., Fineberg, N. A., Grant, J. E., & Chamberlain, S. R. (2019). Cognitive deficits in problematic internet use: Meta-analysis of 40 studies. *The British Journal of Psychiatry*, *215*(5), 639–646. https://doi.org/10.1192/bjp.2019.3
231. Ioannidis, K., Treder, M. S., Chamberlain, S. R., Kiraly, F., Redden, S. A., Stein, D. J., Lochner, C., & Grant, J. E. (2018). Problematic internet use as an age-related multifaceted problem: Evidence from a two-site survey. *Addictive Behaviors*, *81*, 157–166. https://doi.org/10.1016/j.addbeh.2018.02.017
232. Jabès, A., Klencklen, G., Ruggeri, P., Michel, C. M., Banta Lavenex, P., & Lavenex, P. (2021). Resting-State EEG Microstates Parallel Age-Related Differences in Allocentric Spatial Working Memory Performance. *Brain Topography*, *34*(4), 442–460. https://doi.org/10.1007/s10548-021-00835-3
233. Jackson-Koku, G. (2016). Beck Depression Inventory. *Occupational Medicine*, *66*(2), 174–175. https://doi.org/10.1093/occmed/kqv087
234. *JASP Team*. (2024). [Computer software]. https://jasp-stats.org/
235. Jentsch, J. D., & Pennington, Z. T. (2014). Reward, Interrupted: Inhibitory Control and Its Relevance to Addictions. *Neuropharmacology*, *76*, 479–486. https://doi.org/10.1016/j.neuropharm.2013.05.022
236. Jeong, B. S., Han, D. H., Kim, S. M., Lee, S. W., & Renshaw, P. F. (2016). White matter connectivity and Internet gaming disorder. *Addiction Biology*, *21*(3), 732–742. https://doi.org/10.1111/adb.12246
237. Jeronimus, B. F., Kotov, R., Riese, H., & Ormel, J. (2016). Neuroticism's prospective association with mental disorders halves after adjustment for baseline symptoms and psychiatric history, but the adjusted association hardly decays with time: A meta-analysis on 59 longitudinal/prospective studies with 443 313 participants. *Psychological Medicine*, *46*(14), 2883–2906. https://doi.org/10.1017/S0033291716001653
238. Jodo, E., & Kayama, Y. (1992). Relation of a negative ERP component to response inhibition in a Go/No-go task. *Electroencephalography and Clinical Neurophysiology*, *82*(6), 477–482. https://doi.org/10.1016/0013-4694(92)90054-l
239. Joos, K., Gilles, A., Van de Heyning, P., De Ridder, D., & Vanneste, S. (2014). From sensation to percept: The neural signature of auditory event-related potentials. *Neuroscience & Biobehavioral Reviews*, *42*, 148–156. https://doi.org/10.1016/j.neubiorev.2014.02.009
240. Jupp, B., Caprioli, D., Saigal, N., Reverte, I., Shrestha, S., Cumming, P., Everitt, B. J., Robbins, T. W., & Dalley, J. W. (2013). Dopaminergic and GABA-ergic markers of impulsivity in rats: Evidence for anatomical localisation in ventral striatum and prefrontal cortex. *The European*

Journal of Neuroscience, *37*(9), 1519–1528. https://doi.org/10.1111/ejn.12146
241. Jupp, B., & Dalley, J. W. (2014). Convergent pharmacological mechanisms in impulsivity and addiction: Insights from rodent models. *British Journal of Pharmacology*, *171*(20), 4729–4766. https://doi.org/10.1111/bph.12787
242. Kaess, M., Klar, J., Kindler, J., Parzer, P., Brunner, R., Carli, V., Sarchiapone, M., Hoven, C. W., Apter, A., Balazs, J., Barzilay, S., Bobes, J., Cozman, D., Gomboc, V., Haring, C., Kahn, J.-P., Keeley, H., Meszaros, G., Musa, G. J., … Wasserman, D. (2021). Excessive and pathological Internet use – Risk-behavior or psychopathology? *Addictive Behaviors*, *123*, 107045. https://doi.org/10.1016/j.addbeh.2021.107045
243. Kamarajan, C., Porjesz, B., Jones, K. A., Choi, K., Chorlian, D. B., Padmanabhapillai, A., Rangaswamy, M., Stimus, A. T., & Begleiter, H. (2005). Alcoholism is a disinhibitory disorder: Neurophysiological evidence from a Go/No-Go task. *Biological Psychology*, *69*(3), 353–373. https://doi.org/10.1016/j.biopsycho.2004.08.004
244. Kamijo, K., Nishihira, Y., Hatta, A., Kaneda, T., Wasaka, T., Kida, T., & Kuroiwa, K. (2004). Differential influences of exercise intensity on information processing in the central nervous system. *European Journal of Applied Physiology*, *92*(3), 305–311. https://doi.org/10.1007/s00421-004-1097-2
245. Kang, W., & Malvaso, A. (2024). Frequent internet use is associated with better episodic memory performance. *Scientific Reports*, *14*, 24914. https://doi.org/10.1038/s41598-024-75788-1
246. Kaptsis, D., King, D. L., Delfabbro, P. H., & Gradisar, M. (2016). Withdrawal symptoms in internet gaming disorder: A systematic review. *Clinical Psychology Review*, *43*, 58–66. https://doi.org/10.1016/j.cpr.2015.11.006
247. Kapus, K., Nyulas, R., Nemeskeri, Z., Zadori, I., Muity, G., Kiss, J., Feher, A., Fejes, E., Tibold, A., & Feher, G. (2021). Prevalence and Risk Factors of Internet Addiction among Hungarian High School Students. *International Journal of Environmental Research and Public Health*, *18*(13), 6989. https://doi.org/10.3390/ijerph18136989
248. Karamacoska, D., Barry, R. J., & Steiner, G. Z. (2018). Electrophysiological underpinnings of response variability in the Go/NoGo task. *International Journal of Psychophysiology: Official Journal of the International Organization of Psychophysiology*, *134*, 159–167. https://doi.org/10.1016/j.ijpsycho.2018.09.008
249. Karamacoska, D., Barry, R. J., Steiner, G. Z., Coleman, E. P., & Wilson, E. J. (2018). Intrinsic EEG and task-related changes in EEG affect Go/NoGo task performance. *International Journal of Psychophysiology: Official Journal of the International Organization of Psychophysiology*, *125*, 17–28. https://doi.org/10.1016/j.ijpsycho.2018.01.015

250. Kardefelt-Winther, D. (2017). Conceptualizing Internet use disorders: Addiction or coping process? *Psychiatry and Clinical Neurosciences*, *71*(7), 459–466. https://doi.org/10.1111/pcn.12413
251. Kashif, S., Pandey, S., & Warriach, Z. I. (2021). Neurophysiological Markers of Internet Gaming Disorder: A Literature Review of Electroencephalography Studies. *Cureus*, *13*(9), e17866. https://doi.org/10.7759/cureus.17866
252. Kayiş, A. R., Satici, S. A., Yilmaz, M., Şimşek, D., Ceyhan, E., & Bakioğlu, F. (2016). Big five-personality trait and internet addiction: A meta-analytic review. *Computers in Human Behavior*, *63*, 35–40. https://doi.org/10.1016/j.chb.2016.05.012
253. Kayser, A. (2019). Dopamine and Gambling Disorder: Prospects for Personalized Treatment. *Current Addiction Reports*, *6*(2), 65–74. https://doi.org/10.1007/s40429-019-00240-8
254. Kelley, N. J., Hortensius, R., Schutter, D. J. L. G., & Harmon-Jones, E. (2017). The relationship of approach/avoidance motivation and asymmetric frontal cortical activity: A review of studies manipulating frontal asymmetry. *International Journal of Psychophysiology: Official Journal of the International Organization of Psychophysiology*, *119*, 19–30. https://doi.org/10.1016/j.ijpsycho.2017.03.001
255. Kenemans, J. L., Bekker, E. M., Lijffijt, M., Overtoom, C. C. E., Jonkman, L. M., & Verbaten, M. N. (2005). Attention deficit and impulsivity: Selecting, shifting, and stopping. *International Journal of Psychophysiology: Official Journal of the International Organization of Psychophysiology*, *58*(1), 59–70. https://doi.org/10.1016/j.ijpsycho.2005.03.009
256. Keune, P. M., Schönenberg, M., Wyckoff, S., Mayer, K., Riemann, S., Hautzinger, M., & Strehl, U. (2011). Frontal alpha-asymmetry in adults with attention deficit hyperactivity disorder: Replication and specification. *Biological Psychology*, *87*(2), 306–310. https://doi.org/10.1016/j.biopsycho.2011.02.023
257. Keune, P. M., Wiedemann, E., Schneidt, A., & Schönenberg, M. (2015). Frontal brain asymmetry in adult attention-deficit/hyperactivity disorder (ADHD): Extending the motivational dysfunction hypothesis. *Clinical Neurophysiology*, *126*(4), 711–720. https://doi.org/10.1016/j.clinph.2014.07.008
258. Khalaf, A. M., Alubied, A. A., Khalaf, A. M., & Rifaey, A. A. (2023). The Impact of Social Media on the Mental Health of Adolescents and Young Adults: A Systematic Review. *Cureus*, *15*(8), e42990. https://doi.org/10.7759/cureus.42990
259. Khalsa, S. S., Adolphs, R., Cameron, O. G., Critchley, H. D., Davenport, P. W., Feinstein, J. S., Feusner, J. D., Garfinkel, S. N., Lane, R. D., Mehling, W. E., Meuret, A. E., Nemeroff, C. B., Oppenheimer, S., Petzschner, F. H., Pollatos, O., Rhudy, J. L., Schramm, L. P., Simmons, W. K., Stein, M. B., … Zucker, N. (2018). Interoception and Mental

Health: A Roadmap. *Biological Psychiatry: Cognitive Neuroscience and Neuroimaging*, *3*(6), 501–513. https://doi.org/10.1016/j.bpsc.2017.12.004
260. Khan, A., Uddin, R., & Lee, E.-Y. (2021). Excessive recreational Internet use was associated with poor mental health in adolescents. *Acta Paediatrica*, *110*(2), 571–573. https://doi.org/10.1111/apa.15528
261. Khanna, A., Pascual-Leone, A., Michel, C. M., & Farzan, F. (2015). Microstates in resting-state EEG: Current status and future directions. *Neuroscience and Biobehavioral Reviews*, *49*, 105–113. https://doi.org/10.1016/j.neubiorev.2014.12.010
262. Kim, M. G., & Kim, J. (2010). Cross-validation of reliability, convergent and discriminant validity for the problematic online game use scale. *Computers in Human Behavior*, *26*(3), 389–398. https://doi.org/10.1016/j.chb.2009.11.010
263. Kim, M., Lee, T. H., Choi, J.-S., Kwak, Y. B., Hwang, W. J., Kim, T., Lee, J. Y., Lim, J.-A., Park, M., Kim, Y. J., Kim, S. N., Kim, D. J., & Kwon, J. S. (2017). Neurophysiological correlates of altered response inhibition in internet gaming disorder and obsessive-compulsive disorder: Perspectives from impulsivity and compulsivity. *Scientific Reports*, *7*(1), https://doi.org/10.1038/srep41742
264. Király, O., Griffiths, M. D., Urbán, R., Farkas, J., Kökönyei, G., Elekes, Z., Tamás, D., & Demetrovics, Z. (2014). Problematic Internet Use and Problematic Online Gaming Are Not the Same: Findings from a Large Nationally Representative Adolescent Sample. *Cyberpsychology, Behavior and Social Networking*, *17*(12), 749–754. https://doi.org/10.1089/cyber.2014.0475
265. Király, O., Nagygyörgy, K., Koronczai, B., Griffiths, M. D., & Demetrovics, Z. (2015). Assessment of problematic Internet use and online video gaming. In *Mental health in the digital age: Grave dangers, great promise* (pp. 46–68). Oxford University Press. https://doi.org/10.1093/med/9780199380183.003.0003
266. Klimesch, W., Sauseng, P., & Hanslmayr, S. (2007). EEG alpha oscillations: The inhibition–timing hypothesis. *Brain Research Reviews*, *53*(1), 63–88. https://doi.org/10.1016/j.brainresrev.2006.06.003
267. Ko, C. H., Yen, J. Y., Yen, C. F., Chen, C. S., & Chen, C. C. (2012). The association between Internet addiction and psychiatric disorder: A review of the literature. *European Psychiatry,* *27*(1), 1–8. https://doi.org/10.1016/j.eurpsy.2010.04.011
268. Ko, C.-H., Liu, G.-C., Hsiao, S., Yen, J.-Y., Yang, M.-J., Lin, W.-C., Yen, C.-F., & Chen, C.-S. (2009). Brain activities associated with gaming urge of online gaming addiction. *Journal of Psychiatric Research*, *43*(7), 739–747. https://doi.org/10.1016/j.jpsychires.2008.09.012
269. Koenig, T., Diezig, S., Kalburgi, S. N., Antonova, E., Artoni, F., Brechet, L., Britz, J., Croce, P., Custo, A., Damborská, A., Deolindo, C., Heinrichs, M., Kleinert, T., Liang, Z., Murphy, M. M., Nash, K., Nehaniv, C.,

Schiller, B., Smailovic, U., … Michel, C. M. (2024). EEG-Meta-Microstates: Towards a More Objective Use of Resting-State EEG Microstate Findings Across Studies. *Brain Topography*, *37*(2), 218–231. https://doi.org/10.1007/s10548-023-00993-6

270. Korn, U., Krylova, M., Heck, K. L., Häußinger, F. B., Stark, R. S., Alizadeh, S., Jamalabadi, H., Walter, M., Galuske, R. A. W., & Munk, M. H. J. (2021). EEG-Microstates Reflect Auditory Distraction After Attentive Audiovisual Perception Recruitment of Cognitive Control Networks. *Frontiers in Systems Neuroscience*, *15*, 751226. https://doi.org/10.3389/fnsys.2021.751226
271. Koronczai, B., Kökönyei, G., Griffiths, M. D., & Demetrovics, Z. (2019). The Relationship Between Personality Traits, Psychopathological Symptoms, and Problematic Internet Use: A Complex Mediation Model. *Journal of Medical Internet Research*, *21*(4), e11837. https://doi.org/10.2196/11837
272. Koronczai, B., Urbán, R., Kökönyei, G., Paksi, B., Papp, K., Kun, B., Arnold, P., Kállai, J., & Demetrovics, Z. (2011). Confirmation of the Three-Factor Model of Problematic Internet Use on Off-Line Adolescent and Adult Samples. *Cyberpsychology, Behavior and Social Networking*, *14*(11), 657–664. https://doi.org/10.1089/cyber.2010.0345
273. Kotagal, S. (2015). Sleep in Neurodevelopmental and Neurodegenerative Disorders. *Seminars in Pediatric Neurology*, *22*(2), 126–129. https://doi.org/10.1016/j.spen.2015.03.003
274. Kozak, K., Lucatch, A. M., Lowe, D. J. E., Balodis, I. M., MacKillop, J., & George, T. P. (2019). The neurobiology of impulsivity and substance use disorders: Implications for treatment. *Annals of the New York Academy of Sciences*, *1451*(1), 71–91. https://doi.org/10.1111/nyas.13977
275. Kuhn, B. N., Kalivas, P. W., & Bobadilla, A.-C. (2019). Understanding Addiction Using Animal Models. *Frontiers in Behavioral Neuroscience*, *13*, 262. https://doi.org/10.3389/fnbeh.2019.00262
276. Kühn, S., Gleich, T., Lorenz, R. C., Lindenberger, U., & Gallinat, J. (2014). Playing Super Mario induces structural brain plasticity: Gray matter changes resulting from training with a commercial video game. *Molecular Psychiatry*, *19*(2), 265–271. https://doi.org/10.1038/mp.2013.120
277. Kuperczko, D., Kenyeres, P., Darnai, G., Kovacs, N., & Janszky, J. (2022). Sudden gamer death: Non-violent death cases linked to playing video games. *BMC Psychiatry*, *22*, 824. https://doi.org/10.1186/s12888-022-04373-5
278. Kuss, D. J., & Griffiths, M. D. (2012). Internet and Gaming Addiction: A Systematic Literature Review of Neuroimaging Studies. *Brain Sciences*, *2*(3), 347–374. https://doi.org/10.3390/brainsci2030347
279. Kuss, D. J., & Lopez-Fernandez, O. (2016). Internet addiction and problematic Internet use: A systematic review of clinical research. *World*

Journal of Psychiatry, *6*(1), 143–176. https://doi.org/10.5498/wjp.v6.i1.143

280. Kuss, D. J., Pontes, H. M., & Griffiths, M. D. (2018). Neurobiological Correlates in Internet Gaming Disorder: A Systematic Literature Review. *Frontiers in Psychiatry*, *9*, 166. https://doi.org/10.3389/fpsyt.2018.00166
281. Kuss, D. J., van Rooij, A. J., Shorter, G. W., Griffiths, M. D., & van de Mheen, D. (2013). Internet addiction in adolescents: Prevalence and risk factors. *Computers in Human Behavior*, *29*(5), 1987–1996. https://doi.org/10.1016/j.chb.2013.04.002
282. Kutas, M., McCarthy, G., & Donchin, E. (1977). Augmenting mental chronometry: The P300 as a measure of stimulus evaluation time. *Science, 197*(4305), 792–795. https://doi.org/10.1126/science.887923
283. Laconi, S., Rodgers, R. F., & Chabrol, H. (2014). The measurement of Internet addiction: A critical review of existing scales and their psychometric properties. *Computers in Human Behavior*, *41*, 190–202. https://doi.org/10.1016/j.chb.2014.09.026
284. Laconi, S., Urbán, R., Kaliszewska-Czeremska, K., Kuss, D. J., Gnisci, A., Sergi, I., Barke, A., Jeromin, F., Groth, J., Gamez-Guadix, M., Ozcan, N. K., Siomos, K., Floros, G. D., Griffiths, M. D., Demetrovics, Z., & Király, O. (2019). Psychometric Evaluation of the Nine-Item Problematic Internet Use Questionnaire (PIUQ-9) in Nine European Samples of Internet Users. *Frontiers in Psychiatry*, *10*, 136. https://doi.org/10.3389/fpsyt.2019.00136
285. Landa, L., Krpoun, Z., Kolarova, M., & Kasparek, T. (2014). Event-related Potentials and Their Applications. *Activitas Nervosa Superior*, *56*(1), 17–23. https://doi.org/10.1007/BF03379603
286. Larson, M. J., Clayson, P. E., & Clawson, A. (2014). Making sense of all the conflict: A theoretical review and critique of conflict-related ERPs. *International Journal of Psychophysiology*, *93*(3), 283–297. https://doi.org/10.1016/j.ijpsycho.2014.06.007
287. Lassi, M., Fabbiani, C., Mazzeo, S., Burali, R., Vergani, A. A., Giacomucci, G., Moschini, V., Morinelli, C., Emiliani, F., Scarpino, M., Bagnoli, S., Ingannato, A., Nacmias, B., Padiglioni, S., Micera, S., Sorbi, S., Grippo, A., Bessi, V., & Mazzoni, A. (2023). Degradation of EEG microstates patterns in subjective cognitive decline and mild cognitive impairment: Early biomarkers along the Alzheimer's Disease continuum? *NeuroImage: Clinical*, *38*, 103407. https://doi.org/10.1016/j.nicl.2023.103407
288. Lee, D., Namkoong, K., Lee, J., & Jung, Y.-C. (2018). Abnormal gray matter volume and impulsivity in young adults with Internet gaming disorder. *Addiction Biology*, *23*(5), 1160–1167. https://doi.org/10.1111/adb.12552
289. Lee, J., Hwang, J. Y., Park, S. M., Jung, H. Y., Choi, S.-W., Kim, D. J., Lee, J.-Y., & Choi, J.-S. (2014). Differential resting-state EEG patterns associated with comorbid depression in Internet addiction. *Progress in*

Neuro-Psychopharmacology and Biological Psychiatry, *50*, 21–26. https://doi.org/10.1016/j.pnpbp.2013.11.016
290. Lee, J.-Y., & Kang, H.-B. (2014). EEG and ERP based Degree of Internet Game Addiction Analysis. *Journal of Korea Multimedia Society*, *17*, 1325–1334. https://doi.org/10.9717/kmms.2014.17.11.1325
291. Lee, S.-Y., Lee, H. K., & Choo, H. (2017). Typology of Internet gaming disorder and its clinical implications. *Psychiatry and Clinical Neurosciences*, *71*(7), 479–491. https://doi.org/10.1111/pcn.12457
292. Lehmann, D., Ozaki, H., & Pal, I. (1987). EEG alpha map series: Brain micro-states by space-oriented adaptive segmentation. *Electroencephalography and Clinical Neurophysiology*, *67*(3), 271–288. https://doi.org/10.1016/0013-4694(87)90025-3
293. Lejoyeux, M., Mc Loughlin, M., & Adès, J. (2000). Epidemiology of behavioral dependence: Literature review and results of original studies. *European Psychiatry*, *15*(2), 129–134. https://doi.org/10.1016/s0924-9338(00)00201-7
294. Lemenager, T., Neissner, M., Koopmann, A., Reinhard, I., Georgiadou, E., Müller, A., Kiefer, F., & Hillemacher, T. (2020). COVID-19 Lockdown Restrictions and Online Media Consumption in Germany. *International Journal of Environmental Research and Public Health*, *18*(1), 14. https://doi.org/10.3390/ijerph18010014
295. Li, H., Turel, O., & He, Q. (2023). Neural Basis of Altered Impulsivity in Individuals With Internet Gaming Disorder: State-of-the-art Review. *Current Addiction Reports*, *10*(2), 107–121. https://doi.org/10.1007/s40429-023-00481-8
296. Li, H., Yue, J., Wang, Y., Zou, F., Zhang, M., & Wu, X. (2021). Negative Effects of Mobile Phone Addiction Tendency on Spontaneous Brain Microstates: Evidence From Resting-State EEG. *Frontiers in Human Neuroscience*, *15*, 636504. https://doi.org/10.3389/fnhum.2021.636504
297. Li, Q., Wang, Y., Yang, Z., Dai, W., Zheng, Y., Sun, Y., & Liu, X. (2020). Dysfunctional cognitive control and reward processing in adolescents with Internet gaming disorder. *Psychophysiology*, *57*(2), e13469. https://doi.org/10.1111/psyp.13469
298. Li, X., Dong, F., Zhang, Y., Wang, J., Wang, Z., Sun, Y., Zhang, M., Xue, T., Ren, Y., Lv, X., Yuan, K., & Yu, D. (2022). Altered resting-state electroencephalography microstate characteristics in young male smokers. *Frontiers in Psychiatry*, *13*, 1008007. https://doi.org/10.3389/fpsyt.2022.1008007
299. Li, Y.-Y., Sun, Y., Meng, S.-Q., Bao, Y.-P., Cheng, J.-L., Chang, X.-W., Ran, M.-S., Sun, Y.-K., Kosten, T., Strang, J., Lu, L., & Shi, J. (2021). Internet Addiction Increases in the General Population During COVID-19: Evidence From China. *The American Journal on Addictions*, *30*(4), 389–397. https://doi.org/10.1111/ajad.13156
300. Lijffijt, M., Lane, S. D., Meier, S. L., Boutros, N. N., Burroughs, S., Steinberg, J. L., Moeller, F. G., & Swann, A. C. (2009). P50, N100, and

P200 sensory gating: Relationships with behavioral inhibition, attention, and working memory. *Psychophysiology*, *46*(5), 1059–1068. https://doi.org/10.1111/j.1469-8986.2009.00845.x

301. Lissak, G. (2018). Adverse physiological and psychological effects of screen time on children and adolescents: Literature review and case study. *Environmental Research*, *164*, 149–157. https://doi.org/10.1016/j.envres.2018.01.015
302. Littel, M., van den Berg, I., Luijten, M., van Rooij, A. J., Keemink, L., & Franken, I. H. A. (2012). Error processing and response inhibition in excessive computer game players: An event-related potential study. *Addiction Biology*, *17*(5), 934–947. https://doi.org/10.1111/j.1369-1600.2012.00467.x
303. Liu, L., Yao, Y.-W., Fang, X.-Y., Xu, L.-X., Hu, M.-J., Zhang, J.-T., & Potenza, M. N. (2024). Compulsivity-related behavioral features of problematic usage of the internet: A scoping review of paradigms, progress, and perspectives. *Journal of Behavioral Addictions*, *13*(2), 429–449. https://doi.org/10.1556/2006.2024.00023
304. Liu, S., Wu, P., Han, X., Wang, M., Kan, Y., Qin, K., & Lan, J. (2024). Mom, dad, put down your phone and talk to me: How parental phubbing influences problematic internet use among adolescents. *BMC Psychology*, *12*(1), 125. https://doi.org/10.1186/s40359-024-01620-0
305. Liu, Y., Chen, Y., Fraga-González, G., Szpak, V., Laverman, J., Wiers, R. W., & Richard Ridderinkhof, K. (2022). Resting-state EEG, Substance use and Abstinence After Chronic use: A Systematic Review. *Clinical EEG and Neuroscience*, *53*(4), 344–366. https://doi.org/10.1177/15500594221076347
306. Liu, Z. (2005). Reading Behavior in the Digital Environment: Changes in Reading Behavior Over the Past Ten Years. *Journal of Documentation*, *61*, 700–712. https://doi.org/10.1108/00220410510632040
307. Logan, G. D., Cowan, W. B., & Davis, K. A. (1984). On the ability to inhibit simple and choice reaction time responses: A model and a method. *Journal of Experimental Psychology. Human Perception and Performance*, *10*(2), 276–291. https://doi.org/10.1037/0096-1523.10.2.276
308. Loh, K. K., & Kanai, R. (2016). How Has the Internet Reshaped Human Cognition? *The Neuroscientist*, *22*(5), 506–520. https://doi.org/10.1177/1073858415595005
309. Lomas, T., Ivtzan, I., & Fu, C. H. Y. (2015). A systematic review of the neurophysiology of mindfulness on EEG oscillations. *Neuroscience & Biobehavioral Reviews*, *57*, 401–410. https://doi.org/10.1016/j.neubiorev.2015.09.018
310. Lombardi, F., Herrmann, H. J., Parrino, L., Plenz, D., Scarpetta, S., Vaudano, A. E., de Arcangelis, L., & Shriki, O. (2023). Beyond pulsed inhibition: Alpha oscillations modulate attenuation and amplification of

neural activity in the awake resting state. *Cell Reports*, *42*(10), 113162. https://doi.org/10.1016/j.celrep.2023.113162
311. Lortie, C. L., & Guitton, M. J. (2013). Internet addiction assessment tools: Dimensional structure and methodological status. *Addiction*, *108*(7), 1207–1216. https://doi.org/10.1111/add.12202
312. Love, T., Laier, C., Brand, M., Hatch, L., & Hajela, R. (2015). Neuroscience of Internet Pornography Addiction: A Review and Update. *Behavioral Sciences*, *5*(3), 388–433. https://doi.org/10.3390/bs5030388
313. Luijten, M., Kleinjan, M., & Franken, I. H. A. (2016). Event-related potentials reflecting smoking cue reactivity and cognitive control as predictors of smoking relapse and resumption. *Psychopharmacology*, *233*(15–16), 2857–2868. https://doi.org/10.1007/s00213-016-4332-8
314. Luijten, M., Machielsen, M. W. J., Veltman, D. J., Hester, R., de Haan, L., & Franken, I. H. A. (2014). Systematic review of ERP and fMRI studies investigating inhibitory control and error processing in people with substance dependence and behavioural addictions. *Journal of Psychiatry & Neuroscience,* *39*(3), 149–169. https://doi.org/10.1503/jpn.130052
315. Luo, Y., Yip, P. S. F., & Zhang, Q. (2025). Positive association between Internet use and mental health among adults aged ≥50 years in 23 countries. *Nature Human Behaviour*, *9*(1), 90–100. https://doi.org/10.1038/s41562-024-02048-7
316. MacKillop, J., Amlung, M. T., Few, L. R., Ray, L. A., Sweet, L. H., & Munafò, M. R. (2011). Delayed reward discounting and addictive behavior: A meta-analysis. *Psychopharmacology*, *216*(3), 305–321. https://doi.org/10.1007/s00213-011-2229-0
317. MacKillop, J., Weafer, J., C Gray, J., Oshri, A., Palmer, A., & de Wit, H. (2016). The latent structure of impulsivity: Impulsive choice, impulsive action, and impulsive personality traits. *Psychopharmacology*, *233*(18), 3361–3370. https://doi.org/10.1007/s00213-016-4372-0
318. Mak, K. K., Scheer, B., Yeh, C.-H., Ohno, S., & Nam, J. K. (2021). Associations of Personality Traits with Internet Addiction: A Cross-Cultural Meta-Analysis with a Multilingual Approach. *Cyberpsychology, Behavior and Social Networking*, *24*(12), 777–798. https://doi.org/10.1089/cyber.2021.0071
319. Mäki-Marttunen, V., Hagen, T., & Espeseth, T. (2019). Proactive and reactive modes of cognitive control can operate independently and simultaneously. *Acta Psychologica*, *199*, 102891. https://doi.org/10.1016/j.actpsy.2019.102891
320. Mantini, D., Perrucci, M. G., Del Gratta, C., Romani, G. L., & Corbetta, M. (2007). Electrophysiological signatures of resting state networks in the human brain. *Proceedings of the National Academy of Sciences of the United States of America*, *104*(32), 13170–13175. https://doi.org/10.1073/pnas.0700668104

321. Marciano, L., Camerini, A.-L., & Schulz, P. J. (2020). Neuroticism in the digital age: A meta-analysis. *Computers in Human Behavior Reports*, *2*, 100026. https://doi.org/10.1016/j.chbr.2020.100026
322. Marcu, G. M., Szekely-Copîndean, R. D., Radu, A.-M., Bucuță, M. D., Fleacă, R. S., Tănăsescu, C., Roman, M. D., Boicean, A., & Băcilă, C. I. (2023). Resting-state frontal, frontlateral, and parietal alpha asymmetry:A pilot study examining relations with depressive disorder type and severity. *Frontiers in Psychology*, *14*, 1087081. https://doi.org/10.3389/fpsyg.2023.1087081
323. Masciantonio, A., & Bourguignon, D. (2023). Motivation Scale for Using Social Network Sites: Comparative Study between Facebook, Instagram, Twitter, Snapchat and LinkedIn. *Psychologica Belgica*, *63*(1), 30–43. https://doi.org/10.5334/pb.1161
324. Massarat, E. A. V., Risa Gelles-Watnick and Navid. (2022, August 10). Teens, Social Media and Technology 2022. *Pew Research Center*. https://www.pewresearch.org/internet/2022/08/10/teens-social-media-and-technology-2022/
325. Meerkerk, G.-J., van den Eijnden, R. J. J. M., Franken, I. H. A., & Garretsen, H. F. L. (2010). Is compulsive internet use related to sensitivity to reward and punishment, and impulsivity? *Computers in Human Behavior*, *26*(4), 729–735. https://doi.org/10.1016/j.chb.2010.01.009
326. Mehling, W. E., Acree, M., Stewart, A., Silas, J., & Jones, A. (2018). The Multidimensional Assessment of Interoceptive Awareness, Version 2 (MAIA-2). *PLoS ONE*, *13*(12), e0208034. https://doi.org/10.1371/journal.pone.0208034
327. Mehling, W. E., Price, C., Daubenmier, J. J., Acree, M., Bartmess, E., & Stewart, A. (2012). The Multidimensional Assessment of Interoceptive Awareness (MAIA). *PLOS ONE*, *7*(11), e48230. https://doi.org/10.1371/journal.pone.0048230
328. Mehroof, M., & Griffiths, M. D. (2010). Online gaming addiction: The role of sensation seeking, self-control, neuroticism, aggression, state anxiety, and trait anxiety. *Cyberpsychology, Behavior and Social Networking*, *13*(3), 313–316. https://doi.org/10.1089/cyber.2009.0229
329. Melynyte, S., Ruksenas, O., & Griskova-Bulanova, I. (2017). Sex differences in equiprobable auditory Go/NoGo task: Effects on N2 and P3. *Experimental Brain Research*, *235*(5), 1565–1574. https://doi.org/10.1007/s00221-017-4911-x
330. Meng, Y., Deng, W., Wang, H., Guo, W., & Li, T. (2015). The prefrontal dysfunction in individuals with Internet gaming disorder: A meta-analysis of functional magnetic resonance imaging studies. *Addiction Biology*, *20*(4), 799–808. https://doi.org/10.1111/adb.12154
331. Metzen, D., Genç, E., Getzmann, S., Larra, M. F., Wascher, E., & Ocklenburg, S. (2022). Frontal and parietal EEG alpha asymmetry: A large-scale investigation of short-term reliability on distinct EEG systems.

Brain Structure & Function, *227*(2), 725–740. https://doi.org/10.1007/s00429-021-02399-1
332. Metzger, L. J., Paige, S. R., Carson, M. A., Lasko, N. B., Paulus, L. A., Pitman, R. K., & Orr, S. P. (2004). PTSD Arousal and Depression Symptoms Associated With Increased Right-Sided Parietal EEG Asymmetry. *Journal of Abnormal Psychology*, *113*(2), 324–329. https://doi.org/10.1037/0021-843X.113.2.324
333. Michel, C. M., & Brunet, D. (2019). EEG Source Imaging: A Practical Review of the Analysis Steps. *Frontiers in Neurology*, *10*, 325. https://doi.org/10.3389/fneur.2019.00325
334. Michel, C. M., & Koenig, T. (2018). EEG microstates as a tool for studying the temporal dynamics of whole-brain neuronal networks: A review. *NeuroImage*, *180*(Pt B), 577–593. https://doi.org/10.1016/j.neuroimage.2017.11.062
335. Mihajlov, M., & Vejmelka, L. (2017). Internet Addiction: A Review of the First Twenty Years. *Psychiatria Danubina*, *29*(3), 260–272. https://doi.org/10.24869/psyd.2017.260
336. Minnix, J. A., & Kline, J. P. (2004). Neuroticism predicts resting frontal EEG asymmetry variability. *Personality and Individual Differences*, *36*(4), 823–832. https://doi.org/10.1016/S0191-8869(03)00155-7
337. Mirzaei, A., Carter, S. R., Patanwala, A. E., & Schneider, C. R. (2022). Missing data in surveys: Key concepts, approaches, and applications. *Research in Social and Administrative Pharmacy*, *18*(2), 2308–2316. https://doi.org/10.1016/j.sapharm.2021.03.009
338. Mitchell, A. M., & Pössel, P. (2012). Frontal brain activity pattern predicts depression in adolescent boys. *Biological Psychology*, *89*(2), 525–527. https://doi.org/10.1016/j.biopsycho.2011.12.008
339. Mizukami, H., Kakigi, R., & Nakata, H. (2019). Effects of stimulus intensity and auditory white noise on human somatosensory cognitive processing: A study using event-related potentials. *Experimental Brain Research*, *237*(2), 521–530. https://doi.org/10.1007/s00221-018-5443-8
340. Moeller, F. G., Barratt, E. S., Dougherty, D. M., Schmitz, J. M., & Swann, A. C. (2001). Psychiatric aspects of impulsivity. *The American Journal of Psychiatry*, *158*(11), 1783–1793. https://doi.org/10.1176/appi.ajp.158.11.1783
341. Montag, C., Bey, K., Sha, P., Li, M., Chen, Y.-F., Liu, W.-Y., Zhu, Y.-K., Li, C.-B., Markett, S., Keiper, J., & Reuter, M. (2015). Is it meaningful to distinguish between generalized and specific Internet addiction? Evidence from a cross-cultural study from Germany, Sweden, Taiwan and China. *Asia-Pacific Psychiatry: Official Journal of the Pacific Rim College of Psychiatrists*, *7*(1), 20–26. https://doi.org/10.1111/appy.12122
342. Moretta, T., & Buodo, G. (2021). Response inhibition in problematic social network sites use: An ERP study. *Cognitive, Affective & Behavioral Neuroscience*, *21*(4), 868–880. https://doi.org/10.3758/s13415-021-00879-9

343. Mu, A., Deng, Z., Wu, X., & Zhou, L. (2021). Does digital technology reduce health disparity? Investigating difference of depression stemming from socioeconomic status among Chinese older adults. *BMC Geriatrics*, *21*(1), 264. https://doi.org/10.1186/s12877-021-02175-0
344. Müller, K. W., Beutel, M. E., Egloff, B., & Wölfling, K. (2014). Investigating risk factors for Internet gaming disorder: A comparison of patients with addictive gaming, pathological gamblers and healthy controls regarding the big five personality traits. *European Addiction Research*, *20*(3), 129–136. https://doi.org/10.1159/000355832
345. Müller, K. W., Dreier, M., & Wölfling, K. (2023). Personality traits and their role as risk modifiers in gaming disorder and internet use disorders. *Current Opinion in Psychiatry*, *36*(1), 75. https://doi.org/10.1097/YCO.0000000000000827
346. Nakata, H., Inui, K., Wasaka, T., Tamura, Y., Kida, T., & Kakigi, R. (2005). Effects of ISI and stimulus probability on event-related go/nogo potentials after somatosensory stimulation. *Experimental Brain Research*, *162*(3), 293–299. https://doi.org/10.1007/s00221-004-2195-4
347. Nakata, H., Sakamoto, K., & Kakigi, R. (2010). Effects of the interstimulus interval on somatosensory go/no-go event-related potentials. *Neuroreport*, *21*(16), 1040–1044. https://doi.org/10.1097/WNR.0b013e32833f7bb5
348. Nakata, H., Takezawa, M., Kamijo, K., & Shibasaki, M. (2021). Modality differences in ERP components between somatosensory and auditory Go/No-go paradigms in prepubescent children. *PLoS ONE*, *16*(11), e0259653. https://doi.org/10.1371/journal.pone.0259653
349. Namkung, H., Kim, S.-H., & Sawa, A. (2018). The Insula: An Underestimated Brain Area in Clinical Neuroscience, Psychiatry, and Neurology. *Trends in Neurosciences*, *41*(8), 551–554. https://doi.org/10.1016/j.tins.2018.05.004
350. Naqvi, N. H., & Bechara, A. (2009). The hidden island of addiction: The insula. *Trends in Neurosciences*, *32*(1), 56–67. https://doi.org/10.1016/j.tins.2008.09.009
351. Naqvi, N. H., & Bechara, A. (2010). The insula and drug addiction: An interoceptive view of pleasure, urges, and decision-making. *Brain Structure and Function*, *214*(5), 435–450. https://doi.org/10.1007/s00429-010-0268-7
352. Naqvi, N. H., Rudrauf, D., Damasio, H., & Bechara, A. (2007). Damage to the Insula Disrupts Addiction to Cigarette Smoking. *Science (New York, N.Y.)*, *315*(5811), 531–534. https://doi.org/10.1126/science.1135926
353. Nazare, K., & Tomescu, M. I. (2024). Valence-specific EEG microstate modulations during self-generated affective states. *Frontiers in Psychology*, *15*, 1300416. https://doi.org/10.3389/fpsyg.2024.1300416
354. Newson, J. J., & Thiagarajan, T. C. (2018). EEG Frequency Bands in Psychiatric Disorders: A Review of Resting State Studies. *Frontiers in*

Human Neuroscience, *12*, 521. https://doi.org/10.3389/fnhum.2018.00521
355. Nicholas, D., Huntington, P., Jamali, H. R., Rowlands, I., & Fieldhouse, M. (2009). Student digital information-seeking behaviour in context. *Journal of Documentation*, *65*. https://doi.org/10.1108/00220410910926149
356. Nie, J., Zhang, W., Chen, J., & Li, W. (2016). Impaired inhibition and working memory in response to internet-related words among adolescents with internet addiction: A comparison with attention-deficit/hyperactivity disorder. *Psychiatry Research*, *236*, 28–34. https://doi.org/10.1016/j.psychres.2016.01.004
357. Nieuwenhuis, S., Yeung, N., & Cohen, J. D. (2004). Stimulus modality, perceptual overlap, and the go/no-go N2. *Psychophysiology*, *41*(1), 157–160. https://doi.org/10.1046/j.1469-8986.2003.00128.x
358. Nieuwenhuis, S., Yeung, N., van den Wildenberg, W., & Ridderinkhof, K. R. (2003). Electrophysiological correlates of anterior cingulate function in a go/no-go task: Effects of response conflict and trial type frequency. *Cognitive, Affective & Behavioral Neuroscience*, *3*(1), 17–26. https://doi.org/10.3758/cabn.3.1.17
359. Nimrod, G. (2020). Changes in Internet Use When Coping With Stress: Older Adults During the COVID-19 Pandemic. *The American Journal of Geriatric Psychiatry: Official Journal of the American Association for Geriatric Psychiatry*, *28*(10), 1020–1024. https://doi.org/10.1016/j.jagp.2020.07.010
360. Nishida, K., Morishima, Y., Yoshimura, M., Isotani, T., Irisawa, S., Jann, K., Dierks, T., Strik, W., Kinoshita, T., & Koenig, T. (2013). EEG microstates associated with salience and frontoparietal networks in frontotemporal dementia, schizophrenia and Alzheimer's disease. *Clinical Neurophysiology: Official Journal of the International Federation of Clinical Neurophysiology*, *124*(6), 1106–1114. https://doi.org/10.1016/j.clinph.2013.01.005
361. Noël, X., Brevers, D., & Bechara, A. (2013). A triadic neurocognitive approach to addiction for clinical interventions. *Frontiers in Psychiatry*, *4*, 179. https://doi.org/10.3389/fpsyt.2013.00179
362. Noroozi, F., Hassanipour, S., Eftekharian, F., Eisapareh, K., & Kaveh, M. H. (2021). Internet Addiction Effect on Quality of Life: A Systematic Review and Meta-Analysis. *The Scientific World Journal*, *2021*. https://doi.org/10.1155/2021/2556679
363. Ocklenburg, S., Mundorf, A., Gerrits, R., Karlsson, E. M., Papadatou-Pastou, M., & Vingerhoets, G. (2024). Clinical implications of brain asymmetries. *Nature Reviews. Neurology*, *20*(7), 383–394. https://doi.org/10.1038/s41582-024-00974-8
364. Office of the U.S. Surgeon General. (2023). *Social media and youth mental health: The U.S. Surgeon General's advisory.* US Department of

Health and Human Services. http://www.ncbi.nlm.nih.gov/books/NBK595227/

365. Oh, H. J., Ozkaya, E., & LaRose, R. (2014). How does online social networking enhance life satisfaction? The relationships among online supportive interaction, affect, perceived social support, sense of community, and life satisfaction. *Computers in Human Behavior*, *30*, 69–78. https://doi.org/10.1016/j.chb.2013.07.053
366. Oh, S. J., Seo, S., Lee, J. H., Song, M. J., & Shin, M.-S. (2018). Effects of smartphone-based memory training for older adults with subjective memory complaints: A randomized controlled trial. *Aging & Mental Health*, *22*(4), 526–534. https://doi.org/10.1080/13607863.2016.1274373
367. Olaniyan, O. T., Adetunji, C. O., Dare, A., Adeyomoye, O., Adeniyi, M. J., & Enoch, A. (2023). Chapter 15—Neural signaling and communication using machine learning. In A. Abraham, S. Dash, S. K. Pani, & L. García-Hernández (Eds.), *Artificial Intelligence for Neurological Disorders* (pp. 245–260). Academic Press. https://doi.org/10.1016/B978-0-323-90277-9.00010-9
368. Ophir, E., Nass, C., & Wagner, A. D. (2009). Cognitive control in media multitaskers. *Proceedings of the National Academy of Sciences of the United States of America*, *106*(37), 15583–15587. https://doi.org/10.1073/pnas.0903620106
369. Opsahl, T., Agneessens, F., & Skvoretz, J. (2010). Node centrality in weighted networks: Generalizing degree and shortest paths. *Social Networks*, *32*(3), 245–251. https://doi.org/10.1016/j.socnet.2010.03.006
370. Osterhout, L., Poliakov, A., Inoue, K., McLaughlin, J., Valentine, G., Pitkanen, I., Frenck-Mestre, C., & Hirschensohn, J. (2008). Second-language learning and changes in the brain. *Journal of Neurolinguistics*, *21*(6), 509–521. https://doi.org/10.1016/j.jneuroling.2008.01.001
371. Owens, J., Adolescent Sleep Working Group, & Committee on Adolescence. (2014). Insufficient sleep in adolescents and young adults: An update on causes and consequences. *Pediatrics*, *134*(3), e921-932. https://doi.org/10.1542/peds.2014-1696
372. Pan, Y.-C., Chiu, Y.-C., & Lin, Y.-H. (2020). Systematic review and meta-analysis of epidemiology of internet addiction. *Neuroscience and Biobehavioral Reviews*, *118*, 612–622. https://doi.org/10.1016/j.neubiorev.2020.08.013
373. Pandey, A. K., Kamarajan, C., Manz, N., Chorlian, D. B., Stimus, A., & Porjesz, B. (2016). Delta, theta, and alpha event-related oscillations in alcoholics during Go/NoGo task: Neurocognitive deficits in execution, inhibition, and attention processing. *Progress in Neuro-Psychopharmacology & Biological Psychiatry*, *65*, 158–171. https://doi.org/10.1016/j.pnpbp.2015.10.002
374. Papachristou, H., Nederkoorn, C., Havermans, R., Bongers, P., Beunen, S., & Jansen, A. (2013). Higher levels of trait impulsiveness and a less effective response inhibition are linked to more intense cue-elicited

craving for alcohol in alcohol-dependent patients. *Psychopharmacology*, *228*(4), 641–649. https://doi.org/10.1007/s00213-013-3063-3

375. Papastylianou, D. (2013). Relating on the Internet, Personality Traits and Depression: Research and Implications. *The European Journal of Counselling Psychology*, *2*, 65–78. https://doi.org/10.5964/ejcop.v2i1.6
376. Papousek, I., Harald Freudenthaler, H., & Schulter, G. (2011). Typical performance measures of emotion regulation and emotion perception and frontal EEG asymmetry in an emotional contagion paradigm. *Personality and Individual Differences*, *51*(8), 1018–1022. https://doi.org/10.1016/j.paid.2011.08.013
377. Park, M., Choi, J.-S., Park, S. M., Lee, J.-Y., Jung, H. Y., Sohn, B. K., Kim, S. N., Kim, D. J., & Kwon, J. S. (2016). Dysfunctional information processing during an auditory event-related potential task in individuals with Internet gaming disorder. *Translational Psychiatry*, *6*(1). https://doi.org/10.1038/tp.2015.215
378. Park, M., Kim, Y., Kim, D., Choi, J. (2017). Differential neurophysiological correlates of information processing in Internet gaming disorder and alcohol use disorder measured by event-related potentials. *Scientific Reports,* 7, 9062. https://doi.org/10.1038/s41598-017-09679-z
379. Park, M., Kim, Y., Kim, D., Choi, J. (2017b). Sustained dysfunctional information processing in patients with Internet gaming disorder 6-month follow-up ERP study. *Medicine*, *96*(36). https://doi.org/10.1097/MD.0000000000007995
380. Pastor, Y., García-Jiménez, A., & López-de-Ayala, M.-C. (2022). Regulatory strategies for smartphone use and problematic internet use in adolescence. *Anales de Psicología*, *38*(2), 269–277. https://doi.org/10.6018/analesps.461771
381. Patton, J. H., Stanford, M. S., & Barratt, E. S. (1995). Factor structure of the Barratt impulsiveness scale. *Journal of Clinical Psychology*, *51*(6), 768–774.
382. Paulus, M. P., & Stewart, J. L. (2014). Interoception and Drug Addiction. *Neuropharmacology*, *76*, 10.1016/j.neuropharm.2013.07.002. https://doi.org/10.1016/j.neuropharm.2013.07.002
383. Pelchen, L. (2024, March 1). *Internet Usage Statistics In 2024*. Forbes Home. https://www.forbes.com/home-improvement/internet/internet-statistics/
384. Peng, P., & Liao, Y. (2023). Six addiction components of problematic social media use in relation to depression, anxiety, and stress symptoms: A latent profile analysis and network analysis. *BMC Psychiatry*, *23*, 321. https://doi.org/10.1186/s12888-023-04837-2
385. Perrault, A. A., Bayer, L., Peuvrier, M., Afyouni, A., Ghisletta, P., Brockmann, C., Spiridon, M., Hulo Vesely, S., Haller, D. M., Pichon, S., Perrig, S., Schwartz, S., & Sterpenich, V. (2019). Reducing the use of screen electronic devices in the evening is associated with improved sleep

and daytime vigilance in adolescents. *Sleep*, *42*(9), zsz125. https://doi.org/10.1093/sleep/zsz125
386. Perrin, F., Pernier, J., Bertrand, O., & Echallier, J. F. (1989). Spherical splines for scalp potential and current density mapping. *Electroencephalography and Clinical Neurophysiology*, *72*(2), 184–187. https://doi.org/10.1016/0013-4694(89)90180-6
387. Petersen, K. U., Weymann, N., Schelb, Y., Thiel, R., & Thomasius, R. (2009). Pathological Internet use—Epidemiology, diagnostics, co-occurring disorders and treatment. *Fortschritte Der Neurologie-Psychiatrie*, *77*(5), 263–271. https://doi.org/10.1055/s-0028-1109361
388. Petit, G., Kornreich, C., Noël, X., Verbanck, P., & Campanella, S. (2012). Alcohol-related context modulates performance of social drinkers in a visual Go/No-Go task: A preliminary assessment of event-related potentials. *PloS One*, *7*(5), e37466. https://doi.org/10.1371/journal.pone.0037466
389. Petrosyan, A. (2025, January 13). *Global internet user penetration 2014-2024*. Statista. https://www.statista.com/statistics/325706/global-internet-user-penetration/
390. Petrosyan, A. (2024). *Topic: Internet usage worldwide*. Statista. https://www.statista.com/topics/1145/internet-usage-worldwide/
391. Petry, N. M., Rehbein, F., Ko, C.-H., & O'Brien, C. P. (2015). Internet Gaming Disorder in the DSM-5. *Current Psychiatry Reports*, *17*(9), 72. https://doi.org/10.1007/s11920-015-0610-0
392. Pew Research Center. (2024, November 13). Internet, Broadband Fact Sheet. *Pew Research Center*. https://www.pewresearch.org/internet/fact-sheet/internet-broadband/
393. Pezze, M. A., Dalley, J. W., & Robbins, T. W. (2009). Remediation of attentional dysfunction in rats with lesions of the medial prefrontal cortex by intra-accumbens administration of the dopamine D2/3 receptor antagonist sulpiride. *Psychopharmacology*, *202*(1), 307–313. https://doi.org/10.1007/s00213-008-1384-4
394. Picton, T. W., Bentin, S., Berg, P., Donchin, E., Hillyard, S. A., Johnson, R., Miller, G. A., Ritter, W., Ruchkin, D. S., Rugg, M. D., & Taylor, M. J. (2000). Guidelines for using human event-related potentials to study cognition: Recording standards and publication criteria. *Psychophysiology*, *37*(2), 127–152.
395. Pipinis, E., Melynyte, S., Koenig, T., Jarutyte, L., Linkenkaer-Hansen, K., Ruksenas, O., & Griskova-Bulanova, I. (2017). Association Between Resting-State Microstates and Ratings on the Amsterdam Resting-State Questionnaire. *Brain Topography*, *30*(2), 245–248. https://doi.org/10.1007/s10548-016-0522-2
396. Pires, L., Leitão, J., Guerrini, C., & Simões, M. R. (2014). Event-Related Brain Potentials in the Study of Inhibition: Cognitive Control, Source Localization and Age-Related Modulations. *Neuropsychology Review*, *24*(4), 461–490. https://doi.org/10.1007/s11065-014-9275-4

397. Plonsky, L., & Oswald, F. L. (2014). How Big Is "Big"? Interpreting Effect Sizes in L2 Research. *Language Learning*, *64*(4), 878–912. https://doi.org/10.1111/lang.12079
398. Polich, J. (2003). Theoretical Overview of P3a and P3b. In J. Polich (Ed.), *Detection of Change: Event-Related Potential and fMRI Findings* (pp. 83–98). Springer US. https://doi.org/10.1007/978-1-4615-0294-4_5
399. Polich, J., & Criado, J. R. (2006). Neuropsychology and neuropharmacology of P3a and P3b. *International Journal of Psychophysiology*, *60*(2), 172–185. https://doi.org/10.1016/j.ijpsycho.2005.12.012
400. Pollatos, O., Mönkemöller, K., Groppe, K., & Elsner, B. (2023). Interoceptive accuracy is associated with benefits in decision making in children. *Frontiers in Psychology*, *13*, 1070037. https://doi.org/10.3389/fpsyg.2022.1070037
401. Pop, L. M., Iorga, M., & Iurcov, R. (2022). Body-Esteem, Self-Esteem and Loneliness among Social Media Young Users. *International Journal of Environmental Research and Public Health*, *19*(9), 5064. https://doi.org/10.3390/ijerph19095064
402. Porjesz, B., & Begleiter, H. (2003). Alcoholism and human electrophysiology. *Alcohol Research & Health*, *27*(2), 153–160.
403. Poskanzer, C., Denis, D., Herrick, A., & Stickgold, R. (2021). Using EEG microstates to examine post-encoding quiet rest and subsequent word-pair memory. *Neurobiology of Learning and Memory*, *181*, 107424. https://doi.org/10.1016/j.nlm.2021.107424
404. Pössel, P., Lo, H., Fritz, A., & Seemann, S. (2008). A longitudinal study of cortical EEG activity in adolescents. *Biological Psychology*, *78*(2), 173–178. https://doi.org/10.1016/j.biopsycho.2008.02.004
405. Prensky, M. (2001). Do They Really Think Differently? Digital Natives, Digital Immigrants, Part II. *On The Horizon*, *9*, 1–6. https://doi.org/10.1108/10748120110424843
406. Qi, Y., Liu, Y., Yan, Z., Zhang, X., & He, Q. (2023). Spontaneous brain microstates correlate with impaired inhibitory control in internet addiction disorder. *Psychiatry Research. Neuroimaging*, *334*, 111686. https://doi.org/10.1016/j.pscychresns.2023.111686
407. Rahmani, S., & Lavasani, M. G. (2011). The Relationship Between Internet Dependency with Sensation Seeking and Personality. *Procedia - Social and Behavioral Sciences*, *30*, 272–277. https://doi.org/10.1016/j.sbspro.2011.10.054
408. Ramautar, J. R., Kok, A., & Ridderinkhof, K. R. (2004). Effects of stop-signal probability in the stop-signal paradigm: The N2/P3 complex further validated. *Brain and Cognition*, *56*(2), 234–252. https://doi.org/10.1016/j.bandc.2004.07.002
409. Ramey, T., & Regier, P. S. (2019). Cognitive Impairment in Substance Use Disorders. *CNS Spectrums*, *24*(1), 102–113. https://doi.org/10.1017/S1092852918001426

410. Randall, W. M., & Smith, J. L. (2011). Conflict and inhibition in the cued-Go/NoGo task. *Clinical Neurophysiology: Official Journal of the International Federation of Clinical Neurophysiology*, *122*(12), 2400–2407. https://doi.org/10.1016/j.clinph.2011.05.012
411. Reglitz, M. (2020). The Human Right to Free Internet Access. *Journal of Applied Philosophy*, *37*(2), 314–331. https://doi.org/10.1111/japp.12395
412. Reznik, S. J., & Allen, J. J. B. (2018). Frontal asymmetry as a mediator and moderator of emotion: An updated review. *Psychophysiology*, *55*(1). https://doi.org/10.1111/psyp.12965
413. Robbins, T., & Clark, L. (2015). Behavioral addictions. *Current Opinion in Neurobiology*, *30*, 66–72. https://doi.org/10.1016/j.conb.2014.09.005
414. Roche, R. A. P., Garavan, H., Foxe, J. J., & O'Mara, S. M. (2005). Individual differences discriminate event-related potentials but not performance during response inhibition. *Experimental Brain Research*, *160*(1), 60–70. https://doi.org/10.1007/s00221-004-1985-z
415. Rømer Thomsen, K., Callesen, M. B., Hesse, M., Kvamme, T. L., Pedersen, M. M., Pedersen, M. U., & Voon, V. (2018). Impulsivity traits and addiction-related behaviors in youth. *Journal of Behavioral Addictions*, *7*(2), 317–330. https://doi.org/10.1556/2006.7.2018.22
416. Rubia, K., Russell, T., Overmeyer, S., Brammer, M. J., Bullmore, E. T., Sharma, T., Simmons, A., Williams, S. C., Giampietro, V., Andrew, C. M., & Taylor, E. (2001). Mapping motor inhibition: Conjunctive brain activations across different versions of go/no-go and stop tasks. *NeuroImage*, *13*(2), 250–261. https://doi.org/10.1006/nimg.2000.0685
417. S A, A., C, S., P, D., G, A., Maniyan Lathikakumari, A., V Thomas, S., & N Menon, R. (2024). Analysis of EEG microstates as biomarkers in neuropsychological processes—Review. *Computers in Biology and Medicine*, *173*, 108266. https://doi.org/10.1016/j.compbiomed.2024.108266
418. Şalvarlı, Ş. İ., & Griffiths, M. D. (2022). The Association Between Internet Gaming Disorder and Impulsivity: A Systematic Review of Literature. *International Journal of Mental Health and Addiction*, *20*(1), 92–118. https://doi.org/10.1007/s11469-019-00126-w
419. Sánchez-Fernández, M., Borda-Mas, M., Horvath, Z., & Demetrovics, Z. (2024). Similarities and differences in the psychological factors associated with generalised problematic internet use, problematic social media use, and problematic online gaming. *Comprehensive Psychiatry*, *134*, 152512. https://doi.org/10.1016/j.comppsych.2024.152512
420. Sanders, J., Hershberger, A. R., & Cyders, M. A. (2020). UPPS Model of Impulsivity. In V. Zeigler-Hill & T. K. Shackelford (Eds.), *Encyclopedia of Personality and Individual Differences* (pp. 5674–5683). Springer International Publishing. https://doi.org/10.1007/978-3-319-24612-3_2131

421. Sanders, J., & Williams, R. (2019). The Relationship Between Video Gaming, Gambling, and Problematic Levels of Video Gaming and Gambling. *Journal of Gambling Studies*, *35*(2), 559–569. https://doi.org/10.1007/s10899-018-9798-3
422. Satapathy, P., Khatib, M. N., Balaraman, A. K., R, R., Kaur, M., Srivastava, M., Barwal, A., Prasad, G. V. S., Rajput, P., Syed, R., Sharma, G., Kumar, S., Singh, M. P., Bushi, G., Chilakam, N., Pandey, S., Brar, M., Mehta, R., Sah, S., … Samal, S. K. (2025). Burden of gaming disorder among adolescents: A systemic review and meta-analysis. *Public Health in Practice (Oxford, England)*, *9*, 100565. https://doi.org/10.1016/j.puhip.2024.100565
423. Schiller, B., Sperl, M. F. J., Kleinert, T., Nash, K., & Gianotti, L. R. R. (2024). EEG Microstates in Social and Affective Neuroscience. *Brain Topography*, *37*(4), 479–495. https://doi.org/10.1007/s10548-023-00987-4
424. Schiltz, H. K., McVey, A. J., Barrington, A., Haendel, A. D., Dolan, B. K., Willar, K. S., Pleiss, S., Karst, J. S., Vogt, E., Murphy, C. C., Gonring, K., & Van Hecke, A. V. (2018). Behavioral inhibition and activation as a modifier process in autism spectrum disorder: Examination of self-reported BIS/BAS and alpha EEG asymmetry. *Autism Research*, *11*(12), 1653–1666. https://doi.org/10.1002/aur.2016
425. Schimmenti, A., & Caretti, V. (2010). Psychic retreats or psychic pits?: Unbearable states of mind and technological addiction. *Psychoanalytic Psychology*, *27*(2), 115–132. https://doi.org/10.1037/a0019414
426. Schlegel, F., Lehmann, D., Faber, P. L., Milz, P., & Gianotti, L. R. R. (2012). EEG microstates during resting represent personality differences. *Brain Topography*, *25*(1), 20–26. https://doi.org/10.1007/s10548-011-0189-7
427. Schneider, M., Chau, L., Mohamadpour, M., Stephens, N., Arya, K., & Grant, A. (2016). EEG asymmetry and BIS/BAS among healthy adolescents. *Biological Psychology*, *120*, 142–148. https://doi.org/10.1016/j.biopsycho.2016.09.004
428. Scholz, J., Klein, M. C., Behrens, T. E. J., & Johansen-Berg, H. (2009). Training induces changes in white-matter architecture. *Nature Neuroscience*, *12*(11), 1370–1371. https://doi.org/10.1038/nn.2412
429. Schou Andreassen, C., Billieux, J., Griffiths, M. D., Kuss, D. J., Demetrovics, Z., Mazzoni, E., & Pallesen, S. (2016). The relationship between addictive use of social media and video games and symptoms of psychiatric disorders: A large-scale cross-sectional study. *Psychology of Addictive Behaviors*, *30*(2), 252–262. https://doi.org/10.1037/adb0000160
430. Seabrook, E. M., Kern, M. L., & Rickard, N. S. (2016). Social Networking Sites, Depression, and Anxiety: A Systematic Review. *JMIR Mental Health*, *3*(4), e50. https://doi.org/10.2196/mental.5842

431. Seeber, M., & Michel, C. M. (2021). Synchronous Brain Dynamics Establish Brief States of Communality in Distant Neuronal Populations. *eNeuro*, *8*(3), ENEURO.0005-21.2021. https://doi.org/10.1523/ENEURO.0005-21.2021
432. Shapira, N. A., Lessig, M. C., Goldsmith, T. D., Szabo, S. T., Lazoritz, M., Gold, M. S., & Stein, D. J. (2003). Problematic internet use: Proposed classification and diagnostic criteria. *Depression and Anxiety*, *17*(4), 207–216. https://doi.org/10.1002/da.10094
433. Shi, Y., Tang, Z., Gan, Z., Hu, M., & Liu, Y. (2023). Association Between Family Atmosphere and Internet Addiction Among Adolescents: The Mediating Role of Self-Esteem and Negative Emotions. *International Journal of Public Health*, *68*, 1605609. https://doi.org/10.3389/ijph.2023.1605609
434. Skowronek, J., Seifert, A., & Lindberg, S. (2023). The mere presence of a smartphone reduces basal attentional performance. *Scientific Reports*, *13*(1), 9363. https://doi.org/10.1038/s41598-023-36256-4
435. Smirni, D., Smirni, P., Lavanco, G., & Caci, B. (2023). Premorbid Personality Traits as Risk Factors for Behavioral Addictions: A Systematic Review of a Vulnerability Hypothesis. *Children*, *10*(3), 467. https://doi.org/10.3390/children10030467
436. Smith, D. E., & Seymour, R. B. (2004). The Nature of Addiction. In *Handbook of addictive disorders: A practical guide to diagnosis and treatment* (pp. 3–30). John Wiley & Sons, Inc.
437. Smith, E. E., Reznik, S. J., Stewart, J. L., & Allen, J. J. B. (2017). Assessing and conceptualizing frontal EEG asymmetry: An updated primer on recording, processing, analyzing, and interpreting frontal alpha asymmetry. *International Journal of Psychophysiology*, *111*, 98–114. https://doi.org/10.1016/j.ijpsycho.2016.11.005
438. Smith, J. L., & Douglas, K. M. (2011). On the use of event-related potentials to auditory stimuli in the Go/NoGo task. *Psychiatry Research: Neuroimaging*, *193*(3), 177–181. https://doi.org/10.1016/j.pscychresns.2011.03.002
439. Smith, J. L., Johnstone, S. J., & Barry, R. J. (2006). Effects of pre-stimulus processing on subsequent events in a warned Go/NoGo paradigm: Response preparation, execution and inhibition. *International Journal of Psychophysiology*, *61*(2), 121–133. https://doi.org/10.1016/j.ijpsycho.2005.07.013
440. Smith, J. L., Johnstone, S. J., & Barry, R. J. (2008). Movement-related potentials in the Go/NoGo task: The P3 reflects both cognitive and motor inhibition. *Clinical Neurophysiology*, *119*(3), 704–714. https://doi.org/10.1016/j.clinph.2007.11.042
441. Smith, J. L., Smith, E. A., Provost, A. L., & Heathcote, A. (2010). Sequence effects support the conflict theory of N2 and P3 in the Go/NoGo task. *International Journal of Psychophysiology: Official Journal of the*

International Organization of Psychophysiology, *75*(3), 217–226. https://doi.org/10.1016/j.ijpsycho.2009.11.002
442. Sokhadze, E., Stewart, C., Hollifield, M., & Tasman, A. (2008). Event-Related Potential Study of Executive Dysfunctions in a Speeded Reaction Task in Cocaine Addiction. *Journal of Neurotherapy*, *12*(4), 185–204. https://doi.org/10.1080/10874200802502144
443. Sokhadze, T., Casanova, M., Casanova, E., Lamina, E., Kelly, D., & Khachidze, I. (2017). Event-related Potentials (ERP) in Cognitive Neuroscience Research and Applications. *NeuroRegulation*, *4*, 14–27. https://doi.org/10.15540/nr.4.1.14
444. Sönmez, M., Kahyacı Kılıç, E., Çöl, I., Gorgulu, Y., & Kose, R. (2016). Decreased interoceptive awareness in patients with substance use disorders. *Journal of Substance Use*, *22*, 1–6. https://doi.org/10.3109/14659891.2016.1143048
445. Sparrow, B., Liu, J., & Wegner, D. M. (2011). Google effects on memory: Cognitive consequences of having information at our fingertips. *Science*, *333*(6043), 776–778. https://doi.org/10.1126/science.1207745
446. Sperry, S. H., Lynam, D. R., Walsh, M. A., Horton, L. E., & Kwapil, T. R. (2016). Examining the multidimensional structure of impulsivity in daily life. *Personality and Individual Differences*, *94*, 153–158. https://doi.org/10.1016/j.paid.2016.01.018
447. Spinella, M. (2002). Correlations between orbitofrontal dysfunction and tobacco smoking. *Addiction Biology*, *7*(4), 381–384. https://doi.org/10.1080/1355621021000005964
448. Stanford, M. S., Mathias, C. W., Dougherty, D. M., Lake, S. L., Anderson, N. E., & Patton, J. H. (2009). Fifty years of the Barratt Impulsiveness Scale: An update and review. *Personality and Individual Differences*, *47*(5), 385–395. https://doi.org/10.1016/j.paid.2009.04.008
449. Starcevic, V. (2013). Is Internet addiction a useful concept? *The Australian and New Zealand Journal of Psychiatry*, *47*(1), 16–19. https://doi.org/10.1177/0004867412461693
450. Starcevic, V., & Aboujaoude, E. (2017). Internet addiction: Reappraisal of an increasingly inadequate concept. *CNS Spectrums*, *22*(1), 7–13. https://doi.org/10.1017/S1092852915000863
451. Statista. (2025, February 13). *Internet and social media users in the world 2025*. Statista. https://www.statista.com/statistics/617136/digital-population-worldwide/
452. Stevens, M. W., Dorstyn, D., Delfabbro, P. H., & King, D. L. (2021). Global prevalence of gaming disorder: A systematic review and meta-analysis. *The Australian and New Zealand Journal of Psychiatry*, *55*(6), 553–568. https://doi.org/10.1177/0004867420962851
453. Su, W., Han, X., Jin, C., Yan, Y., & Potenza, M. N. (2019). Are males more likely to be addicted to the internet than females? A meta-analysis involving 34 global jurisdictions. *Computers in Human Behavior*, *99*, 86–100. https://doi.org/10.1016/j.chb.2019.04.021

454. Sun, Y., Li, Y., Bao, Y., Meng, S., Sun, Y., Schumann, G., Kosten, T., Strang, J., Lu, L., & Shi, J. (2020). Brief Report: Increased Addictive Internet and Substance Use Behavior During the COVID-19 Pandemic in China. *The American Journal on Addictions*, *29*(4), 268–270. https://doi.org/10.1111/ajad.13066
455. Sun, Y., Wang, H., & Bo, S. (2019). Altered topological connectivity of internet addiction in resting-state EEG through network analysis. *Addictive Behaviors*, *95*, 49–57. https://doi.org/10.1016/j.addbeh.2019.02.015
456. Sun, Y.-K., Sun, Y., Lin, X., Lu, L., & Shi, J. (2017). Similarities and Differences in Neuroimaging. In X. Zhang, J. Shi, & R. Tao (Eds.), *Substance and Non-substance Addiction* (pp. 73–89). Springer. https://doi.org/10.1007/978-981-10-5562-1_5
457. Sur, S., & Sinha, V. K. (2009). Event-related potential: An overview. *Industrial Psychiatry Journal*, *18*(1), 70–73. https://doi.org/10.4103/0972-6748.57865
458. Sussman, S., & Sussman, A. N. (2011). Considering the Definition of Addiction. *International Journal of Environmental Research and Public Health*, *8*(10). https://doi.org/10.3390/ijerph8104025
459. Szabo, A., Allen, J., Stephens, C., & Alpass, F. (2019). Longitudinal Analysis of the Relationship Between Purposes of Internet Use and Well-being Among Older Adults. *The Gerontologist*, *59*(1), 58–68. https://doi.org/10.1093/geront/gny036
460. Tarailis, P., Koenig, T., Michel, C. M., & Griškova-Bulanova, I. (2024). The Functional Aspects of Resting EEG Microstates: A Systematic Review. *Brain Topography*, *37*(2), 181–217. https://doi.org/10.1007/s10548-023-00958-9
461. Tarailis, P., Šimkutė, D., Koenig, T., & Griškova-Bulanova, I. (2021). Relationship between Spatiotemporal Dynamics of the Brain at Rest and Self-Reported Spontaneous Thoughts: An EEG Microstate Approach. *Journal of Personalized Medicine*, *11*(11), 1216. https://doi.org/10.3390/jpm11111216
462. Tarokh, L., Saletin, J. M., & Carskadon, M. A. (2016). Sleep in adolescence: Physiology, cognition and mental health. *Neuroscience and Biobehavioral Reviews*, *70*, 182–188. https://doi.org/10.1016/j.neubiorev.2016.08.008
463. Tesler, N., Gerstenberg, M., & Huber, R. (2013). Developmental changes in sleep and their relationships to psychiatric illnesses. *Current Opinion in Psychiatry*, *26*(6), 572–579. https://doi.org/10.1097/YCO.0b013e328365a335
464. Tian, Y., Zhao, Y., Lv, F., Qin, N., & Chen, P. (2021). Associations Among the Big Five Personality Traits, Maladaptive Cognitions, and Internet Addiction Across Three Time Measurements in 3 Months During the COVID-19 Pandemic. *Frontiers in Psychology*, *12*, 654825. https://doi.org/10.3389/fpsyg.2021.654825

465. Tomé, D., Barbosa, F., Nowak, K., & Marques-Teixeira, J. (2015). The development of the N1 and N2 components in auditory oddball paradigms: A systematic review with narrative analysis and suggested normative values. *Journal of Neural Transmission, 122*(3), 375–391. https://doi.org/10.1007/s00702-014-1258-3
466. Tomescu, M. I., Papasteri, C. C., Sofonea, A., Boldasu, R., Kebets, V., Pistol, C. A. D., Poalelungi, C., Benescu, V., Podina, I. R., Nedelcea, C. I., Berceanu, A. I., & Carcea, I. (2022). Spontaneous thought and microstate activity modulation by social imitation. *NeuroImage*, *249*, 118878. https://doi.org/10.1016/j.neuroimage.2022.118878
467. Tomescu, M. I., Papasteri, C., Sofonea, A., Berceanu, A. I., & Carcea, I. (2024). Personality Moderates Intra-Individual Variability in EEG Microstates and Spontaneous Thoughts. *Brain Topography*, *37*(4), 524–535. https://doi.org/10.1007/s10548-023-01019-x
468. Tomescu, M. I., Van der Donck, S., Perisanu, E. M., Berceanu, A. I., Alaerts, K., Boets, B., & Carcea, I. (2024). Social functioning predicts individual changes in EEG microstates following intranasal oxytocin administration: A double-blind, cross-over randomized clinical trial. *Psychophysiology*, *61*(8), e14581. https://doi.org/10.1111/psyp.14581
469. Tseng, Y.-L., Su, Y.-K., Chou, W.-J., Miyakoshi, M., Tsai, C.-S., Li, C.-J., Lee, S.-Y., & Wang, L.-J. (2024). Neural Network Dynamics and Brain Oscillations Underlying Aberrant Inhibitory Control in Internet Addiction. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *32*, 946–955. https://doi.org/10.1109/TNSRE.2024.3363756
470. Turel, O., He, Q., Brevers, D., & Bechara, A. (2018). Delay discounting mediates the association between posterior insular cortex volume and social media addiction symptoms. *Cognitive, Affective, & Behavioral Neuroscience*, *18*(4), 694–704. https://doi.org/10.3758/s13415-018-0597-1
471. Turel, O., He, Q., Wei, L., & Bechara, A. (2021). The role of the insula in internet gaming disorder. *Addiction Biology*, *26*(2), e12894. https://doi.org/10.1111/adb.12894
472. Twenge, J. M., Spitzberg, B. H., & Campbell, W. K. (2019). Less in-person social interaction with peers among U.S. adolescents in the 21st century and links to loneliness. *Journal of Social and Personal Relationships*, *36*(6), 1892–1913. https://doi.org/10.1177/0265407519836170
473. Umemoto, A., Panier, L. Y. X., Cole, S. L., Kayser, J., Pizzagalli, D. A., & Auerbach, R. P. (2021). Resting Posterior Alpha Power and Adolescent Major Depressive Disorder. *Journal of Psychiatric Research*, *141*, 233–240. https://doi.org/10.1016/j.jpsychires.2021.07.003
474. United Nations. (2016). The promotion, protection and enjoyment of human rights on the Internet: Resolution / adopted by the Human Rights *Council on 1 July 2016*. https://digitallibrary.un.org/record/845727

475. Van Ameringen, M., Simpson, W., Patterson, B., Turna, J., & Khalesi, Z. (2018). INTERNET ADDICTION OR PSYCHOPATHOLOGY IN DISGUISE? RESULTS FROM A SURVEY OF COLLEGE-AGED INTERNET USERS. *European Neuropsychopharmacology*, *28*(6), 762. https://doi.org/10.1016/j.euroneuro.2017.10.003
476. Van Rooij, A. J., & Prause, N. (2014). A critical review of "Internet addiction" criteria with suggestions for the future. *Journal of Behavioral Addictions*, *3*(4), 203–213. https://doi.org/10.1556/JBA.3.2014.4.1
477. Vargas, T., Maloney, J., Gupta, T., Damme, K. S. F., Kelley, N. J., & Mittal, V. A. (2019). Measuring facets of reward sensitivity, inhibition, and impulse control in individuals with problematic Internet use. *Psychiatry Research*, *275*, 351–358. https://doi.org/10.1016/j.psychres.2019.03.032
478. Vassileva, J., & Conrod, P. J. (2019). Impulsivities and addictions: A multidimensional integrative framework informing assessment and interventions for substance use disorders. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *374*(1766), 20180137. https://doi.org/10.1098/rstb.2018.0137
479. Verdejo-Garcia, A., Clark, L., & Dunn, B. D. (2012). The role of interoception in addiction: A critical review. *Neuroscience and Biobehavioral Reviews*, *36*(8), 1857–1869. https://doi.org/10.1016/j.neubiorev.2012.05.007
480. Walker, E., Ploubidis, G., & Fancourt, D. (2019). Social engagement and loneliness are differentially associated with neuro-immune markers in older age: Time-varying associations from the English Longitudinal Study of Ageing. *Brain, Behavior, and Immunity*, *82*, 224–229. https://doi.org/10.1016/j.bbi.2019.08.189
481. Wang, B.-Q., Yao, N.-Q., Zhou, X., Liu, J., & Lv, Z.-T. (2017). The association between attention deficit/hyperactivity disorder and internet addiction: A systematic review and meta-analysis. *BMC Psychiatry*, *17*(1), 260. https://doi.org/10.1186/s12888-017-1408-x
482. Wang, G. Y., & Griskova-Bulanova, I. (2018). Electrophysiological activity is associated with vulnerability of Internet addiction in non-clinical population. *Addictive Behaviors*, *84*, 33–39. https://doi.org/10.1016/j.addbeh.2018.03.025
483. Wang, H., Mou, S., Pei, X., Zhang, X., Shen, S., Zhang, J., Shen, X., & Shen, Z. (2025). The power spectrum and functional connectivity characteristics of resting-state EEG in patients with generalized anxiety disorder. *Scientific Reports*, *15*, 5991. https://doi.org/10.1038/s41598-025-90362-z
484. Wang, H.-Y., & Cheng, C. (2022). The Associations Between Gaming Motivation and Internet Gaming Disorder: Systematic Review and Meta-analysis. *JMIR Mental Health*, *9*, e23700. https://doi.org/10.2196/23700
485. Wang, L., Ding, X., Zhang, W., & Yang, S. (2021). Differences in EEG Microstate Induced by Gaming: A Comparison Between the Gaming

Disorder Individual, Recreational Game Users and Healthy Controls. *IEEE Access*, *9*, 32549–32558. https://doi.org/10.1109/ACCESS.2021.3060112
486. Wang, L., Shen, H., Lei, Y., Zeng, L.-L., Cao, F., Su, L., Yang, Z., Yao, S., & Hu, D. (2017). Altered default mode, fronto-parietal and salience networks in adolescents with Internet addiction. *Addictive Behaviors*, *70*, 1–6. https://doi.org/10.1016/j.addbeh.2017.01.021
487. Wang, Y., Yin, Y., Sun, Y., Zhou, Y., Chen, X., Ding, W., Wang, W., Li, W., Xu, J., & Du, Y. (2015). Decreased prefrontal lobe interhemispheric functional connectivity in adolescents with internet gaming disorder: A primary study using resting-state FMRI. *PloS One*, *10*(3), e0118733. https://doi.org/10.1371/journal.pone.0118733
488. Wang, Y.-P., & Gorenstein, C. (2013). Assessment of depression in medical patients: A systematic review of the utility of the Beck Depression Inventory-II. *Clinics*, *68*(9), 1274–1287. https://doi.org/10.6061/clinics/2013(09)15
489. Wardle, H., Degenhardt, L., Marionneau, V., Reith, G., Livingstone, C., Sparrow, M., Tran, L. T., Biggar, B., Bunn, C., Farrell, M., Kesaite, V., Poznyak, V., Quan, J., Rehm, J., Rintoul, A., Sharma, M., Shiffman, J., Siste, K., Ukhova, D., … Saxena, S. (2024). The *Lancet Public Health* Commission on gambling. *The Lancet Public Health*, *9*(11), e950–e994. https://doi.org/10.1016/S2468-2667(24)00167-1
490. Wegmann, E., Müller, S. M., Ostendorf, S., & Brand, M. (2018). Highlighting Internet-Communication Disorder as Further Internet-Use Disorder When Considering Neuroimaging Studies. *Current Behavioral Neuroscience Reports*, *5*(4), 295–301. https://doi.org/10.1007/s40473-018-0164-7
491. Wei, L., Zhang, S., Turel, O., Bechara, A., & He, Q. (2017). A Tripartite Neurocognitive Model of Internet Gaming Disorder. *Frontiers in Psychiatry*, *8*. https://doi.org/10.3389/fpsyt.2017.00285
492. Weinstein, A., & Lejoyeux, M. (2010). Internet Addiction or Excessive Internet Use. *The American Journal of Drug and Alcohol Abuse*, *36*(5), 277–283. https://doi.org/10.3109/00952990.2010.491880
493. Weinstein, A. M. (2017). An Update Overview on Brain Imaging Studies of Internet Gaming Disorder. *Frontiers in Psychiatry*, *8*, 185. https://doi.org/10.3389/fpsyt.2017.00185
494. Weng, C.-B., Qian, R.-B., Fu, X.-M., Lin, B., Han, X.-P., Niu, C.-S., & Wang, Y.-H. (2013). Gray matter and white matter abnormalities in online game addiction. *European Journal of Radiology*, *82*(8), 1308–1312. https://doi.org/10.1016/j.ejrad.2013.01.031
495. Wéry, A., Deleuze, J., Canale, N., & Billieux, J. (2018). Emotionally laden impulsivity interacts with affect in predicting addictive use of online sexual activity in men. *Comprehensive Psychiatry*, *80*, 192–201. https://doi.org/10.1016/j.comppsych.2017.10.004

496. Wessel, J. R. (2018). Prepotent motor activity and inhibitory control demands in different variants of the go/no-go paradigm. *Psychophysiology*, *55*(3). https://doi.org/10.1111/psyp.12871
497. Whiteside, S. P., & Lynam, D. R. (2001). The Five Factor Model and impulsivity: Using a structural model of personality to understand impulsivity. *Personality and Individual Differences*, *30*(4), 669–689. https://doi.org/10.1016/S0191-8869(00)00064-7
498. WHO. (2019). *World Health Organization. International Statistical Classification of Diseases and Related Health Problems. 11th ed.*
499. Widiger, T. A., & Oltmanns, J. R. (2017). Neuroticism is a fundamental domain of personality with enormous public health implications. *World Psychiatry*, *16*(2), 144–145. https://doi.org/10.1002/wps.20411
500. Wiebking, C., & Northoff, G. (2014). Interoceptive awareness and the insula—Application of Neuroimaging Techniques in Psychotherapy. *GSTF Journal of Psychology (JPsych)*, *1*(1), 8. https://doi.org/10.7603/s40790-014-0008-1
501. Winstanley, C. A., Eagle, D. M., & Robbins, T. W. (2006). Behavioral models of impulsivity in relation to ADHD: Translation between clinical and preclinical studies. *Clinical Psychology Review*, *26*(4), 379–395. https://doi.org/10.1016/j.cpr.2006.01.001
502. World Health Organization. (2015). *Public health implications of excessive use of the internet, computers, smartphones and similar electronic devices: Meeting report, Main Meeting Hall, Foundation for Promotion of Cancer Research, National Cancer Research Centre, Tokyo, Japan, 27-29 August 2014*. World Health Organization. https://iris.who.int/handle/10665/184264
503. World Health Organization. (1948). Summary report on proceedings, minutes and final acts of the International Health Conference held in New York from 19 June to 22 July 1946. United Nations, World Health Organization, Interim Commission. https://iris.who.int/handle/10665/85573
504. Wu, X., Guo, J., Wang, Y., Zou, F., Guo, P., Lv, J., & Zhang, M. (2020). The Relationships Between Trait Creativity and Resting-State EEG Microstates Were Modulated by Self-Esteem. *Frontiers in Human Neuroscience*, *14*, 576114. https://doi.org/10.3389/fnhum.2020.576114
505. Xie, X., Cheng, H., & Chen, Z. (2023). Anxiety predicts internet addiction, which predicts depression among male college students: A cross-lagged comparison by sex. *Frontiers in Psychology*, *13*, 1102066. https://doi.org/10.3389/fpsyg.2022.1102066
506. Xu, J., Shen, L., Fei, H., Zhou, W., Wan, F., & Nan, W. (2024). Effect of excessive internet gaming on inhibitory control based on resting EEG and ERP. *iScience*, *27*(8), 110399. https://doi.org/10.1016/j.isci.2024.110399
507. Yan, C., Liu, D., He, Y., Zou, Q., Zhu, C., Zuo, X., Long, X., & Zang, Y. (2009). Spontaneous Brain Activity in the Default Mode Network Is

Sensitive to Different Resting-State Conditions with Limited Cognitive Load. *PLOS ONE*, *4*(5), e5743. https://doi.org/10.1371/journal.pone.0005743
508. Yan, X., Gao, W., Yang, J., & Yuan, J. (2022). Emotion Regulation Choice in Internet Addiction: Less Reappraisal, Lower Frontal Alpha Asymmetry. *Clinical EEG and Neuroscience*, *53*(4), 278–286. https://doi.org/10.1177/15500594211056433
509. Yao, Y.-W., Wang, L.-J., Yip, S. W., Chen, P.-R., Li, S., Xu, J., Zhang, J.-T., Deng, L.-Y., Liu, Q.-X., & Fang, X.-Y. (2015). Impaired decision-making under risk is associated with gaming-specific inhibition deficits among college students with Internet gaming disorder. *Psychiatry Research*, *229*(1), 302–309. https://doi.org/10.1016/j.psychres.2015.07.004
510. Yen, J.-Y., Liu, T.-L., Wang, P.-W., Chen, C.-S., Yen, C.-F., & Ko, C.-H. (2017). Association between Internet gaming disorder and adult attention deficit and hyperactivity disorder and their correlates: Impulsivity and hostility. *Addictive Behaviors*, *64*, 308–313. https://doi.org/10.1016/j.addbeh.2016.04.024
511. Yin, J., Yuan, K., Feng, D., Cheng, J., Li, Y., Cai, C., Bi, Y., Sha, S., Shen, X., Zhang, B., Xue, T., Qin, W., Yu, D., Lu, X., & Tian, J. (2016). Inhibition control impairments in adolescent smokers: Electrophysiological evidence from a Go/NoGo study. *Brain Imaging and Behavior*, *10*(2), 497–505. https://doi.org/10.1007/s11682-015-9418-0
512. Young, K. S. (1998). Internet Addiction: The Emergence of a New Clinical Disorder. *CyberPsychology & Behavior*, *1*(3), 237–244. https://doi.org/10.1089/cpb.1998.1.237
513. Yu, H., Zhao, X., Li, N., Wang, M., & Zhou, P. (2009). Effect of excessive Internet use on the time–frequency characteristic of EEG. *Progress in Natural Science*, *19*(10), 1383–1387. https://doi.org/10.1016/j.pnsc.2008.11.015
514. Yu, J., Abdullah, M. F. I. L., & Mansor, N. S. (2024). EEG components of inhibitory control ability in internet gaming disorder: A systematic review and meta-analysis of randomized controlled trials. *Brain and Behavior*, *14*(1), e3388. https://doi.org/10.1002/brb3.3388
515. Yu, K., Wu, S., & Chi, I. (2021). Internet Use and Loneliness of Older Adults Over Time: The Mediating Effect of Social Contact. *The Journals of Gerontology*, *76*(3), 541–550. https://doi.org/10.1093/geronb/gbaa004
516. Yu, L., & Shek, D. T. L. (2013). Internet addiction in Hong Kong adolescents: A three-year longitudinal study. *Journal of Pediatric and Adolescent Gynecology*, *26*(3 Suppl), S10-17. https://doi.org/10.1016/j.jpag.2013.03.010
517. Yuan, K., Qin, W., Wang, G., Zeng, F., Zhao, L., Yang, X., Liu, P., Liu, J., Sun, J., von Deneen, K. M., Gong, Q., Liu, Y., & Tian, J. (2011). Microstructure Abnormalities in Adolescents with Internet Addiction Disorder. *PLoS ONE*, *6*(6). https://doi.org/10.1371/journal.pone.0020708

518. Zanesco, A. P. (2024). Normative Temporal Dynamics of Resting EEG Microstates. *Brain Topography*, *37*(2), 243–264. https://doi.org/10.1007/s10548-023-01004-4
519. Zanesco, A. P., Denkova, E., & Jha, A. P. (2021). Self-reported Mind Wandering and Response Time Variability Differentiate Prestimulus Electroencephalogram Microstate Dynamics during a Sustained Attention Task. *Journal of Cognitive Neuroscience*, *33*(1), 28–45. https://doi.org/10.1162/jocn_a_01636
520. Zhang, B.-W., Zhao, L., & Xu, J. (2007). Electrophysiological activity underlying inhibitory control processes in late-life depression: A Go/Nogo study. *Neuroscience Letters*, *419*(3), 225–230. https://doi.org/10.1016/j.neulet.2007.04.013
521. Zhang, H., Zhang, H., Shan, L., Xia, Y., & Zhao, Y. (2023). Internet accessibility and incident depressive symptoms in middle aged and older adults in China: A national longitudinal cohort study. *Journal of Affective Disorders*, *340*, 355–361. https://doi.org/10.1016/j.jad.2023.08.050
522. Zhang, J., Li, X., Liu, S., Xu, C., & Zhang, Z. (2024). Frequent media multitasking modulates the temporal dynamics of resting-state electroencephalography networks. *International Journal of Psychophysiology*, *195*, 112265. https://doi.org/10.1016/j.ijpsycho.2023.112265
523. Zhang, J., Yao, Y.-W., Li, C., Zang, Y.-F., Shen, Z., Liu, L., Wang, L., Liu, B., & Fang, X. (2015). Altered resting-state functional connectivity of the insula in young adults with Internet gaming disorder: RsFC of insula in IGD. *Addiction Biology*, *21*. https://doi.org/10.1111/adb.12247
524. Zhang, J.-T., Yao, Y.-W., Potenza, M. N., Xia, C.-C., Lan, J., Liu, L., Wang, L.-J., Liu, B., Ma, S.-S., & Fang, X.-Y. (2016). Effects of craving behavioral intervention on neural substrates of cue-induced craving in Internet gaming disorder. *NeuroImage. Clinical*, *12*, 591–599. https://doi.org/10.1016/j.nicl.2016.09.004
525. Zhang, R., Geng, X., & Lee, T. M. C. (2017). Large-scale functional neural network correlates of response inhibition: An fMRI meta-analysis. *Brain Structure & Function*, *222*(9), 3973–3990. https://doi.org/10.1007/s00429-017-1443-x
526. Zhang, S.-S., Zhong, Y., Li, X., & Peng, M. (2024). Dissociation of prepotent response inhibition and interference control in problematic internet use: Evidence from the Go/No-Go and Flanker tasks. *BMC Psychology*, *12*, 216. https://doi.org/10.1186/s40359-024-01698-6
527. Zhou, F., Montag, C., Sariyska, R., Lachmann, B., Reuter, M., Weber, B., Trautner, P., Kendrick, K. M., Markett, S., & Becker, B. (2019). Orbitofrontal gray matter deficits as marker of Internet gaming disorder: Converging evidence from a cross-sectional and prospective longitudinal design. *Addiction Biology*, *24*(1), 100–109. https://doi.org/10.1111/adb.12570

528. Zhou, H., Gong, L., Su, C., Teng, B., Xi, W., Li, X., Geng, F., & Hu, Y. (2024). White matter integrity of right frontostriatal circuit predicts internet addiction severity among internet gamers. *Addiction Biology*, *29*(5), e13399. https://doi.org/10.1111/adb.13399
529. Zhou, Y., Lin, F., Du, Y., Qin, L., Zhao, Z., Xu, J., & Lei, H. (2011). Gray matter abnormalities in Internet addiction: A voxel-based morphometry study. *European Journal of Radiology*, *79*(1), 92–95. https://doi.org/10.1016/j.ejrad.2009.10.025
530. Zhou, Z., Yuan, G., Yao, J., Li, C., & Cheng, Z. (2010). An event-related potential investigation of deficient inhibitory control in individuals with pathological Internet use. *Acta Neuropsychiatr*. https://doi.org/10.1111/j.1601-5215.2010.00444.x
531. Zhou, Z., Zhou, H., & Zhu, H. (2016). Working memory, executive function and impulsivity in Internet-addictive disorders: A comparison with pathological gambling. *Acta Neuropsychiatrica*, *28*(2), 92–100. https://doi.org/10.1017/neu.2015.54
532. Žukauskienė, R., & Barkauskienė, R. (2006). Psychometric properties of the Lithuanian version of The NEO PI-R. *Psichologija*, *33*, 7–21. https://doi.org/10.15388/Psichol.2006..4320

PUBLICATIONS

Publications included in the thesis:

- **Simkute**, D., Tarailis, P., Griskova-Bulanova, I. (2025). Parietal Alpha Asymmetry as a Correlate of Internet Use Severity in Healthy Adults. [Brain Sciences; accepted]
- **Simkute**, D., Tarailis, P. & Griskova-Bulanova, I. Signs of Problematic Internet use Affect Resting-State EEG Microstates. Brain Topogr 38, 68 (2025). https://doi.org/10.1007/s10548-025-01145-8
- **Simkute**, D., Tarailis, P., Pipinis, E., & Griskova-Bulanova, I. (2025). Assessing the Spectrum of Internet Use in a Healthy Sample: Altered Psychological States and Intact Brain Responses to an Equiprobable Go/NoGo Task. Behavioral Sciences, 15(5), 579. https://doi.org/10.3390/bs15050579.
- **Simkute** D, Wang GY, Griskova-Bulanova I. Interoception, personality, and internet use: Preliminary insights into their association. PLoS One. 2025 Jul 15;20(7):e0328260. doi: 10.1371/journal.pone.0328260. PMID: 40663593; PMCID: PMC12262860.

Conferences on the thesis topic:

- (Oral presentation) „Pilot studies on Association with Spontaneous eye Blinking Rate and Alterations in Brain Activity: an Overview", 13th International Conference of the Lithuanian Neuroscience Association. 26th November, 2021, Vilnius, Lithuania (held online due to the COVID-19 pandemic).
- (Oral presentation) „Internet Usage Habits: Pilot studies on Association with Spontaneous eye Blinking Rate and Alterations in Brain Activity". Conference by COST Action 16207 European Network of Problematic Usage of the Internet "Problematic Internet Use: Moving Forward from Treatment toward Prevention". 6th October, 2021, Lisbon, Portugal.
- (Oral presentation) „Problematic Internet Use and Brain Activity", Lithuanian Congress of Psychologists "Experience without Borders". 23rd April, 2021, Vilnius, Lithuania (held online due to the COVID-19 pandemic).
- (Poster) **Simkute** D, Raciute A, Griskova-Bulanova I. "N2 and P3 components during auditory equiprobable Go/NoGo task in Problematic Internet Use in a sample of non-clinical Internet users". FRM2021 - FENS

Regional Meeting. 25th July, 2021, Kraków, Poland (held online due to the COVID-19 pandemic).

- (Poster) D. Cicchetti, D. **Šimkutė**, I. Griškova-Bulanova. "Associations among patterns of Internet Use and depression, anxiety and impulsivity in a sample of non-clinical internet users".12th International Conference of the Lithuanian Neuroscience Association. 6th November, 2020, Vilnius, Lithuania.

Other publications:

- **Simkute** D, Dores AR, Barbosa F, Griskova-Bulanova I. Problematic Gaming and Gambling: A Systematic Review of Task-Specific EEG Protocols. J Gambl Stud. 2024 Dec;40(4):2153-2187. doi: 10.1007/s10899-024-10332-4. Epub 2024 Jul 13. PMID: 39002089.
- Tarailis P, **Šimkutė** D, Griškova-Bulanova I. Global Functional Connectivity is Associated with Mind Wandering Domain of Comfort. Brain Topogr. 2024 Sep;37(5):796-805. doi: 10.1007/s10548-024-01042-6. Epub 2024 Mar 2. PMID: 38430284.
- Wang GY, **Simkute** D, Griskova-Bulanova I. Neurobiological Link between Stress and Gaming: A Scoping Review. J Clin Med. 2023 Apr 25;12(9):3113. doi: 10.3390/jcm12093113. PMID: 37176554; PMCID: PMC10179187.
- Tarailis P, De Blasio FM, **Simkute** D, Griskova-Bulanova I. Data-Driven EEG Theta and Alpha Components Are Associated with Subjective Experience during Resting State. J Pers Med. 2022 May 29;12(6):896. doi: 10.3390/jpm12060896. PMID: 35743681; PMCID: PMC9225158.
- Pranckeviciene A, Saudargiene A, Gecaite-Stonciene J, Liaugaudaite V, Griskova-Bulanova I, **Simkute** D, Naginiene R, Dainauskas LL, Ceidaite G, Burkauskas J. Validation of the patient health questionnaire-9 and the generalized anxiety disorder-7 in Lithuanian student sample. PLoS One. 2022 Jan 27;17(1):e0263027. doi: 10.1371/journal.pone.0263027. PMID: 35085349; PMCID: PMC8794093.
- Tarailis P, **Šimkutė** D, Koenig T, Griškova-Bulanova I. Relationship between Spatiotemporal Dynamics of the Brain at Rest and Self-Reported Spontaneous Thoughts: An EEG Microstate Approach. J Pers Med. 2021 Nov 17;11(11):1216. doi: 10.3390/jpm11111216. PMID: 34834568; PMCID: PMC8625384.
- **Simkute** D, Nagula I, Tarailis P, Burkauskas J, Griskova-Bulanova I. Internet Usage Habits and Experienced Levels of Psychopathology: A

Pilot Study on Association with Spontaneous Eye Blinking Rate. J Pers Med. 2021 Apr 9;11(4):288. doi: 10.3390/jpm11040288. PMID: 33918557; PMCID: PMC8068990.

- Gecaite-Stonciene J, Saudargiene A, Pranckeviciene A, Liaugaudaite V, Griskova-Bulanova I, **Simkute** D, Naginiene R, Dainauskas LL, Ceidaite G, Burkauskas J. Impulsivity Mediates Associations Between Problematic Internet Use, Anxiety, and Depressive Symptoms in Students: A Cross-Sectional COVID-19 Study. Front Psychiatry. 2021 Jan 28;12:634464. doi: 10.3389/fpsyt.2021.634464. PMID: 33633614; PMCID: PMC7901993.

Other conferences:

- (poster) D, **Simkute**, A. R Dores, F. Barbosa, I. Griskova-Bulanova. "Gaming and Gambling: a systematic review of task-specific EEG protocols". The 14th International Conference of the Lithuanian Neuroscience Association, 25th November, 2022, Vilnius, Lithuania.
- (poster) I. Nagula, D. **Šimkutė**, I. Griškova Bulanova. "Spontaneous eye blink rate as an indicator of dopaminergic transmission in problematic Internet use". The 12th International Conference of the Lithuanian Neuroscience Association, 6th November, 2020, Vilnius, Lithuania.

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- Junior Assistant, Vilnius University Life Sciences Center, Institute of Biosciences (since 2019).
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Teaching experience

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- Workshops on EEG methodology, EEG data preprocessing, and Human EEG: Event-Related Potentials in the “Bioelectric Processes” course for MSc (2021-present).

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Training schools, courses and workshops attended

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Science promotion

Engaged in over 20 public outreach activities outside academia on topics related to internet use, brain function, mental health, and digital hygiene (2020-2025):

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- Provided interviews for radio programs such as LRT Radio “10–12”, “Mąstymo žemėlapis”, “Mokslas skubantiems”, “Pakeliui su klasika”, M-1+ Radio.
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Professional memberships

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SANTRAUKA

1. ĮVADAS

Internetas per pastaruosius dešimtmečius tapo viena svarbiausių šiuolaikinio gyvenimo sudedamųjų dalių – skaičiuojama, kad juo naudojasi daugiau nei du trečdaliai pasaulio gyventojų (Statista, 2025). Sparti internetinių technologijų plėtra lėmė, kad skaitmeninė sąveika tapo neatsiejama kasdienio gyvenimo dalimi, ypač tarp jaunesnių naudotojų, kuriems būdingas nuolatinis prisijungimas prie skaitmeninių platformų (Massarat, 2022; Pew Research Center, 2024). Plačiai paplitęs interneto naudojimas suteikė naujų galimybių ir privalumų: užtikrino momentinę prieigą prie informacijos, sudarė galimybes bendrauti globaliai, pagerino švietimo prieinamumą ir supaprastino paslaugų teikimą (Huang et al., 2021; Lemenager et al., 2020; Nimrod, 2020). Be to, daugelio skaitmeninių platformų dizainas – pasižymintis tokiomis ypatybėmis kaip begalinis slinkimas (angl. *endless scrolling*), įtraukianti aplinka su kintamo atlygio sistemos komponentais (angl. *variable reward system*), dėmesį pritraukiantys skaitmeniniai elementai ir algoritmų pagrindu teikiamas personalizuotas turinys – neatsitiktinai kuriamas taip, kad būtų itin įtraukus ir naudotojai platformose praleistų kuo daugiau laiko (Fineberg et al., 2025; Z. Liu, 2005; Nicholas et al., 2009; Robbins & Clark, 2015). Atitinkamai, pasekmės, susijusios su interneto naudojimu, skiriasi priklausomai nuo jo naudojimo pobūdžio ir intensyvumo.

Nors tikslingas ir sąmoningas naudojimasis internetu gali skatinti asmeninį tobulėjimą ir stiprinti socialinius ryšius, perteklinis ar netinkamas įsitraukimas – plačiai apibrėžiamas kaip probleminis interneto naudojimas (PIN; angl. *Problematic Internet Use*) – gali sukelti reikšmingų psichologinių ir funkcinio veikimo sutrikimų (Fineberg et al., 2022; Ioannidis et al., 2019; Kuss & Lopez-Fernandez, 2016; Lissak, 2018; Sun et al., 2020; Weinstein & Lejoyeux, 2010). Manoma, kad PIN paplitimas siekia apie 7 % pasaulio gyventojų (Pan et al., 2020), o pasaulinė sveikatos organizacija (PSO) internetą pripažino kylančia visuomenės sveikatos problema (World Health Organization, 2015). Taigi internetas – nepakeičiamas įrankis daugeliui kasdienių veiklų atlikti, tačiau tuo pačiu galintis skatinti netinkamą elgesį, darantį neigiamą poveikį asmens funkcionavimui ir gerovei.

Įprastai PIN apibrėžiamas kaip interneto naudojimo kontrolės sutrikimas, sukeliantis reikšmingas neigiamas pasekmes ir pasireiškiantis spektre nuo saikingo iki patologinio įsitraukimo (Anderson et al., 2017; Billieux et al., 2015; Fineberg et al., 2018; Ioannidis et al., 2019; Kaess et al., 2021; Kuss &

Lopez-Fernandez, 2016). PIN taip pat pasižymi priklausomybėms būdingais simptomais, tokiais kaip kompulsinis įsitraukimas, sutrikusi savikontrolė, potraukio (angl. *craving*) būsena, abstinencijos požymiai bei elgesio tąsa nepaisant neigiamų pasekmių (American Psychiatric Association, 2013; Griffiths, 2019; Ioannidis et al., 2019; Mihajlov & Vejmelka, 2017). Vis dėlto šių simptomų raiška ir interpretacija gali reikšmingai skirtis priklausomai nuo interneto naudojimo pobūdžio, o tai lemia nuolatines diskusijas dėl PIN konceptualizavimo ir diagnostinių kriterijų (Aarseth et al., 2017; Baggio et al., 2022; Billieux et al., 2019; Gullo et al., 2022; Kardefelt-Winther, 2017; Kuss & Lopez-Fernandez, 2016; Starcevic & Aboujaoude, 2017).

Šiuo metu PIN nėra formaliai pripažįstamas sutrikimu, o bendro sutarimo stoka šioje srityje reikšmingai riboja tyrimų rezultatų palyginamumą, klinikinio įvertinimo galimybes ir veiksmingų intervencinių strategijų kūrimą. Vis dėlto augant problemos mastui intensyvėja ir tarpdisciplininiai tyrimai, kuriais siekiama identifikuoti PIN sąsajas su fiziniais, psichologiniais, socialiniais, kognityviniais ir neurofiziologiniais veiksniais bei suprasti jų tarpusavio sąveikas (Fineberg et al., 2022; Kuss & Lopez-Fernandez, 2016; Lissak, 2018; Mihajlov & Vejmelka, 2017). Tačiau, nepaisant pažangos, tebėra reikšmingų spragų aiškinant PIN atsiradimo ir palaikymo mechanizmus, o subtilesni aspektai tik pradeda sulaukti tyrėjų dėmesio.

Vienas tokių veiksnių – interocepcija (angl. *interoception*) – gebėjimas jausti ir interpretuoti vidinius kūno signalus (pvz., širdies plakimą, alkį ar visceralinius emocinius pojūčius) (Craig, 2002; Khalsa et al., 2018). Interocepcija yra esminė emocinio sąmoningumo ir emocijų reguliacijos sudedamoji dalis, tačiau jos vaidmuo PIN kontekste iki šiol beveik netyrinėtas. Teoriškai, prasta interocepcinė įžvalga galėtų apsunkinti vidinių būsenų, tokių kaip stresas ar nuobodulys, atpažinimą, o šių sunkumų pasekmės gali apimti ne tik emocinį disbalansą, bet ir įtakoti sprendimų priėmimo procesus (Herman, 2023; Khalsa et al., 2018; Namkung et al., 2018). Priklausomybių nuo psichoaktyviųjų medžiagų tyrimuose mažesnis interocepcinis įsisąmoninimas (angl. *interoceptive awareness*) siejamas su rizikingesniais pasirinkimais ir impulsyvumu – tikėtina, todėl, kad somatiniai „įspėjamieji signalai“, kurie paprastai padeda orientuotis priimant sprendimus, tampa slopinami arba iškraipomi (Herman, 2023; Naqvi & Bechara, 2010; Paulus & Stewart, 2014). Analogiškai, PIN kontekste sumažėjęs gebėjimas sąmoningai suvokti savo kūno pojūčius galėtų skatinti impulsyvesnį ar intensyvesnį naudojimąsi internetu, keliant prielaidą, kad silpnas savo (psicho)fiziologinių kūno signalų suvokimas gali būti vienas iš veiksnių, didinančių polinkį į neadaptyvų elgesį internete. Taigi integruojant iki šiol menkai tyrinėtus konstruktus, tokius kaip interocepcija, į PIN tyrimus, būtų galima gilinti supratimą apie psichofiziologinių veiksnių įtaką netinkamo interneto naudojimo vystymusi.

Be psichologinių ypatumų, kognityviniai ir neurofiziologiniai rodikliai yra reikšmingi veiksniai, padedantys charakterizuoti PIN. Šioje srityje atliktų tyrimų rezultatai dažnai yra panašūs į duomenis, gautus tiriant psichoaktyviųjų medžiagų vartojimo sutrikimus bei elgesio priklausomybes (D'Hondt et al., 2015; Kuss & Griffiths, 2012; Yuan et al., 2011). Vienas iš pagrindinių kognityvinių komponentų, siejamų su priklausomybiniu ir kompulsiniu elgesiu, yra sutrikusi slopinimo kontrolė (angl. *inhibitory control*), t. y. sumažėjęs gebėjimas slopinti netinkamus impulsus ar veiksmus (Beppi et al., 2020; Kozak et al., 2019; Winstanley et al., 2006; Zhang et al., 2017). Asmenys, pasižymintys požymiais, būdingais PIN, taip pat dažnai pasižymi ir sutrikusiu atsako slopinimu (angl. *response inhibition*); tai patvirtina tiek elgsenos, tiek neurovaizdinimo tyrimų rezultatai (Anderson et al., 2017; Argyriou et al., 2017; D'Hondt & Maurage, 2017; Dong & Potenza, 2014).

Vis dėlto šie rezultatai nėra visiškai nuoseklūs. Pavyzdžiui, taikant elektroencefalografijos (EEG) su įvykiu susijusių potencialų (SĮSP; angl. *event-related potentials*) metodiką, atsako slopinimo užduotyse tarp asmenų, pasižyminčių aukštesniu PIN lygiu, nustatomi N2 ir P3 potencialų skirtumai lyginant su kontrolės grupėmis. P3 potencialas laikomas dėmesio resursų perskirstymo bei impulsyvumo kontrolės efektyvumo rodikliu, o N2 siejamas su konflikto aptikimu ir ankstyvaisiais slopinimo mechanizmais (Fogarty et al., 2020a; Luijten et al., 2014; Pires et al., 2014). Kai kuriuose tyrimuose nustatomas šių SĮSP amplitudžių sumažėjimas, kituose – padidėjimas, o dar kituose fiksuojami nereikšmingi nuokrypiai arba pokyčių visai nenustatoma (pvz., Dong et al., 2010; Kim et al., 2017; Li et al., 2020; Littel et al., 2012; Luijten et al., 2014). Taip pat, dalyje šių tyrimų fiksuojami ir užduočių atlikimo skirtumai tarp PIN ir kontrolės grupių, nors kai kuriais atvejais skirtumai tarp grupių fiksuojami tik neurofiziologiniu lygmeniu, o elgesio rodikliai išlieka nepakitę. Tokie rezultatai leidžia kelti prielaidą, kad signalai neurofiziologiniame lygmenyje galėtų būti identifikuojami dar prieš išryškėjant elgsenos pokyčiams. Atitinkamai, tiriant sveikus, reguliariai internetu besinaudojančius asmenis, neurofiziologinių parametrų (pvz., SĮSP) ir kognityvinių užduočių (pvz., atsako slopinimo) elgseninių rodiklių duomenys galėtų atskleisti vertingų įžvalgų apie tai, kaip smegenys apdoroja informaciją ir kontroliuoja impulsus priklausomai nuo interneto naudojimo pobūdžio (visame spektre nuo neprobleminio iki probleminio).

Be užduotimis grįstų eksperimentinių paradigmų, ramybės būsenos smegenų aktyvumo tyrimai suteikia papildomų įžvalgų vertinant bazinį smegenų funkcionavimą. EEG ir funkcinio magnetinio rezonanso tomografijos (fMRT) tyrimai atskleidžia ramybės būsenos smegenų aktyvumo skirtumus tarp intensyviai įvairiomis internetinėmis platformomis besinaudojančių asmenų ir kontrolės grupių (pvz., Burleigh et al., 2020; Lee et al., 2014; Sun et al., 2019; Wang & Griskova-Bulanova, 2018; Wang et al., 2015); atitinkamai, keliama prielaida, kad tokius skirtumus atspindintys rodikliai galėtų būti svarstomi kaip potencialūs biologiniai žymenys (biomarkeriai) PIN identifikavimui ir eigos stebėsenai.

Vienas galimų kandidatų – mikrobūsenos (angl. *microstate*), kurių analizė suteikia galimybę kiekybiškai ir laiko atžvilgiu preciziškai vertinti neurodinamikos rodiklius (Khanna et al., 2015; Tarailis et al., 2024). Jau atlikti tyrimai atskleidė neuroninių tinklų sąveikos skirtumus tarp sveikų tiriamųjų ir asmenų, turinčių PIN, internetinių žaidimų sutrikimą (IGD; angl., *Internet Gaming Disorder*) ar kitų su internetu susijusio probleminio elgesio formų (Cui et al., 2021; Li et al., 2021; Qi et al., 2023; Wang et al., 2021). Pavyzdžiui, mikrobūsenų profiliai gali reikšmingai skirtis tarp asmenų, turinčių IGD, kompiuterinius žaidimus laisvalaikiu žaidžiančių asmenų ir visai kompiuterinių žaidimų nežaidžiančių kontrolės grupės dalyvių (Wang et al., 2021), taip pat tarp kompiuterinių veiksmo žaidimų ekspertų ir mėgėjų (Cui et al., 2021). Intensyvių žaidėjų grupėse kai kurios mikrobūsenų klasės pasižymi pakitusia trukme (angl. *duration*) arba pasikartojimo dažniu (angl. *occurrence*). Nors tiriamos imtys ir eksperimentiniai dizainai tarp šių tyrimų skiriasi, jų rezultatai iš esmės yra nuoseklūs. Tai suteikia pagrindą manyti, kad mikrobūsenų analizė galėtų būti taikoma PIN kontekste, diferencijuojant smegenų veiklos dinamikos ypatybes – tiek funkcinio pobūdžio, tiek potencialiai žalingas. Vis dėlto iki šiol atlikta nedaug tyrimų, kuriuose mikrobūsenų analizė būtų taikyta PIN srityje, o neklinikinėse populiacijose ši metodika nebuvo naudota. Tai žymi reikšmingą spragą, atsižvelgiant į šios metodikos potencialą identifikuoti subtilius smegenų veiklos pokyčius dar iki problemiško įsitraukimo elgseninių apraiškų.

Kitas dažnai analizuojamas EEG ramybės būsenos parametras yra alfa dažnio (8-12Hz) bangų aktyvumas. Manoma, kad aktyvumas šiame diapazone atspindi sumažėjusį žievės aktyvumą ir slopinimo procesus, kuriems būdinga plataus masto neuroninių tinklų sinchronizacija smegenyse (Reznik & Allen, 2018; Smith et al., 2017). Vienas iš su alfa bangų aktyvumu susijusių rodiklių – alfa asimetrija, atspindinti hemisferinį (t.y. pusrutulių) alfa galios disbalansą. Alfa asimetrija nuosekliai siejama su afektiniais, motyvaciniais ir kognityviniais procesais, o atipiniai alfa asimetrijos profiliai stebimi įvairių psichiatrinių ir neurovystymosi sutrikimų metu (Ocklenburg et al., 2024; Reznik & Allen, 2018; Smith et al., 2017). Nors ramybės būsenos alfa asimetrija yra vienas iš plačiausiai ištirtų smegenų lateralizacijos rodiklių, iki šiol daugiausia dėmesio skirta frontalinių sričių asimetrijai. Tuo tarpu parietalinės srities alfa asimetrija, nepaisant jos ryšio su dėmesio paskirstymu, emociniu pažeidžiamumu ir su internalizacija siejamais simptomais (Metzen et al., 2022; Schiltz et al., 2018; Umemoto et al., 2021), iš esmės liko nagrinėta menkai (Metzen et al., 2022; Wang et al., 2025). Nors kai kurie pastaraisiais metais atlikti tyrimai identifikavo alfa galios ir susijusių rodiklių pokyčius PIN kontekste (Burleigh et al., 2020; Sun et al., 2019; Wang & Griskova-Bulanova, 2018; Wang et al., 2017), šių duomenų kiekis ribotas. Iki šiol nebuvo atlikta tyrimų, kurie nagrinėtų parietalinės srities alfa asimetriją PIN kontekste, tad klausimas, ar – ir jei taip, kaip – smegenų veiklos lateralizacijos pokyčiai parietalinėje srityje atspindi ankstyvojo probleminio įsitraukimo į internetines veiklas formavimąsi, lieka neatsakytas.

Apibendrinant galima teigti, kad PIN vystosi visuotinio interneto prieinamumo fone ir pasireiškia kontinuume – nuo funkcionalaus įsitraukimo iki galinčio kelti sunkumų kasdienybėje. Vis dėlto tyrimuose PIN dažniausiai vertinamas kaip dichotominė būsena – arba aiškiai išreikštas, arba visai neegzistuojantis – taip ignoruojant laipsnišką progresiją nuo epizodinio ar perteklinio iki probleminio įsitraukimo. Toks požiūris kelia riziką nepastebėti ankstyvų ar iki klinikinių PIN formų, kurios, nors ir neatitinka diagnostinių kriterijų, gali reikšmingai trikdyti kasdienį funkcionavimą. Be to, reguliarūs interneto naudotojai sudaro gerokai didesnę visuomenės dalį nei klinikinės populiacijos, tačiau žinių apie tai, kaip interneto naudojimas pasireiškia šioje platesnėje, neklinikinėje grupėje, stinga.

Išsamesnis, integruotas požiūris – apjungiantis psichologinius, elgseninius ir neurofiziologinius duomenis – bei apimantis asmenis visame interneto naudojimo spektre galėtų reikšmingai praturtinti PIN srities tyrimus. Pavyzdžiui, tiriant sąsajas tarp interneto naudojimo įpročių ir psichologinių bruožų (pvz., depresijos, nerimo ir obsesinio-kompulsinio elgesio simptomų, interocepcinio įsisąmoninimo, asmenybės bruožų) bei neurofiziologinių rodiklių (tokių kaip mikrobūsenos, alfa asimetrija, SĮSP) tarp reguliarių interneto naudotojų, būtų galima išsamiau suprasti rizikos veiksnius ir su jais susijusius neuropsichologinius mechanizmus.

Būtent tokia metodika ir taikoma šiame darbe: interneto naudojimo įpročiai nagrinėjami neklinikinėje imtyje, siekiant identifikuoti subtilius psichologinius ir neurofiziologinius požymius, susijusius su ankstyvu probleminio įsitraukimo formavimusi. Tikimasi, kad šio tyrimo rezultatai prisidės prie aiškesnio PIN sampratos formavimo ir padės tobulinti ankstyvo probleminio įsitraukimo atpažinimo priemones, taip įgalinant prevencinių priemonių taikymą dar iki interneto naudojimui peraugant į reikšmingus kasdienio funkcionavimo sutrikimus.

1.1. Tikslas ir uždaviniai

Šio darbo tikslas buvo įvertinti interneto naudojimo įpročių sąsajas su psichologiniais, asmenybės bruožų, interocepcinio įsisąmoninimo bei neurofiziologiniais rodikliais neklinikinėje populiacijoje, taikant savistatos (angl. *self-report*) klausimynus, atsako slopinimo užduotį ir EEG galvos smegenų elektrinio aktyvumo matavimus. Buvo keliami šie uždaviniai:

- Ištirti sąsajas tarp interneto naudojimo įpročių ir nerimo, depresijos ir obsesinio-kompulsinio pobūdžio simptomų.
- Ištirti sąsajas tarp interneto naudojimo įpročių, interocepcinio įsisąmoninimo aspektų ir asmenybės bruožų taikant tinklinės analizės (angl. *network analysis*) metodą.
- Ištirti sąsajas tarp interneto naudojimo įpročių ir klausos lygių galimybių Go/NoGo užduoties atlikimo elgseninių parametrų.
- Ištirti sąsajas tarp interneto naudojimo įpročių ir su įvykiu susijusių potencialų (N1,P2, N2, P3) parametrų, išmatuotų atliekant klausos lygių galimybių Go/NoGo užduotį.
- Ištirti sąsajas tarp interneto naudojimo įpročių ir ramybės būsenos alfa asimetrijos frontaliniuose ir parietaliniuose smegenų regionuose.
- Ištirti sąsajas tarp interneto naudojimo įpročių ir ramybės būsenos mikrobūsenų parametrų.

1.2. Mokslinis naujumas

Pirmą kartą EEG žymenys (su įvykiu susiję potencialai, mikrobūsenos, alfa asimetrija) buvo tiriami neklinikinėje reguliarių interneto naudotojų populiacijoje, peržengiant įprastą dichotominį PIN skirstymą į sutrikimą turinčius ir sutrikimo neturinčius asmenis.

Taip pat tai pirmasis tyrimas, kuriame ramybės būsenos parietalinė alfa asimetrija analizuojama PIN kontekste.

Tai yra antrasis tyrimas, kuriame interocepcinio įsisamoninimo aspektai nagrinėjami PIN kontekste, ir pirmasis, kuriame tinklinės analizės metodas taikomas tiriant interocepcinio įsisąmoninimo ir asmenybės bruožų sąsajas su PIN neklinikinėje imtyje.

1.3. Praktinis pritaikymas

PIN tyrimų plėtojimas įtraukiant reguliarius interneto naudotojus ir analizuojant psichologinių veiksnių, asmenybės bruožų, interocepcinio įsisamoninimo bei EEG rodiklių sąsajas visame įsitraukimo spektre galėtų:

- Prisidėti prie ankstyvo PIN atpažinimo pastangų, kuriomis siekiama identifikuoti subtilius, subklininius požymius, signalizuojančius apie PIN riziką dar iki išsivystant kliniškai reikšmingam sutrikimui.
- Prisidėti prie neinvazinių diagnostikos priemonių, leidžiančių patikimai identifikuoti ankstyvąsias probleminio interneto naudojimo formas tiek mokslinių tyrimų, tiek psichikos sveikatos priežiūros kontekste, taip sudarant sąlygas savalaikei intervencijai, vystymo.
- Suteikti naujų įžvalgų, ar psichologiniai ir neurofiziologiniai rodikliai, dažnai siejami su PIN, pasireiškia ir tarp reguliarių interneto naudotojų. Gauti duomenys galėtų padėti aiškiau atriboti probleminį naudojimą nuo intensyvaus, bet normatyvaus įsitraukimo, išvengiant kasdienio elgesio patologizavimo.
- Gilinti supratimą apie interneto naudojimo modelius ir pažeidžiamumo veiksnius, kurie gali likti nepastebėti neklinikinėse populiacijose, taip kuriant pagrindą prevencinėms psichikos sveikatos strategijoms ir atsparumo stiprinimui.
- Pasiūlyti įžvalgų psichikos sveikatos specialistams, pedagogams, tyrėjams, politikos formuotojams ir interneto naudotojams apie subklinikinio PIN pobūdį – skatinant geresnį atpažinimą, savistabą ir labiau pritaikytas, sveiką interneto naudojimą palaikančias gaires.

1.4. Ginamieji teiginiai

1. „Nepaisymo“ ir „Pasitikėjimo“ interocepcinio įsisąmoninimo aspektai koreliuoja su interneto naudojimo intensyvumu, rodydami sąsają tarp žemesnio interocepcinio įsisąmoninimo ir problemiškesnio interneto naudojimo. Neurotiškumas sieja sumažėjusį kūno pojūčių suvokimą ir PIN.
2. Elgseniniai klausos lygių galimybių Go/NoGo užduoties atlikimo parametrai neatskleidė sąsajų su interneto naudojimo įpročiais.
3. N1 ir NoGo-P3 komponentai koreliuoja su atskiromis interneto naudojimo sritimis (žaidimai, paieška internete). SĮSP neparodė sąsajų su bendru interneto naudojimo lygiu ir nediferencijavo tarp skirtingo interneto naudojimo intensyvumo grupių.

4. Ramybės būsenos parietalinė alfa asimetrija koreliuoja su interneto naudojimu, rodydama sąsają tarp didesnio kairiojo pusrutulio parietalinės srities aktyvumo ir aukštesnio interneto naudojimo lygio.
5. Ramybės būsenos mikrobūsenos E parametrai (pasirodymo dažnis ir indėlis) koreliuoja su didesniu interneto naudojimu, rodydami, kad didesnis MS E aktyvumas susijęs su intensyvesniu interneto naudojimu.

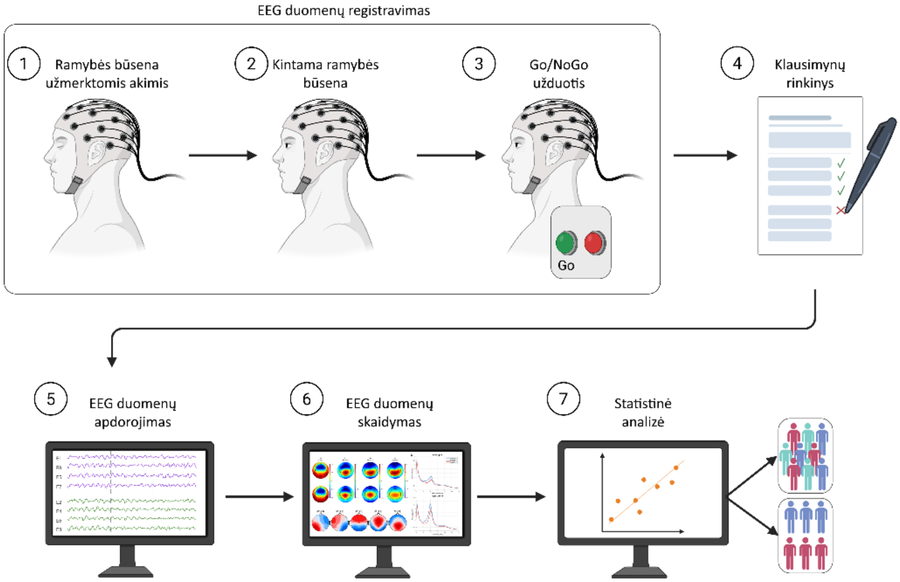
2. METODAI

Eksperimentinės procedūros schema pavaizduota pav.2.1. Kiekvienas eksperimentas prasidėdavo pasiruošimu EEG registravimo sesijai (tiriamųjų supažindinimas su eiga, paruošimas, psichofiziologinių signalų registravimo kokybės patikra). EEG registravimą sudarė trys sąlygos: 5 minučių trukmės ramybės būsena užmerktomis akimis (1), 4 minučių kintama ramybės būsena, sudaryta iš 2 minučių atmerktomis ir 2 minučių užmerktomis akimis (2), ir klausos lygių tikimybių Go/NoGo užduotis (3).

Po EEG sesijos dalyviai pildė klausimynų rinkinį (4), kuriuo buvo vertinami interneto naudojimo įpročiai ir psichologiniai veiksniai, įskaitant emocinę būklę, asmenybės bruožus ir interocepcinį įsisąmoninimą.

Surinkti EEG duomenys buvo apdorojami taikant standartines procedūras (5), išskiriant konkrečiai paradigmai specifinius rodiklius (6): SĮSP iš Go/NoGo užduoties, mikrobūsenų parametrai iš ramybės būsenos (užmerktomis akimis) duomenų ir alfa galios bei asimetrijos indeksai iš kintamos ramybės būsenos duomenų rinkinių.

Galiausiai buvo atliktos statistinės analizės (7), siekiant įvertinti sąsajas tarp interneto naudojimo modelių, elektrofiziologinių rodiklių ir psichologinių ypatybių. Visų duomenų rinkinių analizės metu taikytos dvi analizės strategijos: visos imties mastu ir tarp PIUQ-9 (devynių teiginių probleminio interneto naudojimo klausimynas) pagrindu suformuotų žemo ir aukšto interneto naudojimo grupių.



Pav.2.1. Eksperimentinės procedūros seka.

2.1. Dalyviai

Tyrimo imtį sudarė 161 dalyvis (71 vyras ir 90 moterų) nuo 18 iki 35 metų amžiaus (amžiaus vidurkis 24,21 ± 4,28 metų). Vyrai buvo statistiškai reikšmingai vyresni nei moterys (25,56 ± 4,32, 23,14 ± 43,96, $p < .001$). Didžioji dauguma dalyvių (96,3%) nurodė esantys dešiniarankiai, reikšmingų skirtumų tarp lyčių pagal rankų dominavimą nenustatyta ($p = 0,521$). Kūno masės indeksas (KMI) taip pat skyrėsi pagal lytį – vyrų KMI buvo reikšmingai aukštesnis nei moterų ($p < .001$, 23,82 ± 4,29 vs. 21,76 ± 3,04 kg/m^2, bendras grupės vidurkis 22,68 ± 3,78 kg/m^2). Dauguma dalyvių (50,3 %) nurodė turintys aukštąjį išsilavinimą, reikšmingų skirtumų tarp lyčių pagal išsilavinimo lygį nenustatyta ($p = 0,062$). Dalyvių demografinės charakteristikos pateiktos 2.1 lentelėje.

Tyrimo dalyviai turėjo normalią arba koreguotą iki normalios regą bei klausą, taip pat patvirtino gerą bendrą sveikatos būklę. Tyrime dalyvavusios moterys buvo ne nėščios, nevartojo hormoninės kontracepcijos ir nurodė, kad jų menstruacijų ciklas buvo reguliarus bent tris mėnesius iki dalyvavimo eksperimente. Atsižvelgiant į tai, kad hormoniniai svyravimai skirtingose menstruacinio ciklo fazėse gali reikšmingai paveikti kognityvinius procesus ir vykdomųjų funkcijų EEG rodiklius (Griskova-Bulanova et al., 2016), moterys buvo tiriamos ankstyvojoje folikulinėje fazėje, t. y. pirmosiomis menstruacijų dienomis, siekiant užtikrinti neurofiziologinių duomenų palyginamumą ir patikimumą. Asmenys, turintys psichikos, neurologinių ar endokrinologinių sutrikimų (tiek buvusių, tiek esamų), vartojantys psichotropines ar psichoaktyviąsias medžiagas (išskyrus nikotiną) arba laikantys save priklausomais ar turintys kliniškai patvirtintų priklausomybių, į tyrimą buvo neįtraukiami.

Dalyvauti tyrime asmenys buvo kviečiami skelbiant informaciją studentų bendruomenėje, socialiniuose tinkluose ir kitose medijų platformose. Visi dalyviai buvo informuoti, kad eksperimento dieną turėtų būti gerai išsimiegoję, o likus bent dviem valandoms iki tyrimo pradžios nevartotų kofeino, energinių gėrimų ir nikotino. Tyrimą patvirtino Vilniaus regiono biomedicininių tyrimų etikos komitetas (Nr. 2019/10-1159-649, patvirtinta 2019 m. spalio 8 d.), tyrimo eiga buvo išsamiai paaiškinta prieš eksperimentą, ir visi tiriamieji pasirašė informuoto sutikimo formą.

Lentelė 1.1. Tiriamųjų demografinės charakteristikos.

Kintamasis	Pakategorė	Dažnis (%)	Vidurkis ± SD	Skirtumas tarp lyčių
Lytis	**Moterys**	90 (55,9)		
	Amžius		23,14 ± 3,96	
	KMI		21,76±3,04	
	Vyrai	71 (44,1)		
	Amžius		25,56 ± 4,32	
	KMI		23,82±4,59	
Amžius (metais)			24,21 ± 4,28	p<0,001*
KMI (kg/m^2)			22,68±3,78	p<0,001*
Rankiškumas	Dešiniarankiai	155 (96,3)		χ^2=1,305, p=0,521**
	Kairiarankiai	5 (3,1)		
	Ambidekstrai	1 (0,6)		
Išsilavinimas	Aukštasis	81 (50,31)		χ^2=7,319, p=0,062**
	Neuniversitetinis	5 (3,11)		
	Profesinis	2 (1,24)		
	Vidurinis	73 (45,34)		

KMI – Kūno masės indeksas, SD – Standartinis nuokrypis. * t-testas nepriklausomoms imtims, ** Pearsono χ^2 kriterijus.

2.1.1. Duomenų praradimo priežastys ir galutinės imtys

Dauguma dalyvių pilnai užpildė visus pateiktus klausimynus (140 iš 161; 87 %). Atskirų klausimynų trūkstamų duomenų dalis svyravo nuo 0 % iki daugiausiai 6,2 %. Atsižvelgiant į aukštą klausimynų užpildymo lygį ir minimalų duomenų praradimą, remiantis literatūroje pateiktomis rekomendacijomis (Mirzaei et al., 2022) trūkstamiems duomenims tvarkyti buvo taikytas porinio išbraukimo metodas (angl. *pairwise deletion*). Atitinkamai, savistatos duomenų analizėse buvo išlaikyta visa tyrimo dalyvių imtis (n=161).

Kalbant apie EEG duomenų rinkinius, duomenų praradimas dėl techninių problemų, prastos užregistruotų duomenų kokybės ar netinkamai įvykdytų užduoties sąlygų svyravo nuo 3,1 % iki 19,25 %, priklausomai nuo konkrečios paradigmos. Atitinkamai, galutines imtis sudarė: 133 dalyviai Go/NoGo užduoties duomenų rinkinyje (vidutinis amžius 24,19 ± 4,27 metų, 74 moterys), 129 dalyviai kintamos ramybės būsenos duomenų rinkinyje (vidutinis amžius 24 ± 4,02 metų, 80 moterų) ir 156 dalyviai ramybės būsenos užmerktomis akimis duomenų rinkinyje (vidutinis amžius – 24,17 ± 4,24 metų, 86 moterys). Dalyvių skaičius, įtrauktas į kiekvieną analizę, pateiktas 2.2 lentelėje.

Lentelė 2.2. Imčių dydžiai, įtraukti į klausimynų ir EEG paradigmų duomenų statistines analizes.

	Visa imtis	Aukšto PIN įverčio grupė	Žemo PIN įverčio grupė
Psichologinių klausimynų dalis	161 (90)	46 (30)	45 (22)
Go/NoGo užduotis	133 (74)	38 (24)	35 (17)
Kintama ramybės būsena *(alfa asimetrija)*	129 (80)	33 (24)	36 (22)
Ramybės būsena užmerktomis akimis *(mikrobūsenos)*	156 (86)	44 (28)	43 (21)

Pastaba. Skliaustuose pateiktas moterų skaičius kiekvienoje imtyje.

2.2. Klausimynai

Visi dalyviai užpildė klausimynų rinkinį, skirtą įvairiems psichologiniams ir asmenybės bruožams įvertinti. Be bendros demografinės informacijos (lytis, amžius, svoris, ūgis, rankiškumas ir išsilavinimas), buvo vertinami interneto naudojimo įpročiai (PIUQ-9 ir DPIU). Taip pat buvo vertinami nerimo (BAI), depresijos (BDI-II) ir obsesijų-kompulsijų (CBOCI) simptomai. Asmenybės bruožai buvo vertinami taikant NEO PI-R klausimyną, o interocepcinis įsisąmoninimas – naudojant MAIA skalę.

2.2.1. Devynių teiginių probleminio interneto naudojimo klausimynas (PIUQ-9)

PIUQ-9 (Koronczai et al., 2011) klausimynas yra sutrumpinta PIUQ (Demetrovics et al., 2008) versija ir yra laikomas patikima priemonė identifikuoti PIN. PIUQ-9 sudaro 9 teiginiai, išlaikantys pradinio, 18 teiginių turinčio, PIUQ klausimyno trijų faktorių struktūrą, apimančią įkirybę (angl. *obsession*), aplaidumą (angl. *neglect*) ir kontrolės sutrikimą (angl. *control disorder*). Dalyviai kiekvieną teiginį vertina penkiabalėje Likerto skalėje nuo „Niekada“ (1) iki „Visada / Beveik visada“ (5). Bendras balas gali svyruoti nuo 9 iki 45, kur aukštesni balai atspindi didesnį įsitraukimą, o preliminari ribinė vertė, indikuojanti probleminį interneto naudojimą, yra 22 balai (Koronczai et al., 2011).

PIUQ-9 pasižymi aukštu vidiniu patikimumu – Cronbacho alfa įvairiose imtyse svyruoja nuo 0,81 iki 0,9 (Laconi et al., 2019), įskaitant ir Lietuvos imtį (α = 0,89) (Burkauskas et al., 2020). Atitinkamai šio tyrimo imtyje Cronbacho alfa siekė 0,81.

2.2.2. Probleminio interneto naudojimo aspektų klausimynas (DPIU)

DPIU (Van Ameringen et al., 2018) skirtas probleminiam interneto naudojimui vertinti, sudarytas remiantis priklausomybės kriterijais pagal Amerikos psichiatrų asociacijos Psichikos sutrikimų diagnostikos ir statistikos vadovą (DSM-IV; American Psychiatric Association, 2013). Klausimynas apima devynias PIN sritis: Pramoginių ir vaizdo įrašų peržiūra, Socialiniai tinklai, Žaidimai, Žinučių rašymas, Pažinčių programos, Azartiniai lošimai, Seksualinio pobūdžio turinys, Pirkimas internete, Informacijos paieška. Kiekvienos dimensijos vertinimas pradedamas trimis atrankiniais klausimais (taip/ne). Pavyzdžiui, Pramoginių ir vaizdo įrašų peržiūros srityje šie klausimai yra: „Ar kada nors jautėte, kad turėtumėte sutrumpinti laiką, praleidžiamą žiūrint vaizdo įrašus?“, „Ar kada erzino aplinkinių kritika dėl Jūsų praleidžiamo laiko žiūrint vaizdo įrašus?“, „Ar kada nors Jūs jautėtės blogai ar kaltinote save dėl praleidžiamo laiko žiūrint vaizdo įrašus?“. Jei bent į du klausimus atsakoma „taip“, siekiant įvertinti galimą probleminį elgesį toje srityje pildomi penki papildomi klausimai, kurie yra vertinami 6 balų Likerto skalėje nuo 0 (visiškai ne/niekada/nesunku) iki 5 (labai/visą laiką/labai sunku).

Kiekvienos dimensijos probleminio naudojimo kriterijus atitinkančių dalyvių skaičiai ir Cronbacho alfa reikšmės buvo šios: Pramoginių ir vaizdo įrašų peržiūra: n = 103, α = 0,8; Socialiniai tinklai: n = 99, α = 0,77; Žaidimai: n = 37, α = 0,86; Žinučių rašymas: n = 43, α = 0,84; Pažinčių programos: n = 12, α = 0,68; Seksualinio pobūdžio turinys: n = 16, α = 0,68; Pirkimas internete: n = 21, α = 0,82; Informacijos paieška: n = 25, α = 0,74. Nė vienas tyrimo dalyvis neatitiko probleminio įsitraukimo kriterijų Azartinių lošimų srityje. Nors kai kurių DPIU dimensijų Cronbacho alfa reikšmės nebuvo vienodai aukštos, jos rodo vidutinį vidinį patikimumą, kuris laikomas tinkamu žvalgybiniams tyrimams (angl. *exploratory research*).

2.2.3. Becko nerimo klausimynas (BAI)

BAI, sukurtas Beck et al. (1988), yra validuotas ir plačiai naudojamas instrumentas, skirtas nerimo simptomų sunkumui įvertinti. BAI sudaro 21 teiginys, kiekvienas vertinamas Likerto tipo skalėje nuo 0 (visiškai ne) iki 3 (stipriai), atsižvelgiant į tai, kaip dažnai asmuo per pastarąsias dvi savaites patyrė tam tikrus nerimo simptomus. Bendras balas gali svyruoti nuo 0 iki 63, o aukštesni balai rodo didesnį nerimo intensyvumą. Atitinkamai išskiriamos nerimo vertinimo kategorijos: 0–7 balai – minimalus, 8–15 balų – žemas, 16–

25 balai – vidutinis, 26–63 balai – aukštas nerimo lygis. BAI rodo puikų vidinį patikimumą – Lietuvos imtyse Cronbacho alfa reikšmės svyruoja nuo 0,91 iki 0,92 (Grigutytė et al., 2023), šio tyrimo imtyje gauta Cronbacho alfa reikšmė $\alpha = 0{,}86$.

2.2.4. Becko depresijos aprašas-II (BDI-II)

BDI-II yra skirtas depresijos simptomų vertinimui ir yra plačiai taikomas tiek moksliniuose tyrimuose, tiek klinikinėje praktikoje (García-Batista et al., 2018; Wang & Gorenstein, 2013). Šį klausimyną sudaro 21 teiginys, vertinamas skalėje nuo 0 (visiškai nesutinku) iki 3 (visiškai sutinku), remiantis asmens patiriamais depresijos simptomais per pastarąsias dvi savaites. Suminis balas svyruoja nuo 0 iki 63, o aukštesni balai atspindi didesnį depresijos sunkumą. Neklinikinėse populiacijose balai virš 20 rodo galimą depresiją, o klinikinėse imtyse depresijos sunkumas skirstomas į minimalią (0–13 balų), žemą (14–19 balų), vidutinio sunkumo (20–28 balai) ir sunkią depresiją (29–63 balai) (Jackson-Koku, 2016).

Lietuvos imtyse vidinis klausimyno patikimumas siekia nuo 0,9 iki 0,94 (Grigutytė et al., 2023), taip pat ir šiame tyrime $\alpha = 0{,}9$, patvirtinanti aukštą šios skalės patikimumą depresijos simptomų vertinimui.

2.2.5. Clarko–Becko obsesijų ir kompulsijų aprašas (CBOCI)

CBOCI (Clark et al., 2005) yra klausimynas, skirtas obsesijų ir kompulsijų (OKS) simptomų dažniui bei sunkumui vertinti. 25 teiginius turinti skalė susideda iš dviejų poskalių: obsesijų (14 teiginių) ir kompulsijų (11 teiginių). Kiekvienas teiginys pateikiamas su keturiais atsakymo variantais (0–3), atspindinčiais didėjantį simptomų dažnumą ar intensyvumą. Bendras balų intervalas yra nuo 0 iki 72, o aukštesni balai rodo didesnį simptomų sunkumą. CBOCI yra patikima ir validi priemonė OKS nustatyti ir stebėti, taikoma tiek klinikiniuose, tiek moksliniuose tyrimuose. Lietuvos imtyse bendros skalės ir poskalių Cronbacho alfa reikšmės svyruoja nuo 0,84 iki 0,94 (Grigutytė et al., 2023), tuo tarpu šio tyrimo imtyje bendras CBOCI patikimumas siekė $\alpha = 0{,}92$, obsesijų poskalės – $\alpha = 0{,}88$, o kompulsijų poskalės – $\alpha = 0{,}87$.

2.2.6. NEO PI-R asmenybės klausimynas (NEO PI-R)

NEO PI-R (Costa & McCrae, 1992), yra išsamus savęs vertinimo klausimynas, skirtas asmenybei vertinti pagal Penkių faktorių modelį (angl. *Five-Factor Model*), kurį sudaro penkios asmenybės dimensijos: neurotiškumas, ekstraversija, atvirumas patyrimui, sutariamumas ir sąmoningumas. Šiame darbe naudota 240 teiginių NEO PI-R versija; kiekvienas teiginys vertinamas penkiabalėje Likerto skalėje nuo „visiškai nesutinku“ iki „visiškai sutinku“. Tiriamųjų prašoma nurodyti, kiek jie sutinka ar nesutinka su įvairiais teiginiais apie savo mintis, jausmus ir elgesį.

NEO PI-R yra išverstas į daugelį kalbų ir plačiai taikomas įvairiose populiacijose asmenybės bruožams vertinti. Faktorių Cronbacho alfa rodo aukštą vidinį suderinamumą, įskaitant Lietuvos imtis (Žukauskienė & Barkauskienė, 2006), taip pat ir dabartinę imtį: neurotiškumas $\alpha = 0{,}92$; atvirumas patyrimui $\alpha = 0{,}9$; ekstraversija $\alpha = 0{,}89$; sutariamumas $\alpha = 0{,}89$; sąmoningumas $\alpha = 0{,}91$.

2.2.7. Daugiamatis interocepcinio įsisąmoninimo klausimynas (MAIA)

MAIA, sukurta Mehling ir bendraautorių (2012), yra savęs vertinimo klausimynas, skirtas interocepciniam įsisąmoninimui – gebėjimui suvokti ir interpretuoti kūno pojūčius – vertinti. Klausimyną sudaro 32 klausimai, vertinami šešiabalėje Likerto skalėje nuo 0 („niekada“) iki 5 („visada“). Klausimynu vertinami aštuoni skirtingi interocepcinio įsisąmoninimo aspektai: Sensorinė pagava (gebėjimas įsisąmoninti nemalonius, malonius ar neutralius kūno pojūčius), Nepaisymas (polinkis likti su diskomfortu jo neužgožiant dėmesio atitraukimu), Nesijaudinimas (gebėjimas patirti kūno pojūčius be ryškaus emocinio veiklą trikdančio streso), Dėmesio reguliavimas (gebėjimas tikslingai sutelkti ir valdyti dėmesį į kūno pojūčius), Emocijų įsisąmoninimas (gebėjimas atpažinti fizinių pojūčių ir emocijų sąsajas), Savireguliacija (gebėjimas remiantis kūno pojūčių įsisąmoninimu reguliuoti emocijas), Įsiklausimas į kūną (polinkis aktyviai „klausyti“ kūno kaip informacijos šaltinio) ir Pasitikėjimas (savo kūno kaip saugaus ir patikimo suvokimas).

MAIA skalė validuota Lietuvos imtyse (Baranauskas et al., 2016; Grabauskaitė et al., 2017). Šiame tyrime gautos Cronbacho alfa reikšmės: bendra skalė $\alpha = 0{,}88$; poskalės – sensorinė pagava $\alpha = 0{,}67$, nepaisymas $\alpha = 0{,}58$, nesijaudinimas $\alpha = 0{,}55$, dėmesio reguliavimas $\alpha = 0{,}83$, emocijų įsisąmoninimas $\alpha = 0{,}81$, savireguliacija $\alpha = 0{,}80$, įsiklausymas į kūną $\alpha = 0{,}82$ ir pasitikėjimas $\alpha = 0{,}87$. Kaip nurodo ir kiti autoriai, dvi poskalės (sensorinė pagava ir nesijaudinimas) pasižymi mažesniu vidiniu suderinamumu; vis dėlto ankstesni tyrimai pagrindžia priemonės validumą ir diskriminacinį pajėgumą (de Jong et al., 2016; Mehling et al., 2018). Nors sukurta patobulinta instrumento versija (MAIA-2) skirta šiems psichometriniams ribotumams mažinti, ji dar nėra adaptuota ir validuota lietuvių kalba, todėl šiame tyrime naudota originalioji versija.

2.3. EEG duomenų registravimas

Tiriamieji patogiai sėdėjo vertikalioje padėtyje nuo tinklo triukšmo izoliuotoje, pritemdytoje ir akustiškai slopinamoje patalpoje. EEG duomenys buvo registruojami naudojant „ANT Neuro“ (The Netherlands) įrangą ir 64 kanalų „WaveGuard“ EEG kepurę su sidabro/sidabro chlorido (Ag/AgCl) elektrodais, išdėstytais pagal tarptautinę 10–10 sistemą. Elektrodų varžos buvo palaikomos mažesnės nei 20 kΩ,. Referentiniai elektrodai buvo M1/M2, įžeminimo elektrodas buvo pritvirtintas šalia Fz, duomenų skaitmenizavimo dažnis – 2048 Hz. Akių judesiams stebėti buvo registruojama elektrookulograma (EOG): vertikalios EOG (VEOG) elektrodai buvo pritvirtinti virš ir po dešiniąja akimi, o horizontalios EOG (HEOG) elektrodai – ties abiejų akių išoriniais kampais.

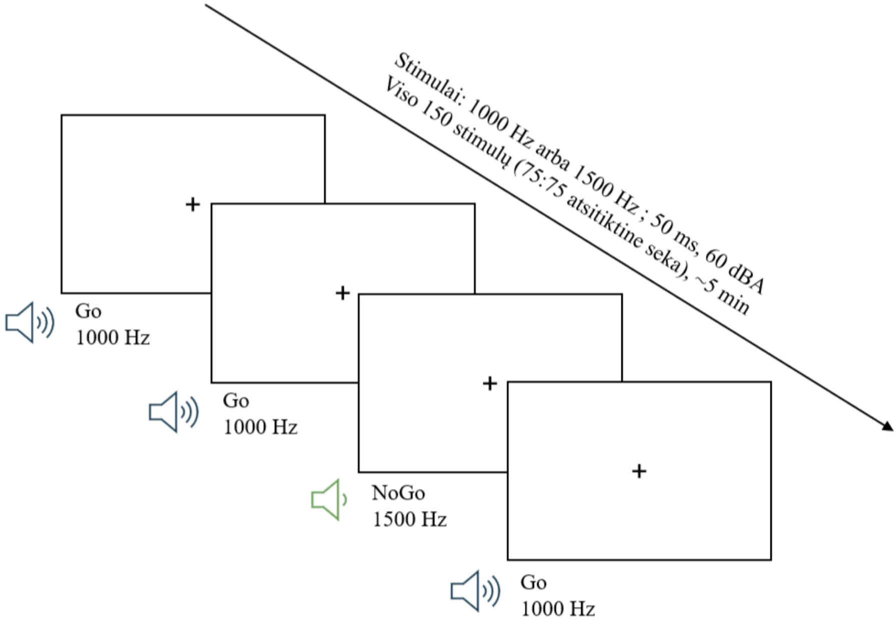
2.4. Užduočių paradigmos

2.4.1. Klausos lygių tikimybių Go/NoGo užduotis

Tyrime naudota klausos lygių tikimybių Go/NoGo paradigma buvo sudaryta iš 150 garsinių stimulų (50 % Go ir 50 % NoGo), t. y. 75 Go ir 75 NoGo bandymų. Vadovaujantis Barry ir bendraautorių (2007) darbais bei ankstesniais mūsų tyrimais (Griskova-Bulanova et al., 2016; Melynyte et al., 2017), per ausines atsitiktine tvarka buvo pateikiami du tonai (1000 Hz ir 1500 Hz; 60 dB(A); 50 ms trukmės; 5 ms pakilimų/kritimų skaičiaus) su fiksuotu 1100 ms tarpu tarp stimulų. Kuris dažnis (1000 Hz ar 1500 Hz) bus priskiriamas Go, o kuris NoGo sąlygai, buvo nusprendžiama atsitiktine tvarka.

Tiriamiesiems nurodyta į pasirodančius stimulus reaguoti kuo greičiau ir tiksliau: pasirodžius Go stimului spausti atsako mygtuką, o NoGo atveju – susilaikyti nuo atsako. Užduoties metu tiriamųjų buvo prašoma išlaikyti žvilgsnį į fiksacijos tašką (+) juodame ekrane. Prieš prasidedant užduočiai visiems tiriamiesiems buvo pateiktas 5 bandymų praktikos blokas. Užduoties iliustracija pateikta pav.2.2.

Atitinkamai, elgseniniai atsakai buvo klasifikuojami kaip teisingas Go (mygtukas paspaustas per 1000 ms nuo Go stimulo pradžios), teisingas NoGo (jokio atsako į NoGo stimulą), neteisingas Go (praleidimo klaida, mygtukas nepaspaustas per 1000 ms nuo Go stimulo pradžios); neteisingas NoGo (neteisingo reagavimo klaida, mygtukas paspaustas pasirodžius NoGo stimului). Reakcijos laikas (RT) Go bandymų metu buvo matuojamas nuo stimulo pradžios iki tiriamojo atsako pateikimo, o atsako tikslumas apskaičiuotas kaip teisingų Go ir NoGo atsakų procentas.



Pav. 2.2. Klausos lygių tikimybių Go/NoGo užduoties scheminis pavaizdavimas.

2.4.2. Kintama ramybės būsena

Pirmąsias dvi kintamos ramybės būsenos sesijos minutes dalyviams buvo nurodyta būti atmerktomis akimis (EO sąlyga). Išgirdus garsinį signalą, žymintį sąlygos pasikeitimą, tiriamieji turėjo užsimerkti ir kitas dvi minutes buvo toliau registruojama ramybės būsena užmerktomis akimis (EC sąlyga). Remiantis tyrimais, 2 min. EEG įrašas yra pakankamas alfa asimetrijos rodiklių vertinimui ir jų patikimumas yra panašūs į 8 min. įrašą (Allen et al., 2004). Visos sesijos metu dalyvių prašyta išlikti stabilioje padėtyje, atsipalaiduoti ir apie nieką konkrečiai negalvoti; EO sąlygos metu tiriamųjų buvo prašoma sufokusuoti žvilgsnį į fiksacijos tašką (baltą kryželį pilkame ekrano fone), o EC sąlygos metu – neužmigti. Siekiant užtikrinti tinkamą instrukcijų laikymąsi, duomenų registravimo metu visų dalyvių EEG įrašai buvo stebimi.

2.4.3. Ramybės būsena užmerktomis akimis

Dalyviams buvo nurodyta visą 5 min. EEG registravimo laikotarpį išlikti užmerktomis akimis; sesijos pradžią ir pabaigą žymėjo garsiniai signalai. Tiriamųjų buvo prašoma sėdėti ramiai, atsipalaiduoti ir neužmigti. Siekiant užtikrinti tinkamą instrukcijų laikymąsi, duomenų registravimo metu visų dalyvių EEG įrašai buvo stebimi.

2.5. EEG duomenų apdorojimas

EEG duomenys buvo apdoroti MATLAB programa (versija R2020a, The MathWorks, Natick, MA, JAV) naudojant EEGLAB plėtinį (Delorme & Makeig, 2004). Pirmiausia pašalintas 50 Hz tinklo triukšmas (naudotas CleanLine įskiepis). Vėliau taikant nepriklausomų komponentų analizę (ICA; ‘runica’, numatytieji nustatymai) pašalinti artefaktai, susiję su akių judesiais ir širdies veikla. Po to įrašai buvo peržiūrimi vizualiai, rankiniu būdu pašalinant triukšmingus kanalus, kurie vėliau rekonstruoti taikant sferinį metodą (Perrin et al., 1989).

2.5.1. Klausos lygių galimybių Go/NoGo užduotis

Po pirminio apdorojimo, Go/NoGo užduoties EEG įrašai buvo išfiltruoti tarp 0,1–25 Hz taikant 2-os eilės *Butterworth* filtrą. Toliau duomenys susegmentuoti į epochas nuo −100 ms (iki stimulo pasirodymo) iki 600 ms (po stimulo pasirodymo) ir suskirstyti į teisingus Go, teisingus NoGo, neteisingus Go ir neteisingus NoGo atsakus. Duomenys perskaičiuoti referentinius elektrodus pakeičiant į visų kanalų vidurkį ir atlikta bazinės linijos korekcija (suvidurkintas priešstimulinis intervalas (−100 – 0 ms)). Į galutinę analizę įtrauktos tik teisingų Go ir teisingų NoGo sąlygų epochos, kiekvienai sąlygai turėjo būti ≥ 40 epochų be artefaktų (vidutiniškai tiriamieji turėjo 60,43 ± 7,45 epochos Go sąlygai ir 58,47 ± 8,03 epochos NoGo sąlygai). Artefaktų neturinčios epochos suvidurkintos kiekvienam tiriamajam.

SĮSP amplitudės (40 ms langas, centruotas ties piku) ir latencijos (piko laiko momentai) išskirtos atsižvelgiant į ankstesnių tyrimų nustatytus laiko langus: N1 – neigiamas pikas 80–190 ms, N2 – neigiamas pikas 190–350 ms, P2 – teigiamas pikas 150–270 ms, P3 – teigiamas pikas 240–600 ms po stimulo pasirodymo. Visi komponentai vertinti vidurio linijos srityse: Fz, FCz, Cz, CPz, Pz.

2.5.2. Kintama ramybės būsena

Kintamos ramybės būsenos rinkinyje duomenys buvo filtruoti tarp 0,1-30 Hz taikant 2-os eilės *Butterworth* filtrą ir duomenys perskaičiuoti referentinius elektrodus pakeičiant į visų elektrodų vidurkį. Duomenys epochuoti į nepersidengiančius, artefaktų neturinčius 2 s trukmės segmentus (vidutiniškai po 53,86±5,13 EO ir 53,76±6,16 EC segmentus), taikant bazinės linijos korekciją per visą segmento trukmę. Tolimesnei analizei įtraukti tik tų tiriamųjų duomenys, kurie kiekvienai sąlygai turėjo ≥40 segmentų be artefaktų.

Galios spektrai (µV²) apskaičiuoti iš EEG duomenų taikant greitąją Fourier transformaciją (FFT; FieldTrip funkcija mtmfft su *Hanning* langu). Vidutinė frontalinė ir parietalinė alfa galia apskaičiuota imant absoliučios galios vidurkį 8–12 Hz juostoje iš frontalinių ir parietalinių elektrodų (frontaliniai: F7, F3, Fz, F4, F8; parietaliniai: P7, P3, Pz, P4, P8) kiekvienai sąlygai (EO, EC).

Alfa asimetrijos indeksas (AAI) buvo apskaičiuotas logaritminiu metodu kaip skirtumas tarp dešinės ir kairės pusės alfa galios (Reznik & Allen, 2018; Smith et al., 2017):

$$AAI = \ln (R - L)$$

kur L ir R – atitinkamai kairiojo (elektrodai F3, F7; P3, P7) ir dešiniojo (elektrodai F4, F8; P4, P8) pusrutulių alfa galios. Analizuotos keturios elektrodų poros, siekiant įvertinti vidurio linijos (F3/F4 ir P3/P4) ir lateralinę (F7/F8 ir P7/P8) asimetriją. AAI apskaičiuotas atskirai EO ir EC sąlygoms. Teigiamos vertės atspindi didesnę dešiniojo pusrutulio alfa galią (t. y. santykinai didesnį kairiojo pusrutulio aktyvumą), neigiamos – didesnę kairiojo pusrutulio alfa galią (santykinai didesnį dešiniojo pusrutulio aktyvumą).

2.5.3. Ramybės būsena užmerktomis akimis

Ramybės būsenos užmerktomis akimis įrašo skaitmenizavimo dažnis sumažintas iki 512 Hz, duomenys išfiltruoti tarp 1–40 Hz taikant 2-os eilės *Butterworth* filtrą ir perskaičiuoti referentinius elektrodus pakeičiant į visų kanalų vidurkį.

EEG mikrobūsenų segmentavimas atliktas naudojant „Cartool“ įrankį (v. 5.01) (Brunet et al., 2011). Kiekvieno dalyvio EEG suskaidytas į 20 atsitiktinių po 6000 laiko taškų turinčių epochų. Kiekvienai epochai globalaus lauko galia (GFP) buvo skaičiuojama kaip standartinis erdvinis nuokrypis, ir topografijos ties GFP pikais pateiktos į k-vidurkių klasterizavimo algoritmą, ignoruojant jų poliariškumą ir taikant minimalų koreliacijos slenkstį (<0,5). Topografijoms normalizuoti pritaikytas erdvinis filtras (Michel & Brunet, 2019). Kiekvienai epochai klasterių skaičius nustatytas tarp 1 ir 12, su 50 atsitiktinių inicializacijų, o optimalus klasterių skaičius kiekvienai epochai parinktas remiantis metakriterijumi (metakriterijus – sintetinė klasterių vertinimo priemonė, gaunama sujungiant šešių skirtingų kriterijų (Silhouettes, Krzanowski-Lai-Lai, Gamma, Davies-Bouldin, Dunn indeksas ir Point Biserial) rezultatus (Cartool’s Reference Guide: Brunet et al., 2011)).

Antrajame etape visų dominuojančių individualių šablonų rinkiniai buvo sujungti ir pateikti antrajai k-vidurkių klasterizacijai; sujungti duomenys buvo perimti (angl. *resample*) į 20 atsitiktinių po 500 laiko taškų turinčių epochų.

Klasterių skaičius svyravo tarp 1 ir 15, su 50 atsitiktinių inicializacijų, ignoruojant poliariškumo skirtumus ir taikant minimalų koreliacijos slenkstį. Iš visų tiriamųjų gautos grupės lygmens topografijos buvo atgal pritaikytos individualiems EEG taikant „winner-takes-all“ principą. Kiekvienam dalyviui buvo apskaičiuoti trys laikiniai parametrai kiekvienai mikrobūsenai: vidutinė trukmė (ms), pasirodymo dažnis (Hz) ir indėlis (%).

2.6. Statistinė analizė

Pirmiausia buvo atliktos visos imties duomenų koreliacinės analizės, siekiant įvertinti sąsajas tarp:

- PIN įverčių ir afektinių simptomų (nerimo, depresijos, OKS),
- PIN įverčių ir interocepcinio įsisąmoninimo (MAIA) bei asmenybės bruožų (NEO PI-R),
- PIN įverčių, elgseninių Go/NoGo užduoties rodiklių ir SĮSP (N1, N2, P2 ir P3) amplitudžių bei latencijų,
- PIN įverčių ir frontalinės bei parietalinės AAI,
- PIN įverčių ir laikinių mikrobūsenų parametrų.

Duomenų pasiskirstymo pagal normalųjį skirstinį prielaida tikrinta Shapiro–Wilko testu, po kurio atlikta Spearmano koreliacinė analizė. Rezultatų patikimumui užtikrinti taikytas neparametrinis savirankos (angl. *Bootstrap*) metodas su 5000 pakartojimų; reikšmingumo lygmuo pasirinktas $\alpha = 0{,}05$, o p vertės koreguotos taikant klaidingų atradimų dažnio (FDR; angl. *False Discovery Rate*) metodą (Benjamini & Hochberg, 1995).

Lygiagrečiai buvo atliekama palyginamoji analizė tarp grupių, siekiant įvertinti skirtumus tarp asmenų, pasižyminčių žemiausiais ir aukščiausiais interneto naudojimo įverčiais. Kvartilių pagrindu dalyviai atrinkti į žemo ir aukšto interneto naudojimo grupes pagal PIUQ-9 balus: žemų PIN įverčių grupę sudarė asmenys, surinkę 10–16 balų (pirmasis kvartilis), o aukštų PIN įverčių – 23–36 balus (ketvirtasis kvartilis). Žemesnioji aukštų PIN įverčių grupės riba (23 balai) artima preliminariam 22 balų ribiniam PIUQ-9 klausimyno įverčiui (Koronczai et al., 2011), kas pagrindžia kvartilių metodo taikymą šio tyrimo imtyje.

Žemo ir aukšto interneto naudojimo grupių palyginimui pirmiausia įvertinta dvimačio normaliojo skirstinio prielaida (Shapiro–Wilko kriterijus) ir patikrinta grupių dispersijų homogeniškumo prielaida (Levene kriterijus). Prielaidoms nepasitvirtinus, grupių palyginimui naudoti Mann–Whitney U testai. Taikytas neparametrinis savirankos metodas su 5000 pakartojimų, p vertės koreguotos taikant FDR metodą (Benjamini & Hochberg, 1995). Reikšmingumo lygmuo pasirinktas $\alpha = 0{,}05$, efekto dydžiui vertinti pateikta rangų biserialinė koreliacija, interpretacijai naudojant ribas ≈0,25 (mažas efektas), ≈0,40 (vidutinis efektas), ≈0,65 (didelis efektas) (Plonsky & Oswald, 2014).

Statistinės analizės atliktos naudojant MS Excel (2053 versija, Microsoft Corporation, 2018), JASP 0.18.3 (JASP Team, 2024) ir SPSS (29.0.2.0 versija, IBM SPSS) programinę įrangą.

2.6.1. Interocepcinis įsisąmoninimas ir PIN: tinklinė analizė

Interocepcinio įsisąmoninimo ir asmenybės bruožų tarpusavio sąsajos, susijusios su interneto naudojimo įpročiais buvo analizuojamos papildomai. Siekiant įvertinti nepriklausomą interocepcinio įsisąmoninimo aspektų (MAIA) ir asmenybės bruožų (NEO PI-R) indėlį į probleminį interneto naudojimą (PIUQ-9) taikytas tiesinės regresijos modelis; standartizuotų liekanų normalumas buvo vertintas vizualiai naudojant Q–Q diagramas, kurios indikavo apytikrį normalumą.

Sąveikoms tarp interocepcinių dimensijų, asmenybės veiksnių ir interneto naudojimo modelių tirti buvo taikytas EBICglasso modelis (Foygel & Drton, 2010). Išplėstinis Bayeso informacijos kriterijus (EBIC) kartu su hiperparametru 0,5 ir neparametriniu saviranskos metodu (1000 pakartotinių imčių) buvo naudoti siekiant balanso tarp specifiškumo, interpretuojamumo ir jautrumo (Epskamp et al., 2018; Foygel & Drton, 2010). Taip pat. siekiant nustatyti kintamųjų reikšmingumą ir sujungtumą tinkle. vertinti kintamųjų centriškumo matai (angl. *centrality measures*): stiprumas (angl. *strength/degree*), artumas (angl. *closeness*), tarpusavio centriškumas (betweenness) ir tikėtina įtaka (angl. *expected influence*) (Opsahl et al., 2010). Rezultatai pavaizduoti kaip svorinio tinklo struktūra (angl. *weighted network structure*), kuriame kiekvienas mazgas (angl. *node*) atitinka kintamąjį, o kiekviena jungtis (angl. *edge*) – koreliaciją; mėlynos jungtys žymi teigiamus, raudonos – neigiamus ryšius. Jungties storis ir spalvos sodrumas atspindi šių koreliacijų stiprumą. Interpretacijai buvo laikytos reikšmingomis tik jungtys, kurių absoliutus svoris > 0,10. Duomenys aprašomajai statistikai analizuoti naudojant IBM SPSS Statistics (IBM SPSS, v29.0.2.0, Armonk, NY), o tinklinei analizei – JASP 0.18.3 (JASP Team, 2024).

Statistinė galia įvertinta atlikus „post hoc“ galios analizę su G*Power (3.1.9.4; Faul et al., 2007). Kelių kintamųjų tiesinės regresijos analizei su devyniais prediktoriais tyrimo imtis suteikė 94 % galios nustatyti bendrą modelio efekto dydį $f^2 = 0,15$. Nors formalios imties dydžio gairės tinklinės analizės kontekste dar tik formuojamos, pateikiamos bendro pobūdžio rekomendacijos, kad didesnės imtys leidžia tiksliau ir stabiliau įvertinti parametrus (Epskamp et al., 2018).

3. REZULTATAI

3.1. Psichologiniai duomenys

Vidutinis visos imties PIUQ-9 įvertis (19,68 ± 5,43) yra žemiau preliminarios 22 balų (žyminčių probleminį interneto naudojimą) ribos (Koronczai et al., 2011). DPIU įverčiai atspindėjo tiriamųjų įsitraukimą į skirtingas interneto veiklas; dažniausios buvo Pramoginių ir vaizdo įrašų peržiūra (n=103) ir Socialiniai tinklai (n=99), o Žaidimai (11,97 ± 5,32) ir Žinučių rašymas (13,77 ± 5,35) pasižymėjo didesniu variabilumu tarp tiriamųjų.

Psichologinių klausimynų vertinimas visos imties mastu atspindėjo vidutinį nerimo lygį tarp tiriamųjų (BAI: 31,83 ± 7,53); tikėtina, jog dalis tiriamųjų patyrė kliniškai reikšmingus nerimo simptomus (Beck et al., 1988). Vidutinis BDI įvertis (10,44 ± 8,72) indikuoja žemą depresijos simptomų lygį imtyje, tačiau taip pat atspindi tikėtiną individualių skirtumų egzistavimą. CBOCI (19,23 ± 11,44) poskalių įverčiai atspindėjo variaciją tarp OKS: obsesijų simptomai (11,68 ± 6,64) buvo intensyvesni nei kompulsijų (7,59 ± 6,02).

Apibendrinus, gauti rezultatai atspindėjo įvairialypę interneto naudojimo elgseną ir nevienodą psichologinių simptomų raišką. Interneto naudojimo modelių, psichologinių charakteristikų, interocepcinio įsisąmoninimo ir asmenybės bruožų vertinimo rezultatų vidurkiai ir standartiniai nuokrypiai pateikiami 3.1 lentelėje.

Lentelė 3.1. Tiriamosios imties interneto naudojimo modelių, psichologinių charakteristikų, interocepcinio įsisąmoninimo ir asmenybės bruožų aprašomoji statistika.

Kintamieji	Imtis (n)	Vidurkis	SD
Interneto naudojimo modeliai (PIUQ-9, DPIU)			
PIUQ-9	161	19,68	5,43
DPIU_bendras balas	161	25,45	18
Pramoginių ir vaizdo įrašų peržiūra	103	9,84	4,49
Socialiniai tinklai	99	9,26	4,33
Žaidimai	37	11,97	5,32
Žinučių rašymas	43	12,77	5,35
Pažinčių programos	12	7,75	3,98
Seksualinio pobūdžio turinys	16	10,25	3,99
Pirkimas internete	21	9,05	4,73

Kintamieji	Imtis (n)	Vidurkis	SD
Informacijos paieška	25	12,56	4,42
Psichologiniai veiksniai			
BAI	160	31,83	7,53
BDI-II	157	10,44	8,72
CBOCI	160	19,23	11,44
CBOCI_Obsesijos	160	11,68	6,64
CBOCI_Kompulsijos	161	7,59	6,02
Interocepcinis įsisąmoninimas (MAIA)			
Sensorinė pagava	159	3,34	0,93
Nepaisymas	159	2,97	0,91
Nesijaudinimas	159	3,02	1,10
Dėmesio reguliavimas	159	3	0,83
Emocijų įsisąmoninimas	151	3,28	1,05
Savireguliacija	151	2,71	1,09
Įsiklausimas į kūną	151	2,26	1,17
Pasitikėjimas	151	3,64	1,02
Asmenybės bruožai (NEO PI-R)			
Neurotiškumas	158	52,63	12
Ekstraversija	159	48,58	11,14
Atvirumas patyrimui	158	58	10,35
Sutariamumas	159	48,98	12,15
Sąmoningumas	160	49,87	10,79

BAI – Becko nerimo klausimynas, BDI – Becko depresijos aprašas-II, CBOCI – Clarko–Becko obsesijų ir kompulsijų aprašas, DPIU – Probleminio interneto naudojimo aspektų klausimynas; MAIA – Daugiamatis interocepcinio įsisąmoninimo klausimynas; NEO PI-R – NEO PI-R asmenybės klausimynas; PIUQ-9 – Probleminio interneto naudojimo klausimynas.

Dėl nedidelio tiriamųjų skaičiaus, atitikusių probleminį naudojimąsi pažinčių programomis (n = 12), seksualinio pobūdžio turiniu (n = 16) ir pirkimu internete (n = 21), šios sritys nebuvo įtrauktos į tolesnę analizę.

3.1.1. Ryšiai tarp probleminio interneto naudojimo klausimynų (PIUQ-9 ir DPIU)

Kaip tikėtasi, nustatytos stiprios koreliacijos tarp PIUQ-9 ir DPIU įverčių, taip pat tarp PIUQ-9 ir daugumos DPIU dimensijų. Koreliacijų rezultatai ir reikšmingų koreliacijų vizualizacijos pateikti 3.2 lentelėje ir 3.1. paveiksle.

3.1.2. Sąsajos tarp interneto naudojimo modelių ir psichologinių klausimynų

Kaip tikėtasi, aukštesni PIUQ-9 ir DPIU įverčiai koreliavo su prastesne psichologine būsena. PIUQ-9 įverčiai teigiamai koreliavo su visų vertintų psichologinių rodiklių įverčiais: BAI ($r_s = 0{,}288$, $p < 0{,}001$*), BDI ($r_s = 0{,}285$, $p < 0{,}001$*), CBOCI_obsesijų ($r_s = 0{,}309$, $p < 0{,}001$*), CBOCI_kompulsijų ($r_s = 0{,}332$, $p < 0{,}001$*), bei bendru CBOCI įverčiu ($r_s = 0{,}377$, $p < 0{,}001$*). Tai rodo, kad aukštesnis įsitraukimas į internetines veiklas susijęs su aukštesniu nerimo, depresijos ir OKS simptomų išreikštumu. Išsamūs rezultatai pateikiami 3.3 lentelėje, o statistiškai reikšmingų koreliacijų grafikai 3.2. paveiksle.

Tarp DPIU dimensijų, Socialinių tinklų naudojimo įverčiai teigiamai koreliavo su nerimo (BAI, $r_s = 0{,}277$, $p = 0{,}005$), depresijos (BDI, $r_s = 0{,}333$, $p = 0{,}001$), bendrais OKS (CBOCI, $r_s = 0{,}267$, $p = 0{,}007$) ir abiejų CBOCI poskalių – obsesijų ($r_s = 0{,}230$, $p = 0{,}023$) ir kompulsijų ($r_s = 0{,}221$, $p = 0{,}028$) – įverčiais. Pramoginių ir vaizdo įrašų peržiūros dimensijos įverčiai teigiamai koreliavo su nerimo (BAI, $r_s = 0{,}300$, $p = 0{,}002$), OKS (CBOCI, $r_s = 0{,}215$, $p = 0{,}029$) ir obsesijų (CBOCI obsesijų poskalė, $r_s = 0{,}242$, $p = 0{,}014$) įverčiais. Žinučių rašymo dimensijos įverčiai teigiamai koreliavo su bendrais OKS (CBOCI, $r_s = 0{,}362$, $p = 0{,}017$) ir obsesijų (CBOCI obsesijų poskalė, $r_s = 0{,}388$, $p = 0{,}010$) įverčiais. Reikšmingų koreliacijų tarp psichologinių klausimynų įverčių ir Žaidimų ir Informacijos paieškos dimensijų įverčių nustatyta nebuvo, kas leidžia manyti, jog interneto naudojimo poveikis psichikos sveikatai skiriasi priklausomai nuo konkrečių veiklų internete. Išsamūs rezultatai pateikiami 3.3 lentelėje.

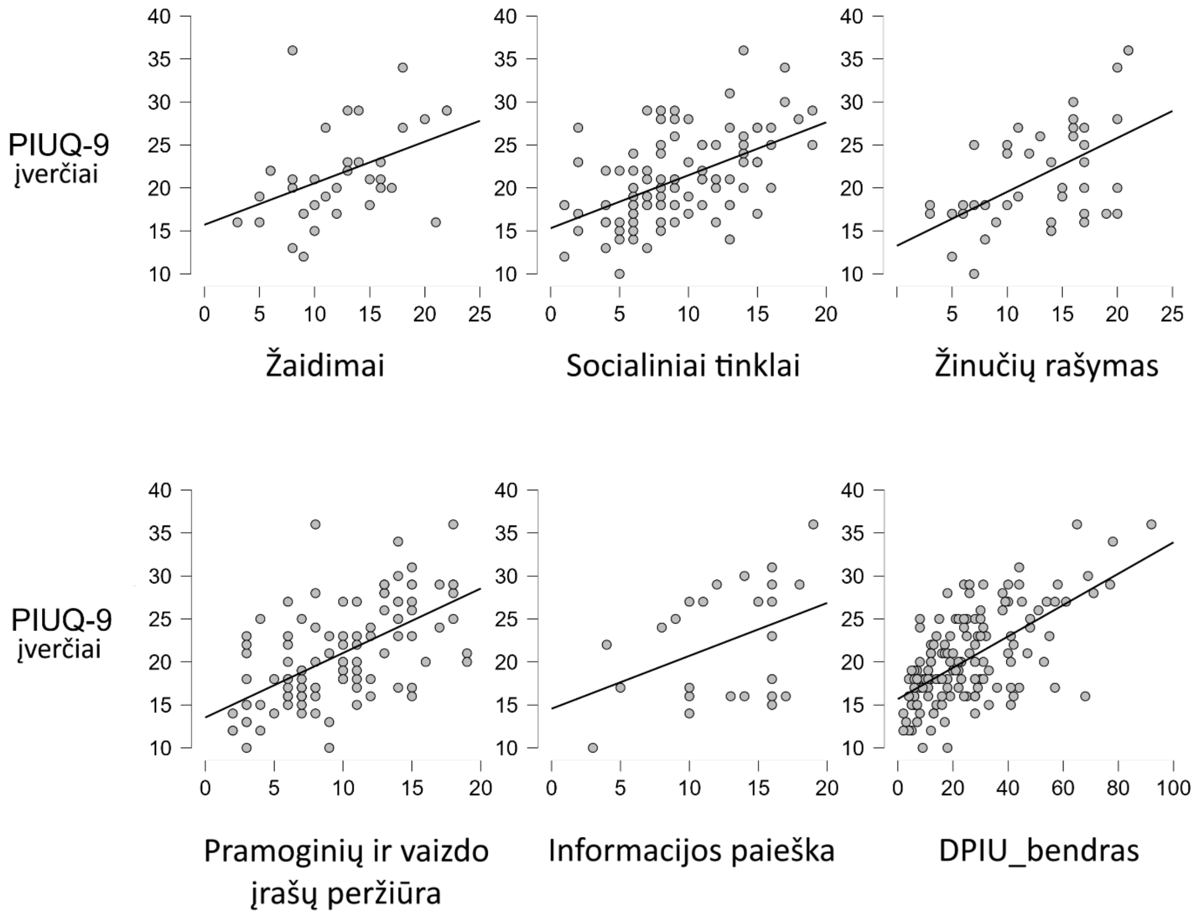
3.1.3. Psichologinių rodiklių skirtumai tarp aukšto ir žemo interneto naudojimo grupių

Žemo interneto naudojimo ($n = 45$; 22 moterys; PIUQ-9 įvertis $13{,}73 \pm 2{,}04$) ir aukšto interneto naudojimo ($n = 46$; 30 moterų; PIUQ-9 įvertis $26{,}67 \pm 3{,}20$) grupės nesiskyrė pagal amžių ($p = 0{,}263$), tačiau reikšmingai skyrėsi visais vertintais psichologiniais aspektais. Psichologinių klausimynų vertinimo rezultatų vidurkiai ir standartiniai nuokrypiai pateikiami 3.4 lentelėje, o grupių palyginimų rezultatai – 3.5 lentelėje.

Lentelė 3.2. Spearmano koreliacijos koeficientai tarp PIN klausimynų įverčių (PIUQ-9 ir DPIU)

Kintamieji		PIUQ-9	Žaidimai	Socialiniai tinklai	Žinučių rašymas	Pramoginių ir vaizdo įrašų peržiūra	Informacijos paieška
Žaidimai	r_s	**0,343***					
	p	0,038					
	n	37					
Socialiniai tinklai	r_s	**0,534***	0,338				
	p	<0,001	0,107				
	n	99	24				
Žinučių rašymas	r_s	**0,49***	0,377	**0,656***			
	p	<0,001	0,283	<0,001			
	n	43	10	34			
Pramoginių ir vaizdo įrašų peržiūra	r_s	**0,598***	0,251	**0,462***	**0,743***		
	p	<0,001	0,198	<0,001	<0,001		
	n	103	28	66	31		
Informacijos paieška	r_s	0,342	0,1	0,295	**0,843***	0,221	
	p	0,095	0,95	0,183	<0,001	0,323	
	n	25	5	22	12	22	
DPIU_bendras	r_s	**0,556***	**0,341***	**0,55***	**0,801***	**0,618***	**0,596***
	p	<0,001	0,039	<0,001	<0,001	<0,001	0,002
	n	145	37	99	43	103	25

* Rezultatų reikšmingumas išliko pritaikius FDR korekciją. r_s – Spearmano koreliacijos koeficientas; p – reikšmingumo lygmuo; n – imties dydis. DPIU – Probleminio interneto naudojimo aspektų klausimynas; PIUQ-9 – Probleminio interneto naudojimo klausimynas. DPIU poskalių imčių dydžių skirtumai paaiškinami menku tiriamųjų persidengimu tarp atskirų dimensijų.

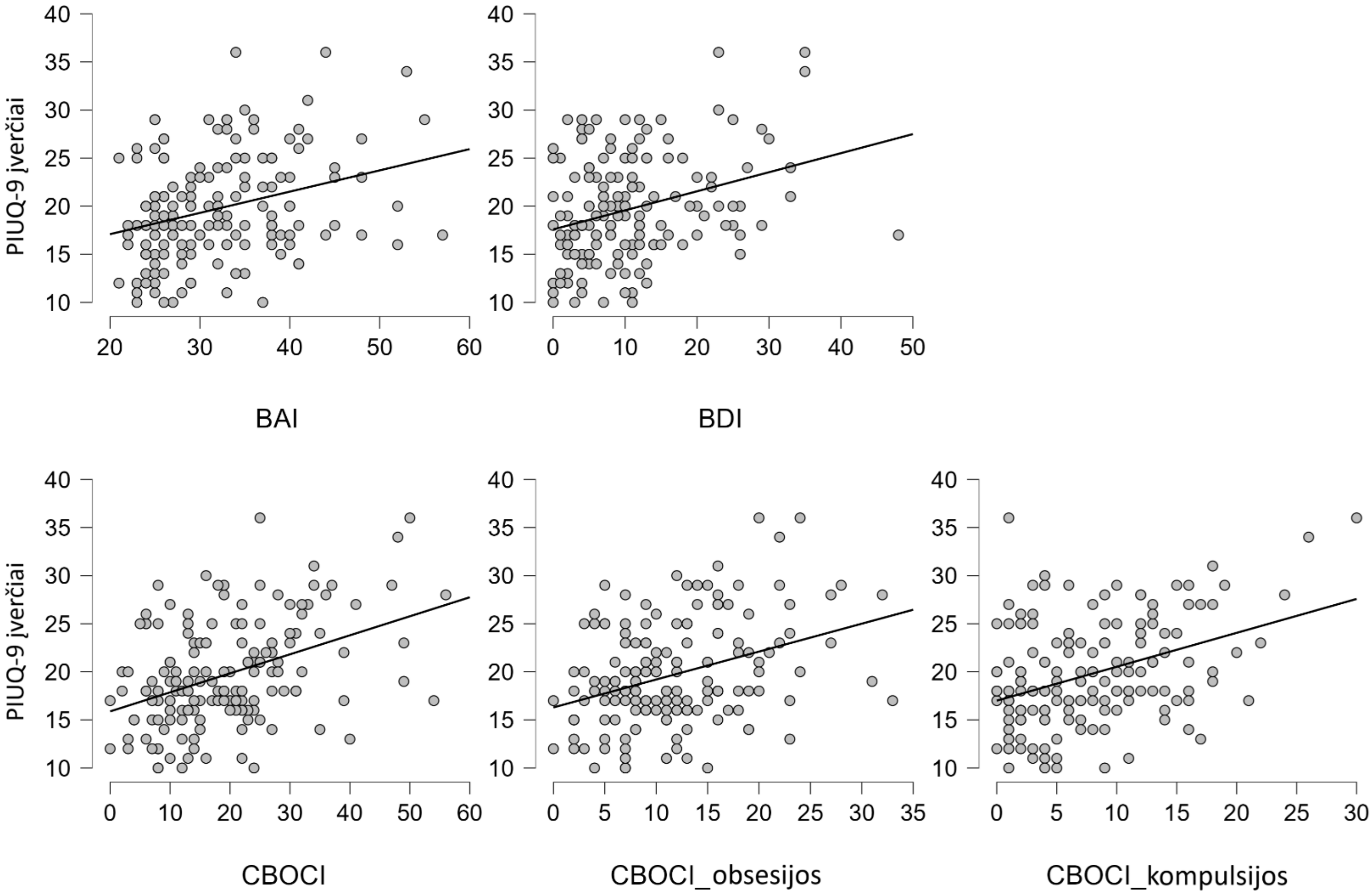


Pav. 3.1. PIUQ-9 klausimyno įverčių koreliacijos su DPIU dimensijų (Žaidimai, Socialiniai tinklai, Žinučių rašymas, Pramoginių ir vaizdo įrašų peržiūra, Informacijos paieška, bendras DPIU) įverčiais.

Lentelė 3.3. Spearmano koreliacijos koeficientai tarp PIN (PIUQ-9 ir DPIU) ir psichologinių klausimynų įverčių.

Kintamieji		BAI	BDI	CBOCI	CBOCI obsesijos	CBOCI kompulsijos
PIUQ-9	r_s	**0,288***	**0,285***	**0,377***	**0,309***	**0,332***
	p	< ,001	< ,001	< ,001	< ,001	< ,001
	n	160	157	160	160	161
Pramoginių ir vaizdo įrašų peržiūra	r_s	**0,3***	0,185	**0,215***	**0,242***	0,135
	p	0,002	0,067	0,029	0,014	0,174
	n	103	99	103	103	103
Žaidimai	r_s	0,076	0,183	0,182	0,192	0,174
	p	0,653	0,286	0,281	0,254	0,303
	n	37	36	37	37	37
Socialiniai tinklai	r_s	**0,277***	**0,33***	**0,267***	**0,23***	**0,221***
	p	0,005	0,001	0,007	0,023	0,028
	n	99	96	99	98	99
Žinučių rašymas	r_s	0,085	**0,346**	**0,362***	**0,388***	0,256
	p	0,588	0,027	0,017	0,01	0,098
	n	43	41	43	43	43
Informacijos paieška	r_s	-0,258	0,317	0,246	0,319	0,08
	p	0,213	0,14	0,235	0,121	0,705
	n	25	23	25	25	25
DPIU_bendras	r_s	**0,369***	**0,315***	**0,342***	**0,347***	**0,228***
	p	< ,001	< ,001	< ,001	< ,001	0,006
	n	145	141	145	144	145

* Rezultatų reikšmingumas išliko pritaikius FDR korekciją. r_s – Spearmano koreliacijos koeficientas; p – reikšmingumo lygmuo; n – imties dydis. BAI – Becko nerimo klausimynas, BDI – Becko depresijos aprašas-II, CBOCI – Clarko–Becko obsesijų ir kompulsijų aprašas, DPIU – Probleminio interneto naudojimo aspektų klausimynas PIUQ-9 – Probleminio interneto naudojimo klausimynas.



Pav. 3.2. PIUQ-9 klausimyno įverčių koreliacijos su psichologinių klausimynų įverčiais. BAI – Becko nerimo klausimynas, BDI– Becko depresijos aprašas-II, CBOCI – Clarko–Becko obsesijų ir kompulsijų aprašas, PIUQ 9 – Probleminio interneto naudojimo klausimynas.

Lentelė 3.4. Psichologinių charakteristikų tarp žemo ir aukšto interneto naudojimo grupių aprašomoji statistika.

Kintamieji	Grupė	n	Vidurkis	SD
PIUQ-9	Aukštas PIN	46	26,67	3,22
	Žemas PIN	45	13,73	2,04
BAI	Aukštas PIN	46	34,96	7,98
	Žemas PIN	44	29,41	6,52
BDI	Aukštas PIN	45	12,82	9,73
	Žemas PIN	44	7,30	5,73
CBOCI	Aukštas PIN	46	24,78	13,04
	Žemas PIN	45	14,47	8,50
CBOCI obsesijos	Aukštas PIN	46	14,46	7,23
	Žemas PIN	45	9,60	5,28
CBOCI kompulsijos	Aukštas PIN	46	10,33	7,14
	Žemas PIN	45	4,96	4,26

BAI – Becko nerimo klausimynas, BDI – Becko depresijos aprašas-II, CBOCI – Clarko–Becko obsesijų ir kompulsijų aprašas, PIUQ 9 – Probleminio interneto naudojimo klausimynas

Lentelė 3.5. Grupių skirtumai tarp psichologinių klausimynų įverčių.

Kintamieji	U	*p*	Efekto dydis	SE Efekto dydis
PIUQ-9	1188	**< ,001***	1	0,121
BAI	575,5	**< ,001***	0,431	0,122
BDI	659	**0,007***	0,334	0,122
CBOCI	536	**< ,001***	0,482	0,121
CBOCI obsesijos	628	**,001***	0,393	0,121
CBOCI kompulsijos	553,5	**< ,001***	0,465	0,121

* Rezultatų reikšmingumas išliko pritaikius FDR korekciją. Mann–Whitney U testas. BAI – Becko nerimo klausimynas, BDI – Becko depresijos aprašas-II, CBOCI – Clarko–Becko obsesijų ir kompulsijų aprašas, PIUQ 9 – Probleminio interneto naudojimo klausimynas. SE efekto dydis — Efekto dydžio standartinė paklaida, Mann–Whitney U kriterijus.

3.1.4. Psichologinių rodiklių analizė EEG duomenų rinkinių pogrupiuose

Ryšiai tarp PIN ir psichologinių klausimynų įverčių skirtingų EEG paradigmų imtyse buvo labai panašūs į visoje imtyje nustatytus ryšius, aprašytus 3.1.2 skirsnyje. Aprašomoji statistika ir detalūs kiekvienos EEG duomenų rinkinio imties koreliacijų rezultatai pateikiami Papildomojoje medžiagoje 1 (atitinkamai SM 1.1 ir SM 1.2 lentelės).

Psichologinių klausimynų įverčių skirtumai tarp grupių šiose imtyse taip pat glaudžiai atitiko rezultatus, aprašytus 3.1.3 skirsnyje. Aprašomoji statistika ir detalūs rezultatai pateikiami Papildomojoje medžiagoje 1 (atitinkamai SM 1.3 ir SM 1.4 lentelės).

3.2. Sąsajos tarp interocepcinio įsisąmoninimo aspektų ir PIN

3.2.1. Sąsajos tarp interocepcinio įsisąmoninimo aspektų ir interneto naudojimo modelių

Nustatytos reikšmingos sąsajos tarp interocepcinio įsisąmoninimo ir interneto naudojimo modelių (3.6 lentelė). PIUQ-9 balai neigiamai koreliavo su Nepaisymu ($r_s = -0{,}359$, $p < 0{,}001$). Tarp interneto naudojimo dimensijų Žinučių rašymo dimensijos įverčiai parodė reikšmingas neigiamas koreliacijas su Dėmesio reguliavimu ($r_s = -0{,}397$, $p = 0{,}008$), Emocijų įsisąmoninimu ($r_s = -0{,}399$, $p = 0{,}011$), Savireguliacija ($r_s = -0{,}456$, $p = 0{,}003$) ir Įsiklausymu į kūną ($r_s = -0{,}470$, $p = 0{,}002$). Reikšmingų sąsajų tarp interocepcinio įsisąmoninimo aspektų ir Pramoginių ir vaizdo įrašų peržiūros, Informacijos paieškos, Socialinių tinklų ir Žaidimų dimensijų nenustatyta.

3.2.2. Sąsajos tarp interocepcinio įsisąmoninimo aspektų ir asmenybės bruožų

Reikšmingos sąsajos nustatytos tarp interocepcinio įsisąmoninimo aspektų ir visų asmenybės bruožų įverčių, išskyrus Sutariamumą (3.6 lentelė). Vis dėlto, pritaikius FDR korekciją, statistiškai reikšmingai su interocepcinio įsisąmoninimo aspektais koreliavo Atvirumas patyrimui ir Neurotiškumas. Konkrečiai, Atvirumas patyrimui teigiamai koreliavo su Įsiklausymo į kūną ($r_s = 0{,}275$, $p < 0{,}001$) ir Emocijų įsisąmoninimo ($r_s = 0{,}284$, $p < 0{,}001$) aspektais, o Neurotiškumas neigiamai koreliavo su Savireguliacija ($r_s = -0{,}390$, $p < 0{,}001$), Dėmesio reguliavimu ($r_s = -0{,}370$, $p < 0{,}001$), Nesijaudinimu ($r_s = -0{,}388$, $p < 0{,}001$) ir Pasitikėjimu ($r_s = -0{,}446$, $p < 0{,}001$).

3.2.3. Skirtingų interocepcinio įsisąmoninimo aspektų ir neurotiškumo indėlis į interneto naudojimo modelius

Tiesinės regresijos analizėje trys kintamieji – Neurotiškumas ($p = 0{,}04$), Pasitikėjimas ($p = 0{,}04$) ir Nepaisymas ($p < 0{,}001$) – pasirodė esantys statistiškai reikšmingi PIN prediktoriai (3.3. pav.). Modelio daugybinės koreliacijos koeficientas $R = 0{,}509$ rodo vidutinio stiprumo teigiamą tiesinį ryšį tarp prediktorių ir PIN; modelis paaiškino 25,9 % PIU įverčio variacijos. Rezultatai pateikiami 3.7 lentelėje.

3.2.4. Interocepcinio įsisąmoninimo, asmenybės bruožų ir probleminio interneto naudojimo tinklinė analizė

Siekiant ištirti įvairių interocepcinio įsisąmoninimo aspektų, asmenybės bruožų ir PIN tarpusavio sąsajas, sudarytas tinklas iš aštuonių interocepcinio įsisąmoninimo kintamųjų, penkių asmenybės bruožų ir dviejų PIN rodiklių (3.4. pav.). Iš 105 galimų jungčių svorio įverčių (angl. *edge weights*) 33 buvo nenuliniai, ir tinklo retumas (angl. *network sparsity*) sudarė 0,686. Svorinių jungčių matrica pateikta Papildomojoje medžiagoje 2, SM 2.1 lentelėje.

Tinklinė analizė atskleidė Neurotiškumą kaip pagrindinį tarpininką („tiltą“) tinkle, jungiantį PIN su interocepcinio įsisąmoninimo kintamaisiais. Kaip tikėtasi, tiek PIUQ-9, tiek DPIU buvo susieti su Neurotiškumu (atitinkamai 0,053 ir 0,129). Tarp interocepcinio įsisąmoninimo aspektų Neurotiškumas buvo neigiamai susijęs su Pasitikėjimu (−0,239) ir Nesijaudinimu (−0,202), taip pat nustatytos silpnesnės sąsajos su Savireguliacija (−0,124).

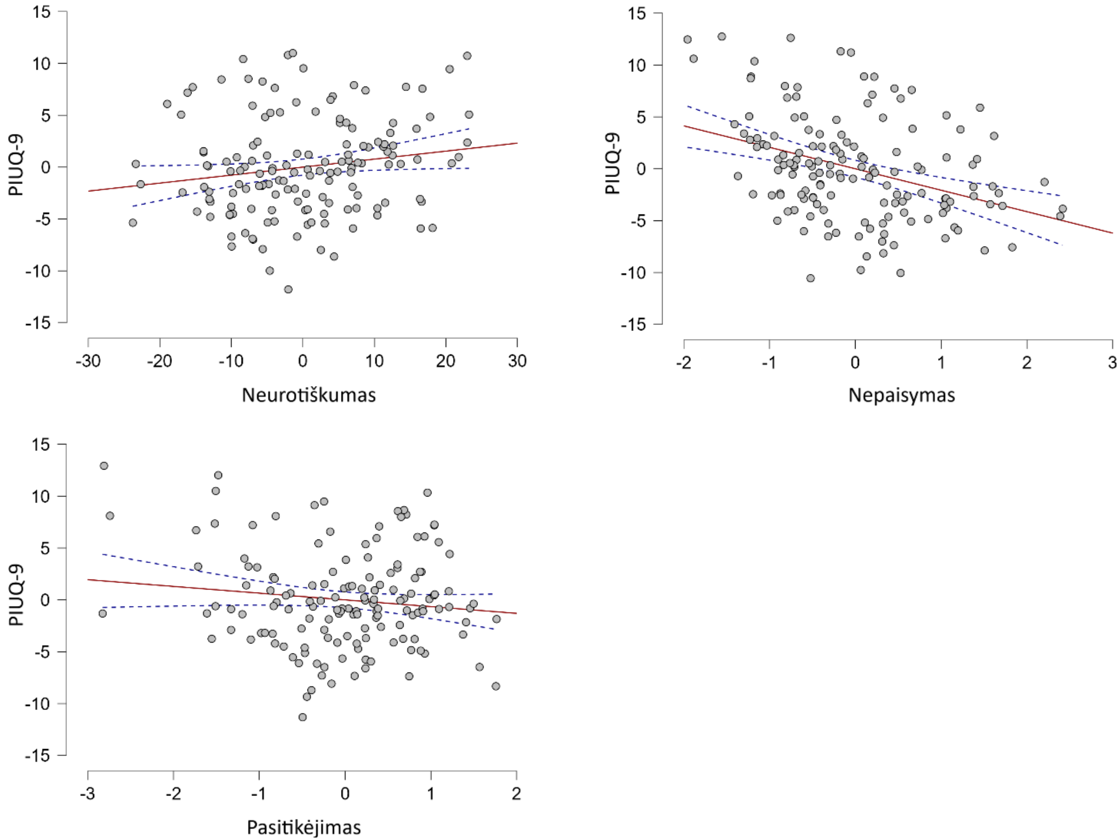
Analizė atskleidė, kad abu PIN klausimynai (PIUQ-9 ir DPIU) buvo susiję tarpusavyje (0,421), tačiau nei vienas iš jų nebuvo stipriai susietas su dauguma interocepcinio įsisąmoninimo aspektų, išskyrus neigiamą ryšį tarp PIUQ-9 ir Nepaisymo (−0,192).

Standartizuoti centriškumo indeksai (tarpusavio centriškumo, artumo, stiprumo ir tikėtinos įtakos) pateikti 3.5. paveiksle. Stiprumo indeksas išryškino Neurotiškumo, Įsiklausymo į kūną ir Savireguliacijos aspektus kaip daugiausiai jungčių turinčius mazgus. Tarpusavio centriškumo požiūriu Neurotiškumas, Savireguliacija ir Įsiklausymas į kūną užima mazgų, jungiančių kitus kintamuosius trumpiausiais keliais, pozicijas. Artumo indeksas parodė, kad Savireguliacija turi didžiausią atvirkštinę trumpiausių kelių sumą iki visų kitų mazgų tinkle. Tikėtinos įtakos požiūriu, didžiausius suminius jungčių svorius (atsižvelgiant į teigiamus ir neigiamus ryšius) turėjo Įsiklausymas į kūną, Savireguliacija ir Dėmesio reguliavimas. Jungčių svorių tikslumas įvertintas taikant savirankos metodo 95 % pasikliautinius intervalus; apskaičiuotos svertinės jungčių matricos ir šių intervalų iliustracija pateikiama Papildomojoje medžiagoje 2, SM 2.1 paveiksle.

Lentelė 3.6. Spearmano koreliacijos koeficientai tarp interocepcinio įsisąmoninimo (IA), asmenybės bruožų ir PIN (PIUQ-9, DPIU).

IA dimensija / Kintamieji	Sensorinė pagava	Nepaisymas	Nesijaudinimas	Dėmesio reguliavimas	Emocijų įsisąmoninimas	Savireguliacija	Įsiklausymas į kūną	Pasitikėjimas
Asmenybės bruožai (NEO PI-R)								
Neurotiškumas	-0,055	-0,151	**-0,388***	**-0,37***	**0,174**	**-0,39***	-0,107	**-0,446***
Ekstraversija	0,045	0,075	0,079	0,058	**0,187**	**0,172**	**0,189**	**0,196**
Atvirumas patyrimui	**0,202**	0,08	-0,053	0,128	**0,284***	**0,181**	**0,275***	0,046
Sutariamumas	-0,029	0,097	-0,067	-0,023	0,065	0,081	0,108	0,079
Sąmoningumas	0,084	0,059	-0,136	0,146	0,04	0,135	0,121	**0,213**
Interneto naudojimo šablonai (PIUQ-9, DPIU)								
PIUQ-9	0,027	**-0,359***	-0,083	0,061	0,103	-0,036	0,063	**-0,162**
DPIU_bendras	0,083	**-0,202**	-0,004	-0,11	0,073	-0,08	0,008	-0,166
Pramoginių ir vaizdo įrašų peržiūra	0,09	-0,19	-0,079	-0,152	-0,007	-0,024	0,013	-0,157
Socialiniai tinklai	-0,081	-0,043	-0,066	-0,069	0,056	0,012	0,01	-0,034
Žaidimai	0,157	-0,085	-0,226	0,116	0,237	0,277	0,305	0,122
Žinučių rašymas	-0,101	0,024	-0,078	**-0,397***	**-0,399***	**-0,456***	**-0,47***	**-0,314**
Informacijos paieška	-0,131	-0,225	**0,439**	-0,108	-0,184	-0,048	-0,343	0,081

* Rezultatų reikšmingumas išliko pritaikius FDR korekciją. DPIU = Probleminio interneto naudojimo aspektų klausimynas; MAIA = Daugiamatis interocepcinio įsisąmoninimo klausimynas; NEO PI-R = NEO PI-R asmenybės klausimynas; PIUQ-9 = Probleminio interneto naudojimo klausimynas.

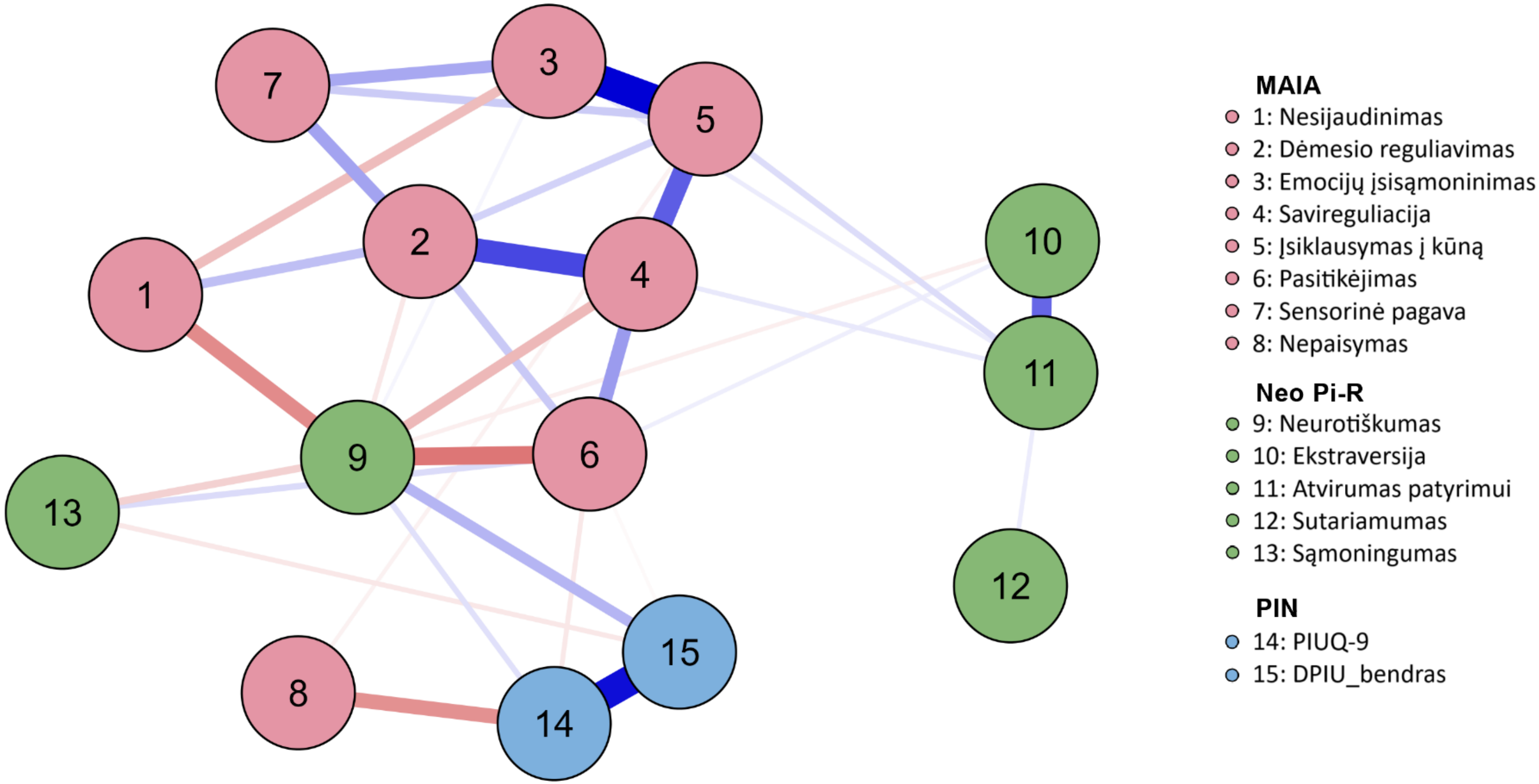


Pav. 3.3. Statistiškai reikšmingų PIN numatomų kintamųjų dalinės regresijos grafikai. Punktyrinės linijos vaizduoja regresijos įverčių 95 % pasikliautinį intervalą.

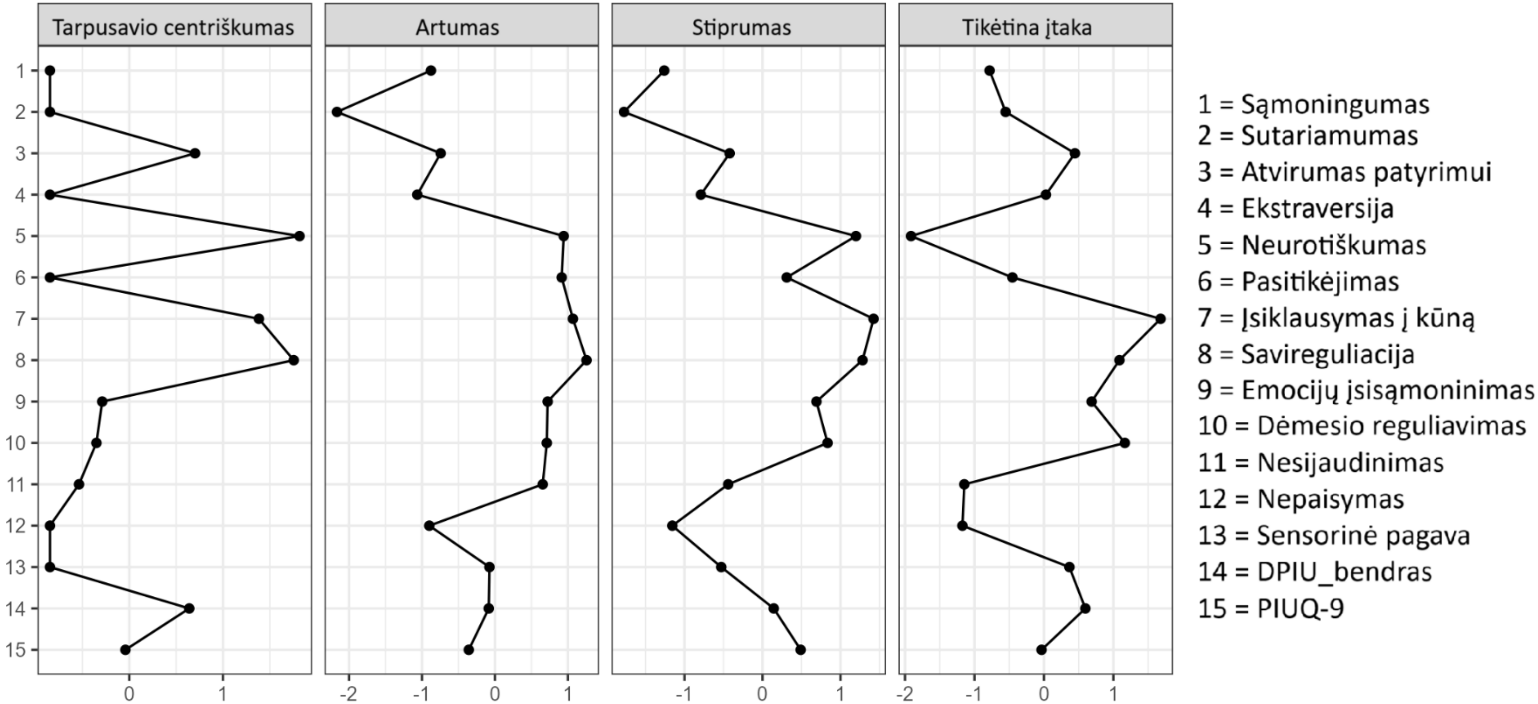
Lentelė 3.7. Tiesinės regresijos modelio rezultatai, vertinantis neurotiškumo ir skirtingų interocepcinio įsisąmoninimo kintamųjų nepriklausomą poveikį Probleminio interneto naudojimo klausimyno (PIUQ-9) balui.

Modelio komponentai	***B***	***SE***	***β***	***t***	***p***	***95% CI***
(konstanta)	20,631	4,279		4,822	**< ,001**	12,171 – 29,092
Neurotiškumas	0,088	0,042	0,199	2,075	**0,04**	0,004 – 0,172
Sensorinė pagava	-0,435	0,526	-0,072	-0,827	0,41	-1,474 – 0,605
Nepaisymas	-1,848	0,457	-0,318	-4,044	**< ,001**	-2,752 – -0,945
Nesijaudinimas	0,182	0,435	0,037	0,418	0,677	-0,678 – 1,042
Dėmesio reguliavimas	1,159	0,658	0,179	1,76	0,081	-0,143 – 2,460
Emocijų įsisąmoninimas	0,422	0,595	0,084	0,708	0,48	-0,755 – 1,598
Savireguliacija	-0,006	0,532	-0,001	-0,011	0,991	-1,057 – 1,045
Įsiklausymas į kūną	-0,164	0,55	-0,036	-0,299	0,766	-1,252 – 0,923
Pasitikėjimas	-0,993	0,478	-0,192	-2,078	**0,04**	-1,938 – -0,048

Reikšmingi rezultatai paryškinti. **B** = nestandartizuotas regresijos koeficientas, **SE** = B standartinė paklaida, **β** = standartizuotas regresijos koeficientas, **t** = t-kriterijaus reikšmė, **p** = p-reikšmė (reikšmingumo lygmuo).



Pav. 3.4. Interocepcinio įsisąmoninimo, asmenybės bruožų ir probleminio interneto naudojimo tinklas. Diagramoje pateikiami 15 kintamųjų (nurodyti dešinėje), o ryšiai tarp jų pavaizduoti EBICglasso dalinėmis koreliacijomis. Teigiamos sąsajos vaizduojamos mėlynomis jungtimis, neigiamos – raudonomis. Jungčių plotis ir spalvos intensyvumas atspindi ryšio stiprumą.



Pav. 3.5. Interocepcinio įsisąmoninimo, asmenybės bruožų ir probleminio interneto naudojimo tinklo centriškumo indeksai. Horizontalioji (x) ašis rodo standartizuotus (Z) centriškumo įverčius, o vertikaliojoje (y) ašyje išvardyti visi tinklo kintamieji. Didesnį centriškumą rodantys kintamieji išsidėstę labiau į dešinę, toliau nuo vertikaliosios ašies.

3.3. Klausos lygių tikimybių Go/NoGo užduotis ir SĮSP

Galutinė 133 dalyvių (74 moterys) imtis turėjo vidutinį PIUQ-9 įvertį 19,85 ± 5,32. Žemo interneto naudojimo grupės (n = 35; 17 moterų) PIUQ-9 vidurkis buvo 13,83 ± 1,95, o aukšto interneto naudojimo grupės (n = 38; 24 moterys) – 26,76 ± 3,00. Amžiaus skirtumų tarp aukšto ir žemo PIUQ-9 įverčio grupių nenustatyta (p = 0,461).

3.3.1. Elgseniniai rezultatai

Vidutinis Go bandymų reakcijos laikas buvo 425 ± 70 ms, o Go sąlygos tikslumas – 96,81 %, kas atitiko vidutiniškai 72,61 ± 4,82 teisingų atsakų. NoGo bandymų vidutinis tikslumas siekė 96,97 %, t. y. 72,73 ± 2,53 sėkmingai nuslopintų atsakų.

3.3.2. Sąsajos tarp PIN klausimynų ir elgseninių Go/NoGo užduoties rezultatų

Reikšmingų koreliacijų tarp PIN klausimynų įverčių ir Go/NoGo užduoties atlikimo rodiklių nenustatyta, išskyrus teigiamą koreliaciją tarp Žaidimų dimensijos įverčių ir Go reakcijos laikų ($r_s = 0{,}32$, p = 0,003), indikuojant, kad didesnis įsitraukimas į Žaidimus gali būti siejamas su lėtesniu atsako vykdymu. Reikšmingų sąsajų tarp bendrų PIN įverčių ir elgseninių rezultatų nebuvimas leidžia manyti, kad reguliarių interneto naudotojų bazinis kognityvinis funkcionavimas nėra paveikiamas elgseniniame lygmenyje. Detalūs koreliacijų rezultatai pateikti Papildomojoje medžiagoje 3, SM 3.1 lentelėje.

Be to, užduoties atlikimo skirtumų tarp žemo ir aukšto interneto naudojimo grupių taip pat nenustatyta (3.8 lentelė). Elgseninių rodiklių rezultatų vidurkiai ir standartiniai nuokrypiai pateikiami Papildomojoje medžiagoje 3, SM 3.2 lentelėje.

Lentelė 3.8. Grupių skirtumai tarp elgseninių Go/NoGo užduoties rezultatų.

Kintamieji	U	*p*	Efekto dydis	SE Efekto dydis
Teisingi_Go	617	0,571	0,072	0,135
Teisingi_NoGo	734	0,436	−0,104	0,135
Go_RT	766	0,267	−0,152	0,135

Go_RT—vidutinis Go reakcijos laikas, SE efekto dydis — Efekto dydžio standartinė paklaida, U— Mann–Whitney U kriterijus.

3.3.3. SĮSP rezultatai

Go ir NoGo sąlygų SĮSP amplitudžių ir latencijų vidurkiai ir standartiniai nuokrypiai pateikiami 3.9 lentelėje. Go-P3 buvo išreikštas parietalinėje, o NoGo-P3 – centrinėje srityse, kas atitinka ankstesnių Go/NoGo užduoties tyrimų rezultatus (Barry et al., 2016; Melynyte et al., 2017). Topografinių žemėlapių, vaizduojančių kiekvieno SĮSP komponento erdvinį pasiskirstymą abiem sąlygomis, iliustracijos pateiktos 3.6. paveiksle.

3.3.3.1. Ryšys tarp interneto naudojimo ir SĮSP komponentų Go sąlygos metu

Nustatyta neigiama koreliacija tarp N1 amplitudės ties Cz elektrodu ir Žaidimų dimensijos įverčių ($r_s = -0{,}467$, $p = 0{,}009$), atspindinti, kad didesnis įsitraukimas į žaidimus siejasi su mažesne N1 amplitudė. Taip pat nustatyta reikšminga neigiama koreliacija tarp N1 latencijos ties CPz elektrodu ir bendro DPIU įverčio ($r_s = -0{,}24$, $p = 0{,}009$), kas leidžia manyti apie galimą ryšį tarp didesnio įsitraukimo į internetines veiklas ir ankstesnių N1 atsakų. Išsamūs rezultatai pateikti Papildomojoje medžiagoje 3: Go amplitudėms – SM 3.3 lentelėje, Go latencijoms – SM 3.4 lentelėje.

3.3.3.2. Ryšys tarp interneto naudojimo ir SĮSP komponentų NoGo sąlygos metu

Neigiama koreliacija tarp N1 amplitudžių ties Cz elektrodu ir Žaidimų dimensijos įverčių ($r_s = -0{,}486$, $p = 0{,}006$) taip pat nustatyti ir NoGo sąlygos metu, atspindinti, kad didesnis įsitraukimas į žaidimus siejasi su žemesniu ankstyvuoju sensoriniu apdorojimu.

Analizuojant NoGo bandymų SĮSP latencijas, nustatyta reikšminga sąsaja tarp P3 latencijos ir Informacijos paieškos srities: teigiamos koreliacijos nustatytos ties trijų elektrodų vietomis (Fz: $r_s = 0{,}503$, $p = 0{,}017$; Cz: $r_s = 0{,}443$, $p = 0{,}039$; Pz: $r_s = 0{,}466$, $p = 0{,}029$). Šie rezultatai leidžia manyti, kad didesnis įsitraukimas į informacijos paiešką internete siejasi su uždelstais P3 atsakais, galimai atspindinčiais didesnę kognityvinę apkrovą arba mažesnį atsako slopinimo efektyvumą. Išsamūs rezultatai pateikiami Papildomojoje medžiagoje 3: NoGo amplitudėms – SM 3.5 lentelėje, NoGo latencijoms – SM 3.6 lentelėje.

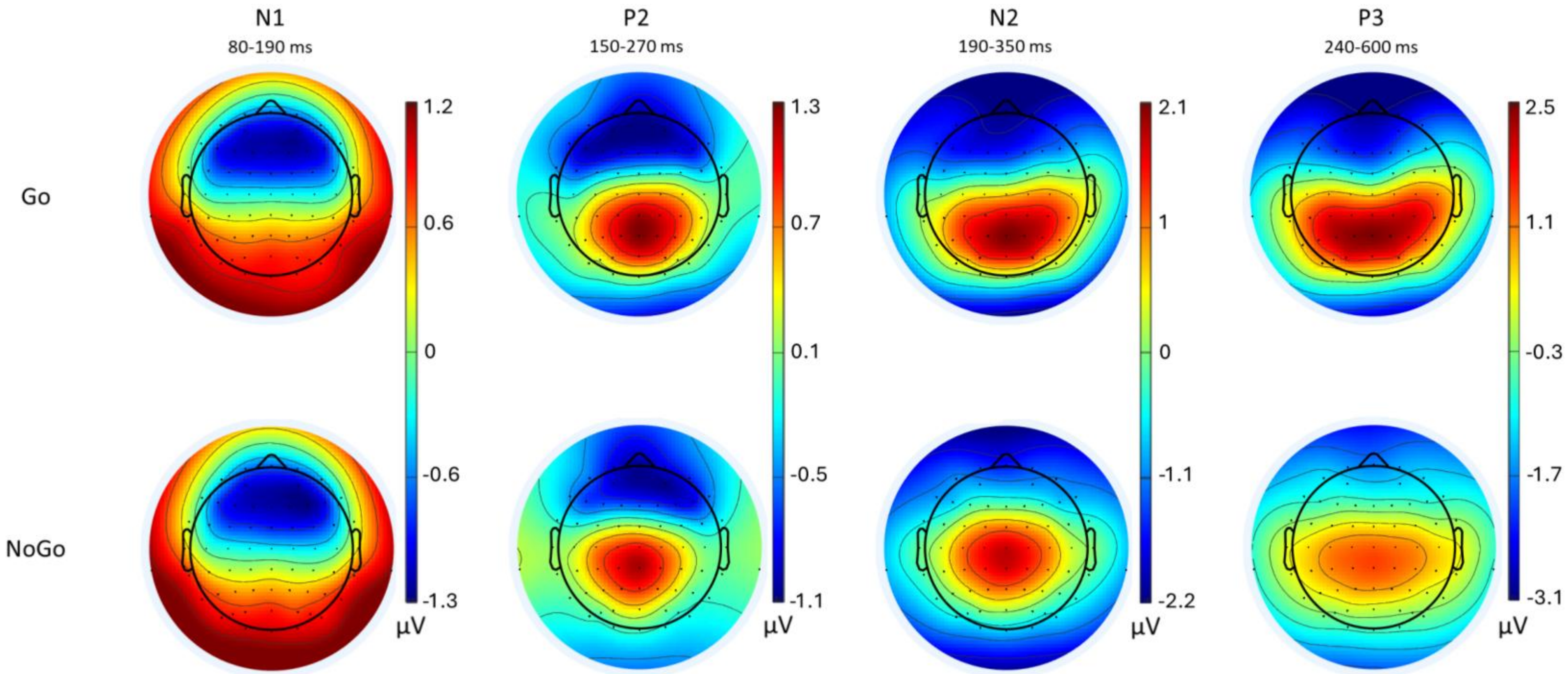
3.3.3.3. SĮSP parametrų palyginimas tarp žemo ir aukšto interneto naudojimo grupių

Skirtumų tarp SĮSP amplitudžių ir latencijų tarp grupių nenustatyta (3.10 lentelė). Suvidurkintos SĮSP bangos kiekvienai grupei Go ir NoGo sąlygų metu pateikiamos 3.7. paveiksle, o komponentų topografijos į Go ir NoGo stimulus – Papildomojoje medžiagoje 3, SM 3.1 paveiksle. SĮSP amplitudžių ir latencijų vidurkiai ir standartiniai nuokrypiai tarp grupių pateikti Papildomojoje medžiagoje 3, SM 3.7 lentelėje

Lentelė 3.9. Go ir NoGo sąlygų SĮSP amplitudžių ir latencijų aprašomoji statistika.

	Go sąlyga				NoGo sąlyga			
Elektrodas	N1	N2	P2	P3	N1	N2	P2	P3
				Amplitudės				
Fz	−2,49 ± 1,4	−2,86 ± 2,3	0,25 ± 1,7	−1,1 ± 2,2	−2,62 ± 1,5	−1,53 ± 1,9	0,28 ± 1,8	1,55 ± 2
FCz	−2,48 ± 1,3	−1,78 ± 2,1	1,1 ± 1,8	0,17 ± 2,5	−2,57 ± 1,4	−0,66 ± 1,8	1,08 ± 1,8	3,06 ± 2,4
Cz	−1,7 ± 1,1	−0,38 ± 1,7	1,64 ± 1,6	1,79 ± 2,5	−1,75 ± 1,1	0,22 ± 1,4	1,5 ± 1,4	3,48 ± 2,2
CPz	−0,85 ± 0,9	0,64 ± 1,5	1,76 ± 1,3	3,33 ± 2,4	−0,85 ± 0,9	0,6 ± 1,2	1,68 ± 1,2	2,95 ± 1,7
Pz	−0,51 ± 0,9	0,67 ± 1,5	1,64 ± 1,3	4,03 ± 2,3	−0,54 ± 0,9	0,15 ± 1,4	0,15 ± 1,4	2,19 ± 1,5
				Latencijos				
Fz	127,12 ± 12,2	280,39 ± 43,1	191,13 ± 20	366,25 ± 68,7	128,44 ± 15,4	248,54 ± 34,9	189,74 ± 28,3	339,57 ± 41,2
FCz	125,25 ± 9,4	263,71 ± 33,4	188,13 ± 17,5	340,19 ± 42,8	126,03 ± 10,5	240,08 ± 31,2	188,32 ± 23	332,07 ± 40,7
Cz	123,37 ± 11,6	259,44 ± 35,4	189,8 ± 21,8	352,71 ± 53,4	124,24 ± 8,3	235 ± 32	184,79 ± 17,7	328,24 ± 43,3
CPz	115,07 ± 18,7	242,3 ± 37,3	189,14 ± 24,5	362,07 ± 61,5	117,18 ± 16,6	237,34 ± 38,4	189,9 ± 29,8	334,85 ± 53,6
Pz	97,12 ± 23,7	224,05 ± 35,9	173,57 ± 28,8	362,52 ± 60,3	99,81 ± 27,3	239,94 ± 42,9	182,9 ± 31	350,18 ± 63

Amplitudės išreikštos mikrovoltais (μV), latencijos – milisekundėmis (ms); nurodomi vidurkiai ± SD.



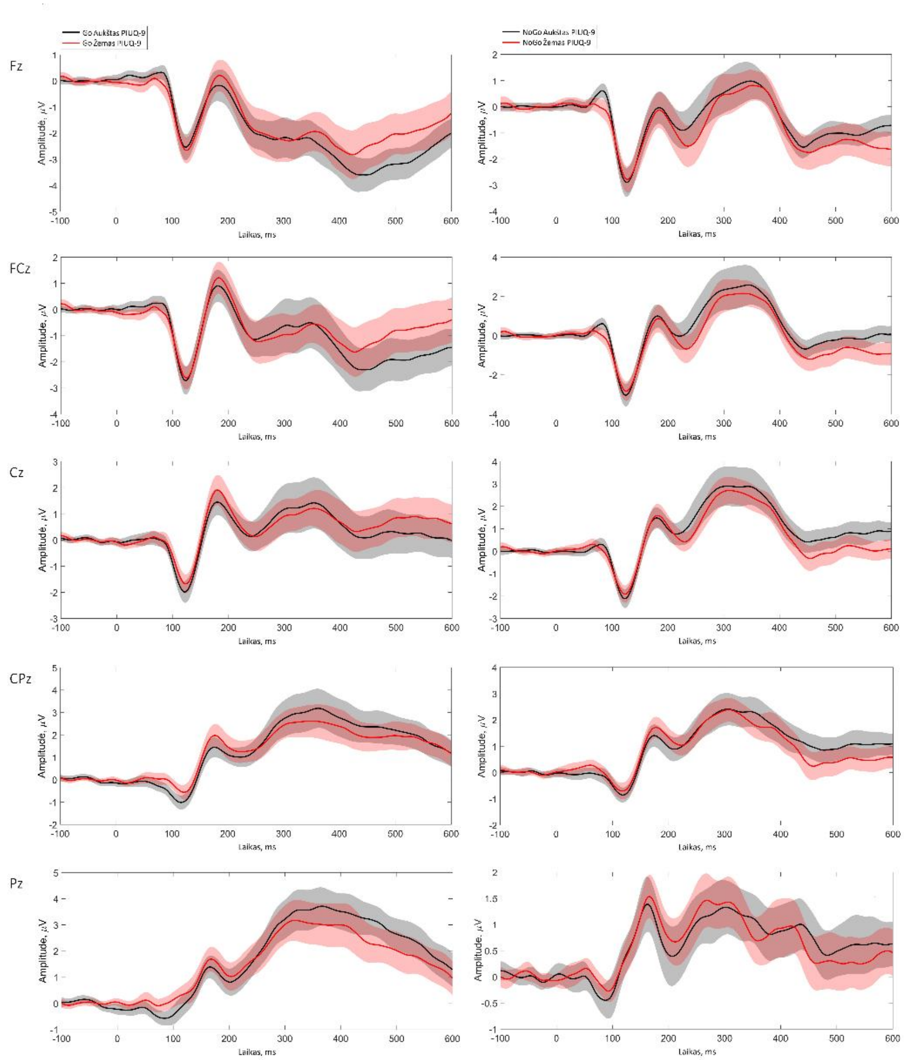
Pav. 3.6. Go ir NoGo stimulų topografiniai žemėlapiai. N1, P2, N2 ir P3 komponentų topografinis pasiskirstymas Go (viršutinė eilutė) ir NoGo (apatinė eilutė) stimulų pateikimo metu.

Lentelė 3.10. Grupių skirtumai tarp SĮSP amplitudžių ir latencijų Go ir NoGo sąlygų metu.

		Amplitudės				Latencijos			
Elektrodas	SĮSP	U	*p*	Efekto dydis	SE Efekto dydis	U	*p*	Efekto dydis	SE Efekto dydis
Go_Fz	N1	709	0,633	0,066	0,135	676,5	0,903	0,017	0,135
	N2	634	0,738	−0,047	0,135	574,5	0,32	−0,136	0,135
	P2	625	0,665	−0,06	0,135	604	0,504	−0,092	0,135
	P3	580	0,353	−0,128	0,135	467	0,029	−0,298	0,135
Go_FCz	N1	652	0,891	−0,02	0,135	616,5	0,596	−0,073	0,135
	N2	622	0,641	−0,065	0,135	727,5	0,494	0,094	0,135
	P2	626	0,673	−0,059	0,135	635,5	0,749	−0,044	0,135
	P3	634	0,738	−0,047	0,135	556,5	0,233	−0,163	0,135
Go_Cz	N1	551	0,211	−0,171	0,135	560,5	0,251	−0,157	0,135
	N2	652	0,891	−0,02	0,135	730,5	0,473	0,098	0,135
	P2	586	0,388	−0,119	0,135	734	0,449	0,104	0,135
	P3	682	0,856	0,026	0,135	738,5	0,42	0,111	0,135
Go_CPz	N1	515	0,099	−0,226	0,135	551,5	0,212	−0,171	0,135
	N2	713	0,602	0,072	0,135	624	0,655	−0,062	0,135
	P2	542	0,177	−0,185	0,135	678	0,89	0,02	0,135
	P3	753	0,336	0,132	0,135	707,5	0,643	0,064	0,135
Go_Pz	N1	440	0,013	−0,338	0,135	587,5	0,395	−0,117	0,135
	N2	665	1	0	0,135	498	0,066	−0,251	0,135
	P2	578	0,342	−0,131	0,135	623,5	0,65	−0,062	0,135
	P3	741	0,407	0,114	0,135	706	0,655	0,062	0,135
NoGo_Fz	N1	644	0,822	−0,032	0,135	689	0,795	0,036	0,135

		Amplitudės				Latencijos			
Elektrodas	SĮSP	U	*p*	Efekto dydis	SE Efekto dydis	U	*p*	Efekto dydis	SE Efekto dydis
	N2	709	0,633	0,066	0,135	685,5	0,825	0,031	0,135
	P2	659	0,952	−0,009	0,135	720,5	0,544	0,083	0,135
	P3	708	0,641	0,065	0,135	742	0,398	0,116	0,135
NoGo_FCz	N1	649	0,865	−0,024	0,135	626,5	0,675	−0,058	0,135
	N2	716	0,579	0,077	0,135	709,5	0,627	0,067	0,135
	P2	719	0,557	0,081	0,135	720,5	0,544	0,083	0,135
	P3	669	0,969	0,006	0,135	692,5	0,766	0,041	0,135
NoGo_Cz	N1	646	0,839	−0,029	0,135	594	0,436	−0,107	0,135
	N2	664	0,996	−0,002	0,135	664	0,996	−0,002	0,135
	P2	659	0,952	−0,009	0,135	680	0,873	0,023	0,135
	P3	697	0,73	0,048	0,135	673	0,934	0,012	0,135
NoGo_CPz	N1	619	0,617	−0,069	0,135	672,5	0,938	0,011	0,135
	N2	575	0,325	−0,135	0,135	683	0,847	0,027	0,135
	P2	622	0,641	−0,065	0,135	675,5	0,912	0,016	0,135
	P3	662	0,978	−0,005	0,135	813	0,103	0,223	0,135
NoGo_Pz	N1	632	0,721	−0,05	0,135	773,5	0,231	0,163	0,135
	N2	578	0,342	−0,131	0,135	794	0,156	0,194	0,135
	P2	588	0,401	−0,116	0,135	654,5	0,912	−0,016	0,135
	P3	603	0,499	−0,093	0,135	752,5	0,337	0,132	0,135

Po FDR korekcijos statistiškai reikšmingų rezultatų neliko. SE efekto dydis — Efekto dydžio standartinė paklaida, U— Mann–Whitney U kriterijus.



Pav. 3.7. Vidutinės SĮSP bangos Go ir NoGo stimulams aukšto ir žemo interneto naudojimo grupėse. Suvidurkintos SĮSP bangos Go (kairysis stulpelis) ir NoGo (dešinysis stulpelis) stimulams vidurio linijos elektrodų vietose (Fz, FCz, Cz, CPz ir Pz) aukštų PIUQ-9 įverčių grupėje (juoda linija) ir žemų PIUQ-9 įverčių grupėje (raudona linija). Šešėliuotos sritys aplink bangas žymi 1,96×standartinės paklaidos intervalą (vidurkis ± 1,96×SP)

3.4. Kintanti ramybės būsena: alfa asimetrija

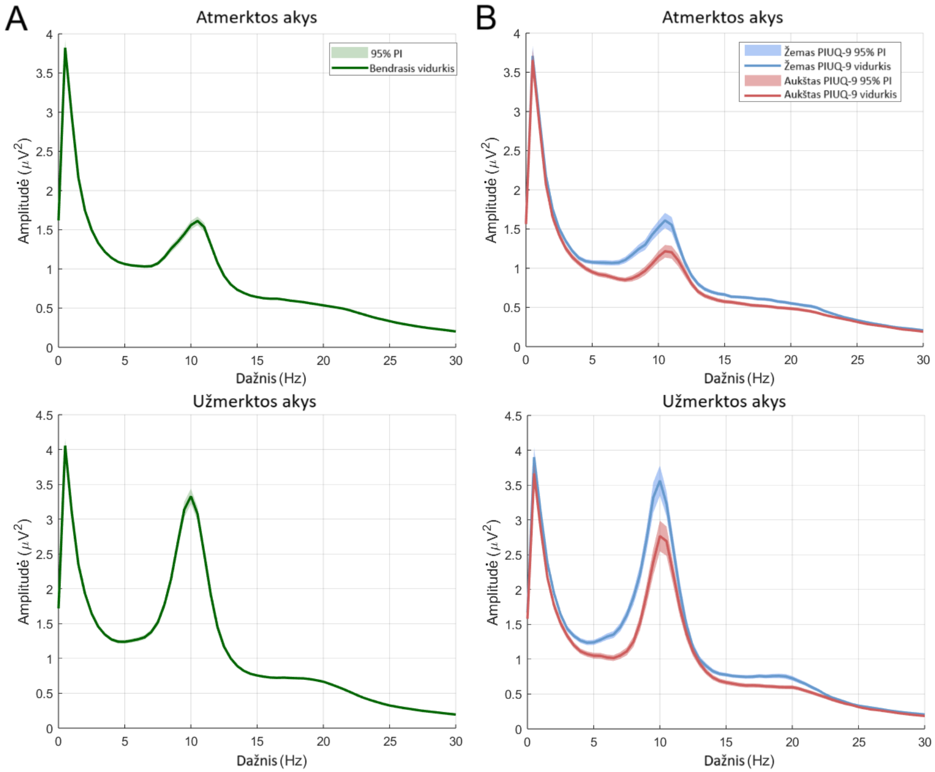
Galutinė 129 dalyvių (80 moterų) imtis turėjo vidutinį PIUQ-9 įvertį 19,39 ± 5,20. Žemo interneto naudojimo grupės (n = 36; 22 moterys) vidurkis buvo 13,72 ± 2,07, o aukšto interneto naudojimo grupės (n = 33; 24 moterys) – 26,49 ± 3,10. Amžiaus skirtumų tarp aukšto ir žemo PIUQ-9 įverčio grupių nenustatyta ($p = 0{,}329$).

3.4.1. Spektrinė analizė

Absoliučios alfa galios vidurkiai ir standartiniai nuokrypiai, įvertintai frontalinėse ir parietalinėse srityse, atmerktų (EO) ir užmerktų akių (EC) sąlygose, pateikiami 3.11 lentelėje; taip pat absoliučios galios vidurkių vizualizacija pateikta 3.8A. paveiksle.

Stebėtos silpnos, bet reikšmingos neigiamos koreliacijos tarp PIUQ-9 balų ir alfa galios frontalinėje ($r_s = -0{,}248$, $p = 0{,}005$) ir parietalinėje ($r_s = 0{,}209$, $p = 0{,}018$) srityse EO metu, taip pat frontalinėje ($r_s = -0{,}241$, $p = 0{,}006$) ir parietalinėje ($r_s = -0{,}183$, $p = 0{,}038$) srityse EC metu. Reikšmingų koreliacijų tarp alfa galios ir vertintų psichologinių kintamųjų nenustatyta. Detalūs koreliacijų rezultatai ir reikšmingas koreliacijas atspindintys grafikai pateikiami Papildomojoje medžiagoje 4, SM 4.1 lentelėje ir SM 4.1 paveiksle.

Kaip tikėtasi, alfa galios palyginimai tarp aukšto ir žemo interneto naudojimo grupių atskleidė reikšmingus skirtumus abiejų sąlygų metu (EO, EC) tiek frontalinėse, tiek parietalinėse srityse. Detalūs rezultatai pateikti 3.12 lentelėje, bendri grupių absoliučios galios vidurkiai pavaizduoti 3.8B. paveiksle, o aprašomoji statistika (vidurkiai ir standartiniai nuokrypiai) – Papildomojoje medžiagoje 4, SM 4.2 lentelėje.



Pav. 3.8. Suvidurkintos absoliučios galios bangos visoje imtyje (n = 129) (A) ir aukšto (n = 33) bei žemo (n = 36) interneto naudojimo grupėse (B). Šešėliuotos sritys žymi 95 % pasikliautinius intervalus aplink vidutinę amplitudę.

Lentelė 3.11. Aprašomoji vidutinės alfa galios (μV) ir alfa asimetrijos įverčių statistika frontalinėje ir parietalinėje srityse atmerktų (EO) ir užmerktų (EC) akių sąlygomis visoje imtyje.

Kintamieji	n	Vidurkis ± SD	Kintamieji	n	Vidurkis ± SD	Kintamieji	n	Vidurkis ± SD
Alfa dažnis (μV)			Alfa asimetrija (EO)			Alfa asimetrija (EC)		
EO_frontalinė	128	0,52±0,39	F3/F4	125	-0,03±0,24	F3/F4	128	-0,05±0,19
EO_parietalinė	128	0,72±0,58	F7/F8	124	-0,05±0,50	F7/F8	128	-0,06±0,43
EC_frontalinė	129	1,71±1,30	P3/P4	122	0,19±0,40	P3/P4	123	0,33±0,48
EC_parietalinė	129	3,05±2,34	P7/P8	120	0,13±0,41	P7/P8	121	0,33±0,55

Lentelė 3.12. Aukšto ir žemo interneto naudojimo grupių skirtumai alfa dažnio diapazone frontalinėje ir parietalinėje srityse atmerktų (EO) ir užmerktų (EC) akių sąlygomis.

Kintamieji	U	*p*	Efekto dydis	SE Efekto dydis
EO_frontalinė	376	**0,008***	-0,367	0,139
EO_parietalinė	428	**0,046***	-0,279	0,139
EC_frontalinė	373	**0,008***	-0,372	0,139
EC_parietalinė	430	**0,049***	-0,276	0,139

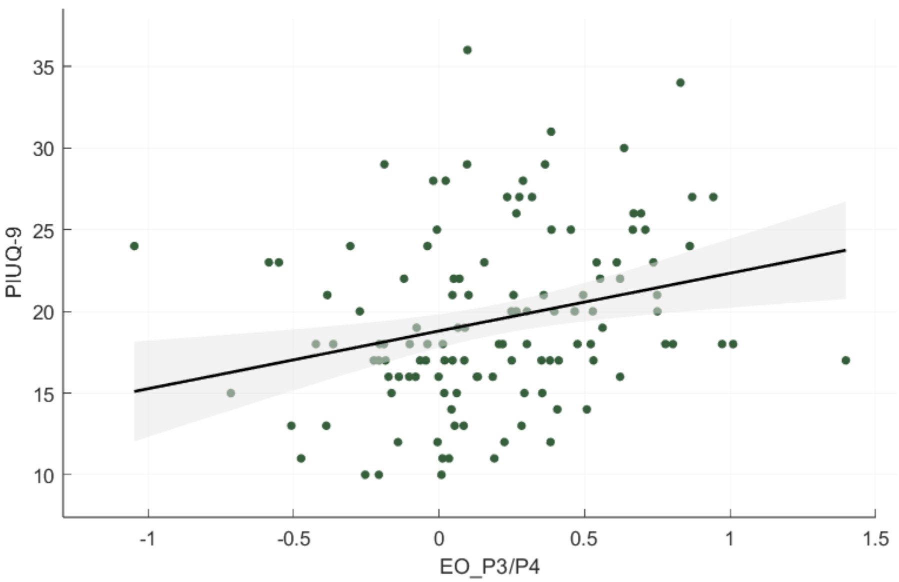
* Rezultatų reikšmingumas išliko pritaikius FDR korekciją. SE efekto dydis — Efekto dydžio standartinė paklaida, U— Mann–Whitney U kriterijus.

3.4.2. Ryšys tarp interneto naudojimo ir alfa asimetrijos indekso

Aprašomoji alfa asimetrijos įverčių statistika (vidurkiai ir standartiniai nuokrypiai) EO ir EC sąlygose pateikiami 3.11 lentelėje. Nustatyta reikšminga teigiama koreliacija tarp PIUQ-9 balų ir alfa asimetrijos įverčių P3/P4 elektrodų poroje (r_s = 0,317, p < 0,001) EO sąlygos metu (3.9. paveikslas). Rezultatas atspindi aukštesnę dešiniosios parietalinės srities alfa galią (taigi didesnį kairiojo pusrutulio aktyvumą) esant aukštesniam interneto naudojimo lygiui. Detalūs rezultatai pateikti 3.13 lentelėje.

Analizės pradžioje stebėta daugiau sąsajų: teigiama koreliacija tarp PIUQ-9 įverčių ir alfa asimetrijos indekso įverčių P7/P8 elektrodų poroje EO sąlygos metu (r_s = 0,190, p = 0,038) ir, vertinant psichologinius kintamuosius, neigiama koreliacija tarp depresijos (BDI) įverčių ir alfa asimetrijos indekso P7/P8 elektrodų poroje EO sąlygoje (rs = 0,199, p = 0,032). Vis dėlto nė viena iš šių sąsajų neišliko reikšminga pritaikius FDR korekciją.

Analizuojant skirtumus tarp aukšto ir žemo interneto naudojimo grupių, aukštų PIUQ-9 įverčių grupė pasižymėjo reikšmingai aukštesnėmis alfa asimetrijos indekso vertėmis P3/P4 elektrodų poroje EO metu nei žemo įverčio grupė (p = 0,002; atitinkamai 0,28 ± 0,46 ir 0,02 ± 0,29) (3.10 paveikslas). Detalūs rezultatai pateikiami 3.14 lentelėje, aprašomoji statistika – Papildomojoje medžiagoje 4, SM 4.2 lentelėje.



Pav. 3.9..Koreliacija tarp PIUQ-9 klausimyno ir alfa asimetrijos įverčių P3/P4 elektrodų poroje, kurioje nustatytas statistinis reikšmingumas. EO – atmerktų akių sąlyga. Šešėliuotos sritys žymi 95 % pasikliautinąjį intervalą regresijos įverčiams.

Lentelė 3.13. Spearmano koreliacijos tarp interneto naudojimo (PIUQ-9) ir alfa asimetrijos įverčių visoms elektrodų poroms (F3/F4, F7/F8, P3/P4, P7/P8) atmerktų (EO) ir užmerktų (EC) akių sąlygomis.

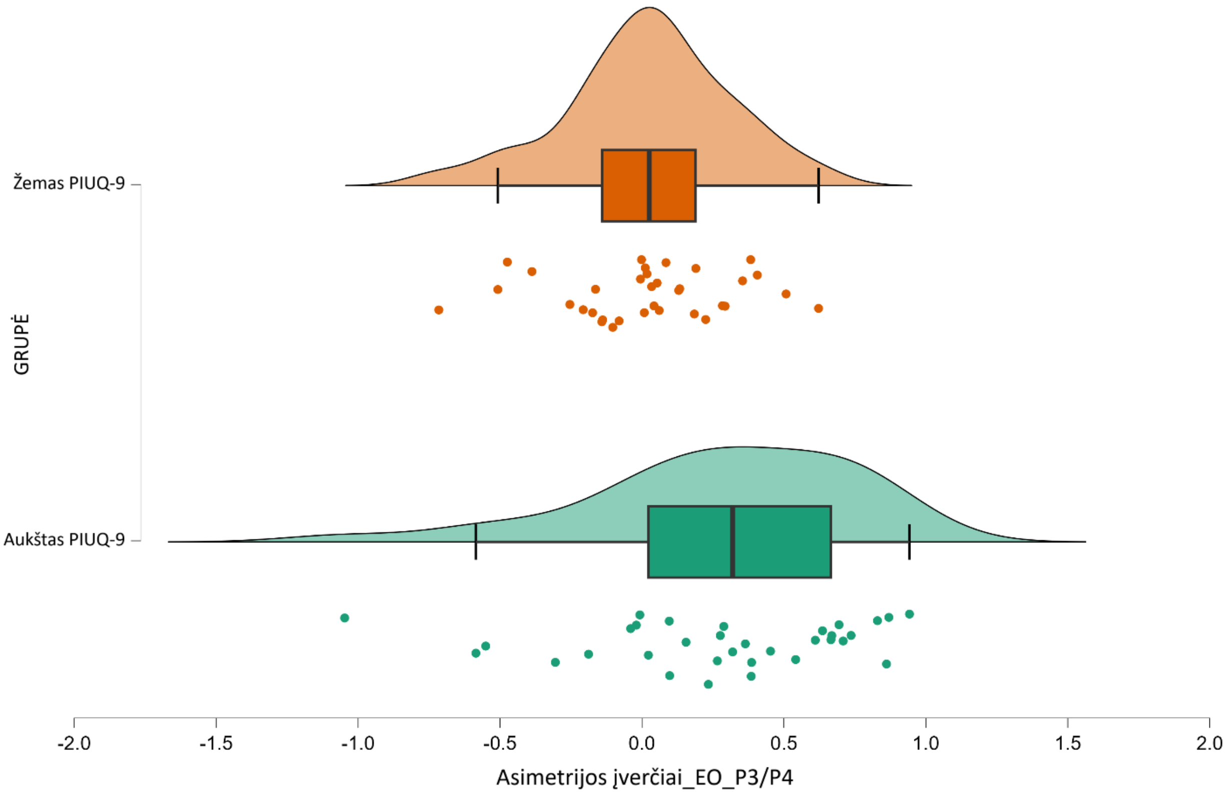
Elektrodų poros		EO	EC
	r_s	0,096	-0,038
F3/F4	*p*	0,286	0,668
	n	125	128
	r_s	0,019	-0,022
F7/F8	*p*	0,834	0,805
	n	124	128
	r_s	**0,317***	0,128
P3/P4	*p*	**< ,001**	0,159
	n	122	123
	r_s	**0,19**	0,176
P7/P8	*p*	**0,038**	0,053
	n	120	121

* Rezultatų reikšmingumas išliko pritaikius FDR korekciją.

Lentelė 3.14. Grupių skirtumai tarp alfa asimetrijos įverčių visoms elektrodų poroms (F3/F4, F7/F8, P3/P4, P7/P8) atmerktų (EO) ir užmerktų (EC) akių sąlygomis.

Kintamieji	U	*p*	Efekto dydis	SE efekto dydis
EO				
F3/F4	674	0,241	0,167	0,14
F7/F8	534	0,6	-0,075	0,14
P3/P4	801	**0,002***	0,428	0,141
P7/P8	704	**0,021**	0,333	0,143
EC				
F3/F4	575	0,825	-0,032	0,139
F7/F8	524	0,406	-0,118	0,139
P3/P4	644	0,409	0,118	0,14
P7/P8	640	0,144	0,212	0,143

* Rezultatų reikšmingumas išliko pritaikius FDR korekciją. SE efekto dydis — Efekto dydžio standartinė paklaida, U— Mann–Whitney U kriterijus.



Pav. 3.10. Parietalinės srities P3/P4 elektrodų poros alfa asimetrijos įverčių „Raincloud" diagramos (branduoliniai tankio įverčiai, dėžutės diagramos ir individualūs duomenų taškai (Allen et al., 2021)) EO sąlygos metu aukšto ir žemo interneto naudojimo grupėms. Individualūs taškai atspindi kiekvieno tiriamojo alfa asimetrijos įvertį.

3.5. Ramybės būsenos mikrobūsenos

Galutinė 156 dalyvių (86 moterys) imtis turėjo vidutinį PIUQ-9 įvertį 19,65 ± 5,29. Žemo interneto naudojimo grupės (n = 43; 21 moteris) PIUQ-9 vidurkis buvo 13,77 ± 2,01, o aukšto PIN įverčio grupės (n = 44; 28 moterys) – 26,54 ± 2,90. Amžiaus skirtumų tarp aukšto ir žemo interneto naudojimo grupių nenustatyta (p = 0,233).

3.5.1. EEG mikrobūsenų žemėlapiai

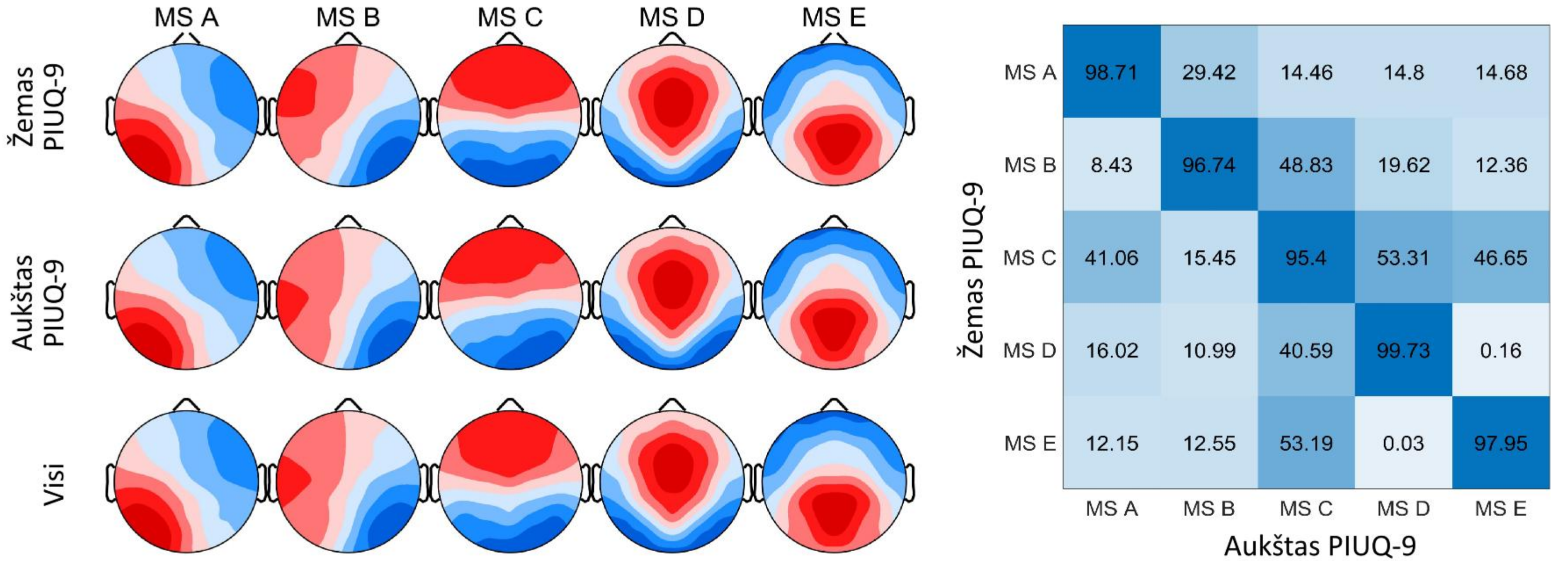
Remiantis nustatytais metakriterijais, optimalus mikrobūsenų topografijų skaičius buvo penki (tiek žemo, tiek aukšto interneto naudojimo grupėms, taip pat visai imčiai). Bendra erdvinė variacija parodė, kad mikrobūsenų žemėlapiai tarp aukšto ir žemo interneto naudojimo grupių yra erdviškai ekvivalentiški (>95 %) (3.11. pav.). Grupių lygmens mikrobūsenų žemėlapiai atitiko prototipines konfigūracijas ir glaudžiai sutapo su įprastai literatūroje aprašomomis mikrobūsenų klasėmis, taip pat su anksčiau nurodytomis meta-mikrobūsenomis (Koenig et al., 2024). Atitinkamai mikrobūsenos buvo pažymėtos pagal atnaujintą mikrobūsenų klasifikavimo sistemą (Tarailis et al., 2024).

3.5.2. Ryšys tarp PIUQ-9 įverčių ir mikrobūsenų laikinių parametrų

Laikiniai mikrobūsenų parametrai (trukmė, pasirodymo dažnis ir indėlis) pateko į normatyvinių 95 % prognozės intervalų ribas, įvertintas pagal 93 tyrimus (Zanesco, 2024). Kiekvienos mikrobūsenos parametrų vidurkiai ir standartiniai nuokrypiai visai imčiai pateikiami 3.15 lentelėje, o vertės tarp grupių – Papildomojoje medžiagoje 5, SM 5.1 lentelėje.

PIUQ-9 įverčiai teigiamai koreliavo su MS E pasirodymo dažniu (r_s = 0,235, p = 0,003), taip pat MS E indėliu (r_s = 0,241, p = 0,002) (3.12. pav.). Detalūs koreliacijų rezultatai pateikiami Papildomojoje medžiagoje 5, SM 5.2 lentelėje.

Grupių palyginimuose tie patys du laikiniai parametrai (pasirodymo dažnis ir indėlis) reikšmingai skyrėsi tarp aukšto ir žemo interneto naudojimo grupių. Konkrečiai, aukšto PIN įverčio grupė turėjo reikšmingai didesnį MS E pasirodymo dažnį nei žemo įverčio grupė (p = 0,006; atitinkamai 2,23 ± 0,76 ir 1,78 ± 0,61). Panašiai MS E laiko dalis buvo reikšmingai didesnė aukšto PIN įverčio grupėje (p = 0,004; 12,36 ± 5,31 % vs. 9,29 ± 3,76 %). Detalūs rezultatai pateikiami 3.16 lentelėje. Individualūs duomenų taškai, kartu su grupių vidurkiais ir standartiniais nuokrypiais, pavaizduoti 3.13 paveiksle.

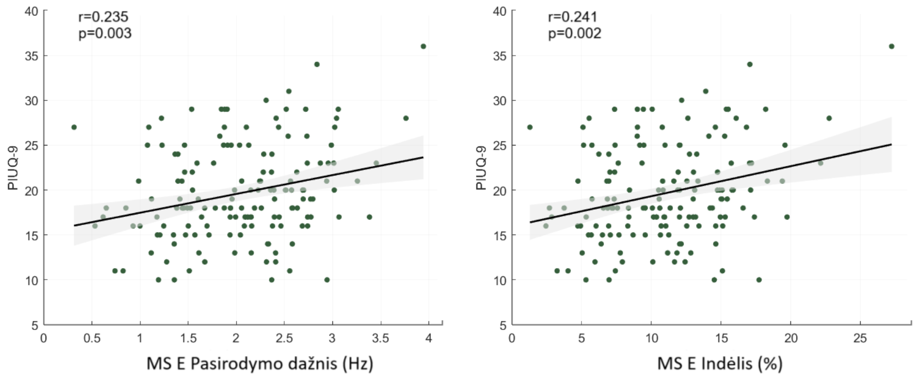


Pav. 3.11. Kairėje: grupinio lygmens topografijos, gautos žemo interneto naudojimo (N = 43), aukšto interneto naudojimo (N = 44) ir visos imties (N = 156) grupėms. Dešinėje: erdvinė dispersijos (%) matrica tarp žemo ir aukšto interneto naudojimo grupių topografijų.

Lentelė 3.15. Mikrobūsenų parametrų aprašomoji statistika.

Mikrobūsena	Trukmė (ms)	Pasikartojimo dažnis (Hz)	Indėlis (%)
MS A	51,87 ± 3,75	2,95 ± 0,61	18,1 ± 4,69
MS B	54,14 ± 4,47	3,25 ± 0,55	21,22 ± 5,4
MS C	68,91 ± 9,57	4,33 ± 0,39	38,79 ± 8,73
MS D	46,6 ± 2,92	2,05 ± 0,53	10,9 ± 3,4
MS E	46,79 ± 3,42	2,04 ± 0,67	11 ± 4,46

Nurodomi vidurkiai ± SD.



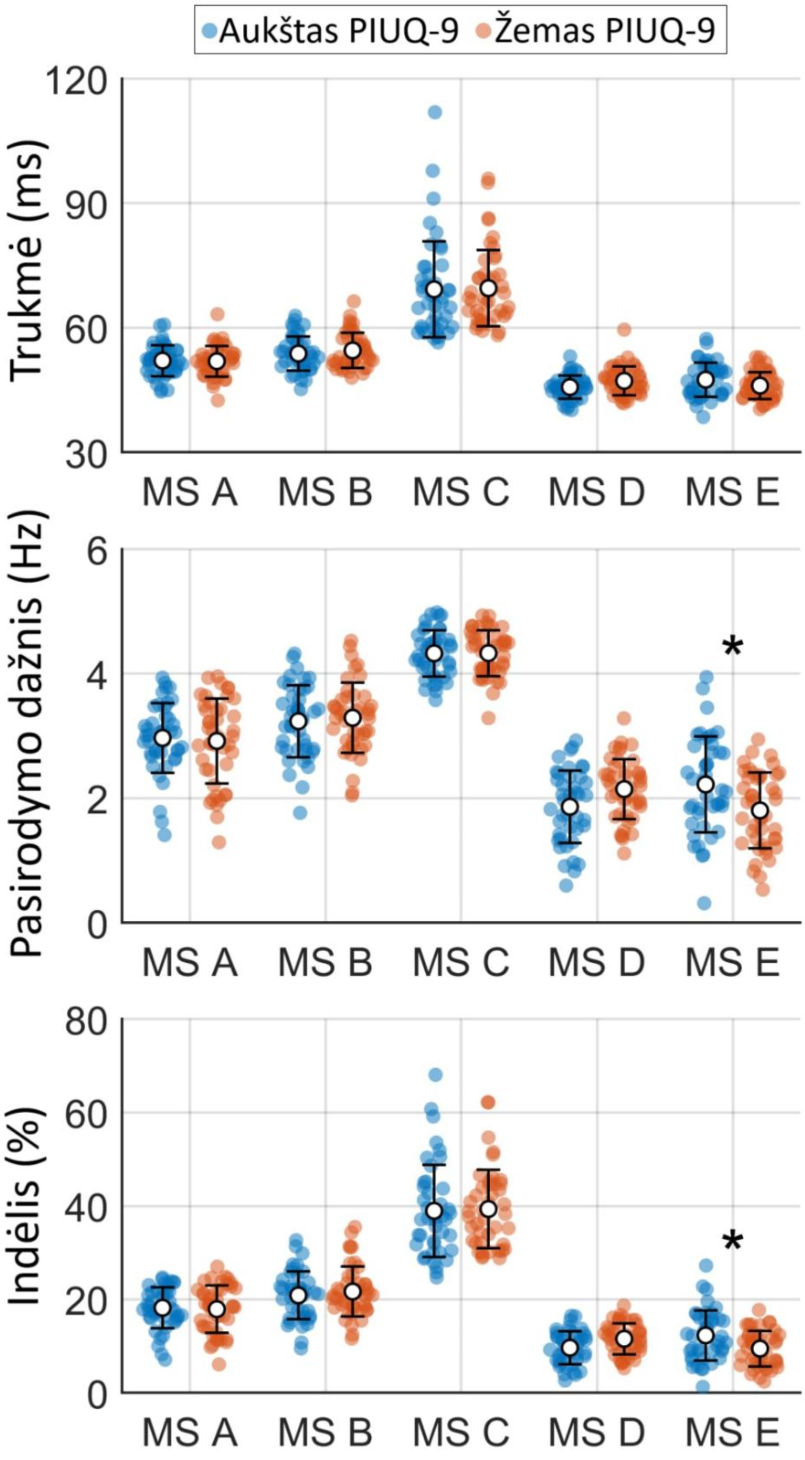
Pav. 3.12. Koreliacijos tarp PIUQ-9 klausimyno įverčių ir mikrobūsenų parametrų, tarp kurių nustatytas statistinis reikšmingumas. Šešėliuotos sritys žymi 95 % pasikliautinąjį intervalą regresijos įverčiams

Papildomai nustatytos reikšmingos sąsajos tarp mikrobūsenų parametrų ir vertintų psichologinių klausimynų įverčių, ypač nerimo (BAI) ir OKS(CBOCI). CBOCI bendras įvertis neigiamai koreliavo su MS D trukme (rs = 0,215, p = 0,007). BAI įverčiai neigiamai koreliavo su MS D trukme (r_s = 0,263, p < 0,001), MS B (r_s = 0,216, p = 0,007) ir MS D (r_s = 0,205, p = 0,010) pasirodymo dažniu, taip pat su MS B (r_s = 0,198, p = 0,014) ir MS D (r_s = 0,237, p = 0,003) indėliu. Taip pat, nustatyta teigiama koreliacija tarp BAI įverčių ir MS C indėliu (r_s = 0,189, p = 0,019). Detalūs rezultatai pateikiami Papildomojoje medžiagoje 5, SM 5.3 lentelėje, o reikšmingos koreliacijos pavaizduotos Papildomojoje medžiagoje 5, SM 5.1 paveiksle.

Lentelė 3.16. Grupių skirtumai tarp mikrobūsenų parametrų.

Kintamieji	**U**	***p***	**Efekto dydis**	**SE Efekto dydis**
Trukmė (ms)				
MS A	984	0,751	0,04	0,124
MS B	927	0,876	-0,02	0,124
MS C	841	0,377	-0,111	0,124
MS D	764	0,124	-0,192	0,124
MS E	1190	**0,038**	0,258	0,124
Pasirodymo dažnis (Hz)				
MS A	957	0,929	0,012	0,124
MS B	920	0,829	-0,027	0,124
MS C	898	0,688	-0,051	0,124
MS D	712	**0,047**	-0,247	0,124
MS E	1270	**0,006***	0,342	0,124
Indėlis (%)				
MS A	965	0,876	0,02	0,124
MS B	938	0,949	-0,008	0,124
MS C	842	0,381	-0,11	0,124
MS D	686	**0,027**	-0,275	0,124
MS E	1281	**0,004***	0,354	0,124

* Rezultatų reikšmingumas išliko pritaikius FDR korekciją. SE efekto dydis — Efekto dydžio standartinė paklaida, U— Mann–Whitney U kriterijus.



Pav. 3.13. Individualūs mikrostatų parametrų įverčiai; balti taškai žymi vidurkius, o klaidų juostos – standartinius nuokrypius. Žvaigždutės (*) žymi FDR korekciją atlaikiusius statistiškai reikšmingus ($p < 0,05$) vidurkių skirtumus.

4. DISKUSIJA

4.1. Psichologinis lygmuo

Šio tyrimo rezultatai sveikų jaunų suaugusiųjų imtyje patvirtina ankstesnių metaanalizių ir sisteminių literatūros apžvalgų rezultatus (Carli et al., 2013; Ho et al., 2014; Kuss & Lopez-Fernandez, 2016; Noroozi et al., 2021), pagrindžiančius tvirtas sąsajas tarp probleminio interneto naudojimo ir nerimo, depresijos bei obsesinių–kompulsinių elgesių simptomų. Reikšmingi psichologiniai skirtumai tarp aukštus ir žemus PIN įverčius turinčių grupių tik patvirtina neigiamą probleminio elgesio internete įtaką psichikos sveikatai.

Paminėtina, jog atskiros DPIU dimensijos rodė skirtingas sąsajas su patiriamos depresijos, nerimo ir obsesijų–kompulsijų simptomais. Pavyzdžiui, socialinių tinklų dimensijos įverčiai koreliavo su visais tirtais psichologiniais rodikliais (nerimu, depresija, obsesijomis ir kompulsijomis), Pramoginių ir vaizdo įrašų peržiūros dimensijos įverčiai koreliavo su nerimu ir obsesiniais simptomais, tuo tarpu Žinučių rašymo dimensija – tik su obsesijomis. Priešingai, Žaidimų ir Informacijos paieškos dimensijos reikšmingų sąsajų su vertintais psichologiniais rodikliais neatskleidė. Šie rezultatai sustiprina hipotezę, kad, nepaisant bendrų pamatinių veiksnių siejančių internetines veiklas (Andreassen et al., 2013; Robbins & Clark, 2015), skirtingos PIN formos gali būti nevienodai susijusios su psichikos sveikatos rodikliais, galbūt atspindėdamos skirtingus psichologinio pažeidžiamumo modelius.

Rezultatai dera su teoriniais modeliais, pagal kuriuos PIN turėtų būti suprantamas ne tik kaip vienalytis sutrikimas, bet ir kaip įvairių veiklų spektras, grindžiamas skirtingais motyvaciniais ir psichologiniais veiksniais (Al-Menayes, 2015; Griffiths, 2014; Király et al., 2014; Lee et al., 2017; Schou Andreassen et al., 2016).

4.2. Interocepcinis įsisąmoninimas, asmenybės bruožai ir PIN

Interocepcinis įsisąmoninimas – gebėjimas tiksliai suvokti vidinius kūno signalus – siejamas su kognityviniais–afektiniais atsakais į su atlygiu susijusius elgesius (įskaitant priklausomybių sutrikimus) ir formuoja subjektyvų kūno grįžtamąjį ryšį, palengvinantį lanksčius ir greitus atsakus (Forkmann et al., 2016; Khalsa et al., 2018; Sönmez et al., 2016; Verdejo-Garcia et al., 2012). Asmenys, kurių interocepcinis įsisąmoninimas pakitęs, dažniau patiria intensyvias potraukio būsenas ir turi didesnę atkryčio riziką reaguodami į stresą ar neigiamus afektus (Herman, 2023; Khalsa et al., 2018; Paulus & Stewart, 2014). Literatūroje keliama prielaida, kad prastas interocepcinis įsisąmoninimas riboja veiksmingą vidinių kūno užuominų panaudojimą, todėl asmenys labiau remiasi išoriniais šaltiniais priimdami sprendimus; neapibrėžtumo sąlygomis tai gali didinti polinkį į netinkamus pasirinkimus (Pollatos et al., 2023).

PIN kontekste šio tyrimo metu nustatyta reikšminga neigiama sąsaja tarp PIN įverčių ir interocepcinio įsisąmoninimo dimensijos Nepaisymas. Konkrečiai, asmenys, labiau linkę užgožti ar vengti kūno diskomforto (Mehling et al., 2012), pasižymėjo problemiškesniu interneto naudojimu. Šie rezultatai rodo, kad prastesnis interocepcinis įsisąmoninimas gali silpninti savireguliacijos pajėgumus ir rizikos vertinimo efektyvumą, paaiškinat polinkį į probleminius interneto naudojimo modelius kaip įveiką nuo diskomforto.

Be to, Neurotiškumas išryškėjo kaip centrinis veiksnys asmenybės bruožų, interocepcinių būsenų ir interneto naudojimo modelių tinkle, ir buvo glaudžiai susijęs su probleminio interneto naudojimo šablonais ir prastesniu interocepciniu įsisąmoninimu. Anksčiau publikuoti tyrimai, įskaitant metaanalizes ir sistemines literatūros apžvalgas, identifikuoja neurotiškumą kaip vieną pagrindinių su PIN susijusių asmenybės bruožų (Jeronimus et al., 2016; Kayiş et al., 2016; Koronczai et al., 2019; Marciano et al., 2020; Müller et al., 2023). Marciano et al. (2020) pabrėžė, kad neurotiškumo įtaka disfunkciniam interneto naudojimui turėtų būti suprantama kaip neurotiškumo sąveikos tarp asmenybės bruožų (pvz., padidėjusio jautrumo neigiamoms emocijoms, emocinio nestabilumo, silpnos savireguliacijos), disfunkcinių įveikos strategijų ir aplinkos veiksnių rezultatas. Šiuo požiūriu neurotiškumas (ne kaip atskiras bruožas, o kaip pamatinės disfunkcijos raiška) stiprina polinkį į probleminį elgesį internete, sustiprindamas esamus psichologinius bruožus ir pažeidžiamumus (pvz., kylančius dėl emocinių ir tarpasmeninių sunkumų) (Jeronimus et al., 2016; Kayiş et al., 2016; Marciano et al., 2020; Tian et al., 2021), taip sudarydamas prielaidas netinkamai įveikai (pvz., atlygį teikiančios patirties ieška įvairiose interneto platformose).

Šiuos teiginius pagrindžia ir šiame tyrime stebėtos neigiamos sąsajos tarp Neurotiškumo ir interocepcinio įsisąmoninimo (Nesijaudinimo, Savireguliacijos ir Pasitikėjimo) aspektų. Šie rezultatai taip pat atitinka Gaggero et al. (2022) duomenis, pagal kuriuos asmenys su stipriau išreikštu neurotiškumu pasižymi žemesniu interocepciniu įsisąmoninimu minėtuose MAIA aspektuose. Pastebėtos sąsajos leidžia manyti, kad aukštesnio neurotiškumo asmenims sunkiau adekvačiai suvokti ir veiksmingai reaguoti į kūno pojūčius: jie patiria didesnį emocinį išsekimą reaguodami į nepatogius pojūčius (Nesijaudinimas), susiduria su sunkumais reguliuojant psichologinį stresą šių būsenų atžvilgiu (Savireguliacija) ir prasčiau geba suvokti savo kūną kaip patikimą ar saugų (Pasitikėjimas) (Mehling et al., 2012). Šie rezultatai taip pat palaiko literatūroje keliamą prielaidą, kad neurotiškumas yra susijęs su silpnesnėmis savireguliacijos galiomis ir gali stiprinti labiau pažeidžiamų asmenų polinkį įsitraukti į skaitmenines veiklas kaip į tam tikrą įveikos mechanizmą (Caplan, 2010; Pastor et al., 2022). Šiame kontekste neurotiškumas gali būti ir pažeidžiamumą PIN atžvilgiu didinantis veiksnys, ir potencialus terapinis taikinys, sprendžiant netinkamus interneto naudojimo modelius.

Iki šiol tik vienas tyrimas nagrinėjo PIN interocepcinio įsisąmoninimo kontekste (Di Carlo et al., 2024). Di Carlo et al. (2024) nustatė reikšmingus skirtumus tarp PIN turinčių ir neturinčių grupių, ypač Nepaisymo, Pasitikėjimo, Nesijaudinimo ir „Emocijų įsisąmoninimo“ srityse. Dabartinis tyrimas patvirtina Nepaisymo ir Pasitikėjimo aspektų sąsajas su PIN, tačiau priešingai nei Di Carlo et al. (2024), sąsajos su Nesijaudinimo ir Emocijų įsisąmoninimo aspektais pasirodė esą labiau specifiškos tam tikroms veikloms internete, nei bendrai PIN. Konkrečiai, Žinučių rašymo dimensijos įverčiai neigiamai koreliavo su dauguma interocepcinio įsisąmoninimo kintamųjų, įskaitant „Dėmesio reguliavimą“, „Savireguliaciją“, „Kūno klausymąsi“, „Emocijų įsisąmoninimą“ ir „Pasitikėjimą“. Tuo tarpu Informacijos paieškos dimensija buvo specifiškai susijusi tik su „Nesijaudinimu“. Likusios sritys (Pramoginių ir vaizdo įrašų peržiūra, Socialiniai tinklai ir Žaidimai) neatskleidė sąsajų su nė vienu interocepcinio įsisąmoninimo aspektu. Toks rezultatas iš dalies gali būti aiškinamas PIN konceptualizacijos ir vertinimo skirtumais: Di Carlo et al. (2024) nagrinėjo bendrą PIN riziką, remdamiesi slenkstine IAT (angl. *Internet Addiction Test*) verte atskiriant PIN ir ne-PIN grupes, tuo tarpu šiame tyrime buvo taikomas daugiamatis požiūris (PIUQ-9 ir DPIU), PIN vertinant kaip tęstinį reiškinį visoje imtyje ir siekiant įvertinti variaciją priklausomai nuo įsitraukimo į skirtingas internetines veiklas. Be to, šio tyrimo rezultatai leidžia manyti, kad didesnio emocinio ir kognityvinio įsitraukimo reikalaujančios veiklos, tokios kaip žinučių rašymas (Camerini et al., 2022; Fante et al., 2013), gali labiau sąveikauti su į kūną orientuotais savireguliacijos mechanizmais; atspindėdamos, kad tam tikri interocepcinio įsisąmoninimo aspektai gali būti jautresni nuo konteksto priklausomam interneto naudojimui nei bendram įsitraukimui į internetines veiklas. Šio tyrimo rezultatai rodo, kad skirtingų internetinių veiklų tipai gali skirtingai sąveikauti su interocepciniais procesais (įtraukdami arba apeidami specifines kūno pojūčių įsisąmoninimo dimensijas) ir atspindi tiek bendrus, tiek konkrečiai veiklai specifinius šablonus.

Apibendrinant, tai antrasis bandymas tirti interocepcinį įsisąmoninimą PIN srityje ir pirmasis, kuriame PIN nagrinėjamas tinklinės analizes metodu, įtraukiant tiek interocepcinio įsisąmoninimo aspektus, tiek asmenybės bruožus. Gauti rezultatai papildo PIN tyrimų sritį, siūlydami, kad interocepcinis įsisąmoninimas gali turėti reikšmingą vaidmenį probleminio interneto naudojimo kontekste.

4.3. Elgseninis lygmuo: klausos lygių tikimybių Go/NoGo užduotis

Priklausomybių tyrimuose, kognityvinės kontrolės (įskaitant atsako slopinimo funkciją) deficitas dažnai siejamas su probleminiu ir priklausomybiniu elgesiu (Littel et al., 2012; Pandey et al., 2016; Ramey & Regier, 2019; Yao et al., 2015; Zhou et al., 2010). Vis dėlto šio tyrimo metu gauti rezultatai šios prielaidos nepatvirtina: sveikų, reguliariai internetu besinaudojančių asmenų imtyje reikšmingų sąsajų tarp interneto naudojimo įpročių ir elgseninių rezultatų atliekant klausos lygių tikimybių Go/NoGo užduotį nustatyta nebuvo, taip pat nerasta skirtumų ir tarp aukšto ir žemo interneto naudojimo grupių.

Nepakitę elgseniniai kognityvinių užduočių atlikimo rodikliai, nepaisant įsitraukimo į probleminį interneto naudojimą, fiksuoti ir kituose tyrimuose (Dong et al., 2010; Vargas et al., 2019; Zhang et al., 2024), rodančiuose, kad paveikti asmenys gali ir nepasižymėti akivaizdžiais elgesio deficitais lyginant su kontrolės grupėmis. Vis dėlto ankstesni darbai taip pat atskleidė, jog optimalus funkcionavimas elgseniniame lygmenyje, asmenims, turintiems su priklausomybėmis susijusių sutrikimų, gali būti kompensuojamas pokyčiais neurofiziologiniame lygmenyje, pvz. matomais kaip skirtumai tarp SĮSP parametrų lyginant su šių sutrikimų neturinčiais asmenimis (Houston & Schlienz, 2018).

Svarbu pažymėti, kad išskaidžius interneto naudojimą į konkrečias veiklas internete, Žaidimų dimensijos įverčiai teigiamai koreliavo su Go reakcijos laikais, kas leidžia manyti apie subtilų atsako vykdymo sulėtėjimą asmenims, labiau įsitraukusiems į žaidimus. Šis rezultatas prieštarauja Littel et al. (2012) rezultatams, kurie į žaidimus įsitraukusių asmenų grupėje nustatė trumpesnius reakcijos laikus. Vis dėlto jų tyrime taip pat fiksuota ir sąsaja tarp reakcijos laikų ir neteisingo reagavimo klaidų (paspaustas atsako mygtukas NoGo sąlygos metu), kuri buvo interpretuota kaip kompromiso tarp greičio ir tikslumo atspindys, tuo tarpu šiame tyrime sąsajų su kitais elgseniniais užduoties atlikimo rodikliais nenustatyta. Kadangi Go reakcijos laikai siejami su kognityvinio apdorojimo efektyvumu ir pasirengimo motoriniam atsakui procesais (Fogarty et al., 2020a; Nakata et al., 2021), šis rezultatas gali atspindėti pokyčius motorinio atsako planavimo procese, o ne bendrą kognityvinį deficitą asmenims, įsitraukusiems į žaidimus.

Apibendrinant, elgseniniai rodikliai, gauti atliekant klausos lygių tikimybių Go/NoGo užduotį, šiame tyrime neatspindėjo probleminio interneto naudojimo neklinikinėse populiacijose.

4.4. Neurofiziologiniai rodikliai

4.4.1. Ankstyvasis sensorinis apdorojimas klausos lygių tikimybių Go/NoGo užduotyje: N1 ir P2

Per pirmąsias 250 ms po stimulo pateikimo ankstyvieji SĮSP daugiausia atspindi automatinius sensorinius ir percepcinius procesus, tokius kaip sensorinės informacijos filtracija (angl. *sensory gating*) ir stimulo diferenciacija (Barry & De Blasio, 2013; Fogarty et al., 2020b; Pires et al., 2014). Nors šie atsakai daugiausia yra egzogeniniai ir priklauso nuo stimulo savybių (Pires et al., 2014; Sokhadze et al., 2017), ankstyvieji dėmesio mechanizmai taip pat gali moduliuoti pirminį sensorinį apdorojimą (Sokhadze et al., 2017). Tai pagrindžia ankstyva frontalinio tinklo aktyvacija, atspindinti, kad net pradinėse stimulo apdorojimo stadijose dalyvauja struktūros atsakingos už informacijos apdorojimą „iš viršaus žemyn“ ir su užduotimi susijusių tikslų palaikymą (Fogarty et al., 2020b).

Aptariant šio tyrimo rezultatus, N1 amplitudės neigiamai koreliavo su Žaidimų dimensijos įverčiais tiek Go, tiek NoGo sąlygose, o N1 latencijos Go sąlygos metu neigiamai koreliavo su bendrais DPIU įverčiais. Kadangi N1 komponentas atspindi ankstyvąjį sensorinės informacijos apdorojimą (pvz., stimulo aptikimą) ir dėmesio paskirstymą (Fogarty et al., 2020a; Joos et al., 2014; Tomé et al., 2015), šie rezultatai rodo, kad didesnis įsitraukimas į internetines veiklas, ypač žaidimus, gali keisti tai, kaip ankstyvose stadijose apdorojama sensorinė informacija. Ankstesnių tyrimų, vertinusių N1 parametrus IGD srityje, rezultatai nevienareikšmiai – lyginant su kontrole, fiksuotos tiek sumažėjusios, tiek padidėjusios N1 amplitudės, o kai kuriais atvejais reikšmingų skirtumų nenustatyta (Duven et al., 2015; Ge et al., 2011; Park et al., 2017b). Vis tik šiame darbe nustatyta sąsaja tarp mažesnių N1 amplitudžių ir didesnio įsitraukimo į žaidimus dera su Park et al. (2017b) rezultatais, kurie taip pat pranešė apie susilpnėjusius N1 atsakus atliekant atsitiktinio įvykio užduotį (angl. *oddball task*) IGD grupėse. Toks amplitudės sumažėjimas gali atspindėti arba sumažėjusį sensorinio apdorojimo efektyvumą, arba, priešingai, mažesnį pastangų poreikį ankstyvuosius dėmesio išteklius nukreipiant į išorinį (klausos) stimulą.

Be to, trumpesnės N1 latencijos, siejamos su didesniu bendru probleminio interneto naudojimo lygiu (ką atspindi DPIU įverčiai), gali atrodyti prieštaringai, kadangi įprastai su įvairiais sutrikimais siejami komponentų pasirodymo uždelsimai (Joos et al., 2014). Vis dėlto ankstesnis N1 pikas gali rodyti padidėjusį budrumą arba padidėjusį reaktyvumą į išorinius dirgiklius asmenims, intensyviau įsitraukusiems į internetines veiklas. Tokią prielaidą pagrindžia ankstesnių tyrimų rezultatai, indikuojantys jog fragmentuotu, greitai kintančiu skaitmeniniu turiniu nuolat veikiami asmenys yra linkę perimti „nuo apačios į viršų" (angl. *bottom-up*) tipo dėmesio stilių (Firth et al., 2019; Ophir et al., 2009). Atitinkamai, ne pailgėjusi, o sutrumpėjusi N1 latencija gali atspindėti pakitusį (ir galbūt mažiau pastangų reikalaujantį) ankstyvosios stadijos dėmesio nukreipimą į išorės stimulus (Duven et al., 2015; Fogarty et al., 2020b; Joos et al., 2014).

Remiantis šio tyrimo rezultatais, tikėtina, kad N1 parametrų variacijos veikiau atspindi ankstyvųjų sensorinių/dėmesio procesų mechanizmus tarp intensyviai internetu besinaudojančių asmenų, užuot buvusios specifiniu IGD biomarkeriu (Kashif et al., 2021).

P2, panašiai kaip ir N1, laikomas komponentu, susijusiu su ankstyvuoju sensoriniu ir percepciniu apdorojimu (Fogarty et al., 2020a) ir, kaip manoma, atspindinčiu stimulų identifikavimo bei klasifikacijos procesus (Crowley & Colrain, 2004; Fogarty et al., 2020b; Sokhadze et al., 2017). Iki šiol tiek P2 funkcinė interpretacija, tiek jo vaidmens PIN kontekste tyrimai yra riboti. Šiame tyrime sąsajų tarp P2 parametrų ir bendrų PIN įverčių ar konkrečių interneto naudojimo sričių nenustatyta; tai atitinka Ge et al. (2011) rezultatus, kurie taip pat nerado P2 skirtumų tarp PIN turinčių asmenų ir kontrolinės grupės atliekant klausos atsitiktinio įvykio užduotis.

4.4.2. Atsako stebėsena ir slopinimas klausos lygių tikimybių Go/NoGo užduotyje: N2 ir P3

Vėlyvieji kognityviniai SĮSP komponentai, ypač N2 ir P3, yra vieni plačiausiai tyrinėjamų kognityvinės kontrolės žymenų (Bruin & Wijers, 2002; Pires et al., 2014). Go/NoGo užduotis yra itin tinkama paradigma šiems vėlyviesiems procesams tirti, kadangi Go ir NoGo sąlygų metu įtraukiami skirtingi neuroniniai mechanizmai (Fogarty, 2020; Fogarty et al., 2018; Pires et al., 2014). Konkrečiai, NoGo bandymai siejami su konfliktų stebėsena ir motoriniu slopinimu (Detandt et al., 2017; Huster et al., 2013), o Go bandymų metu SĮSP daugiausia atspindi motorinio atsako vykdymą ir jo įvertinimą (Fogarty, 2020).

Šiame tyrime reikšmingų sąsajų tarp N2 amplitudžių ir PIN rodiklių nenustatyta. Nors kai kuriuose ankstesniuose tyrimuose fiksuotos sumažėjusios NoGo-N2 amplitudės asmenims, turintiems PIN ar IGD (Dong et al., 2010; Fathi et al., 2024; Lee & Kang, 2014; Zhou et al., 2010), kituose stebėtos padidėjusios amplitudės arba nenuoseklūs N2 atsakai (Chen et al., 2018; Littel et al., 2012). Be to, literatūroje pateikiama duomenų ir apie pailgėjusias N2 latencijas PIN atžvilgiu (Kim et al., 2017; Ge et al., 2011). Reikšmingų N2 sąsajų nebuvimas šiame tyrime sufleruoja, kad konfliktų detekcijos ir stebėsenos procesai neklinikinėse populiacijose gali išlikti nepakitę (Donkers & van Boxtel, 2004; Enriquez-Geppert et al., 2010; Sokhadze et al., 2017; Wessel, 2018).

NoGo-P3 parametrai plačiai nagrinėti psichoaktyvių medžiagų vartojimo sutrikimų, taip pat IGD ir PIN, kontekste (Colrain et al., 2011; Evans et al., 2009; Porjesz & Begleiter, 2003; Sokhadze et al., 2008; Yin et al., 2016; Dong et al., 2010; Gao et al., 2019; Moretta & Buodo, 2021; Park et al., 2016; Park et al., 2017b). Ir nors tyrimų rezultatai taip pat nėra nuoseklūs, sumažėjusi P3 amplitudė buvo siūloma kaip galimas IGD neurofiziologinis žymuo (Park et al., 2016; Yu et al., 2024). Šiame tyrime sąsajų tarp P3 amplitudžių ir vertintų interneto naudojimo rodiklių nenustatyta, kas kelia abejonių dėl šio žymens jautrumo bent jau sveikų, reguliariai internetu besinaudojančių asmenų imtyje.

Vis dėlto nustatytas teigiamas ryšys tarp NoGo-P3 latencijos ir Informacijos paieškos dimensijos įverčių, atspindintis uždelstą stimulo vertinimą ir atsako slopinimo apdorojimą asmenims, dažnai intensyviai ieškantiems informacijos internete (Fogarty et al., 2018; Gajewski & Falkenstein, 2013). P3 latencija laikoma stimulo įvertinimo trukmės žymeniu: trumpesnės latencijos atspindi efektyvesnį kognityvinį funkcionavimą (Kamijo et al., 2004; Kutas et al., 1977; Polich & Criado, 2006). Atitinkamai, šiame darbe stebėtas latencijos pailgėjimas gali atspindėti ir su atsaku susijusio atnaujinimo darbinėje atmintyje užvėlinimą (Fogarty, 2020), ir atsako slopinimo kontrolės trūkumus (Donkers & van Boxtel, 2004; Nieuwenhuis et al., 2004; Randall & Smith, 2011). Vis dėlto, kadangi reikšmingų sąsajų tarp elgseninių užduoties atlikimo rodiklių ir Informacijos paieškos dimensijos įverčių nenustatyta, ilgesnė P3 potencialo latencija galėtų būti vertinama kaip ankstyvas neurokognityvinis požymis, o ne susiformavęs funkcinis deficitas.

Svarbu, kad nepaisant aptartų sąsajų, nustatytų visoje imtyje ir reikšmingų psichologinių skirtumų tarp aukšto ir žemo interneto naudojimo grupių, skirtumų tarp SĮSP parametrų tarp grupių nenustatyta. Tai leidžia manyti, kad nors probleminis įsitraukimas į veiklas internete gali atsispindėti per specifinius neurofiziologinius rodiklius, sveikų dalyvių imtyje tokio įsitraukimo poveikis PIN kontinuume nėra tiesinis ar reikšmingai išreikštas. Ir nors ankstesniuose klinikinių PIN/IGD imčių tyrimuose dažnai fiksuoti SĮSP skirtumai lyginant su kontrolės grupėmis (Chen et al., 2018; Dong et al., 2010; Ge et al., 2011; Yu et al., 2009; Zhou et al., 2010), gauti rezultatai tarp tyrimų yra mišrūs. Atsižvelgiant į šio tyrimo rezultatus ir remiantis anksčiau atliktų tyrimų duomenimis, tikėtina, kad neurofiziologiniai pokyčiai vystosi palaipsniui ir išryškėja tik stipriai išreikšto PIN atvejais. Vis tik, svarbu pabrėžti, kad priežastingumo klausimas (ar SĮSP svyravimai, matomi tarp skirtingų tiriamųjų grupių, prisideda prie PIN formavimosi, ar yra PIN pasekmė) išlieka atviras. Kategorinės dichotomijos tarp PIN ir kontrolinių grupių paieškos ne itin prisideda prie atsakymo į šį klausimą, kas pabrėžia longitudinių ir (ar) PIN traktuojančių kaip sutrikimą pasireiškiantį kontinuume tyrimų svarbą (Anderson et al., 2017).

Apibendrinant, šio tyrimo rezultatai rodo, kad PIN tam tikru mastu gali turėti įtaką neuroniniams procesams susijusiems su ankstyvuoju sensoriniu apdorojimu (N1) ir atsako slopinimu (NoGo-P3), tačiau PIN poveikis atsako/konflikto stebėsenai ir atsako įvykdymui (N2 ir Go-P3) neuroniniame SĮSP lygmenyje neklinikinėse populiacijose nėra išreikštas.

4.4.3. Kintama ramybės būsena: Alfa asimetrija

Remiantis teorija, ramybės būsenos alfa aktyvumo lateralizacija (alfa asimetrija) atspindi į bruožus panašius polinkius į afektines ir motyvacines orientacijas (Davidson, 1992): didesnis santykinis kairiojo pusrutulio frontalinės žievės aktyvumas siejamas su siekimo (angl. *approach*) motyvacija ir teigiamu afektu, o dešiniojo pusrutulio frontalinės žievės dominavimas – su pasitraukimo (angl. *withdrawal*) motyvacija ir neigiamu afektu (de Vries et al., 2023; Kelley et al., 2017; Reznik & Allen, 2018; Smith et al., 2017). Vis dėlto, nors alfa asimetrija yra vienas dažniausiai tyrinėjamų smegenų lateralizacijos rodiklių, dauguma darbų koncentruojasi į frontalines sritis, o parietinė asimetrija ilgą laiką buvo nagrinėta menkai (Metzen et al., 2022; Wang et al., 2025).

Apžvengiant tyrimus PIN ir su internetu susijusių sutrikimų kontekste, publikuoti duomenys indikuoja apie ramybės būsenos smegenų veiklos skirtumus frontalinėse ir parietalinėse srityse lyginant su kontrolinėmis grupėmis, be to, skirtumus atspindintys rodikliai reikšmingai koreliuoja su PIN sunkumu (Burleigh et al., 2020; Sun et al., 2019; Wang et al., 2017). Pavyzdžiui, stebėta sumažėjusi frontalinė ir parietalinė alfa galia perteklinių video žaidėjų imtyje (Xu et al., 2024), taip pat asmenų, turinčių PIN ir gretutinės depresijos simptomų (Lee et al., 2014); vis tik, pastarasis rezultatas rodo, kad alfa galios silpnėjimas nėra specifinis PIN. Burleigh et al. (2020) apžvalgoje apibendrintas alfa koherencijos padidėjimas dešiniajame pusrutulyje (įskaitant parietalines sritis) žaidėjų imtyse, tikriausiai susijęs su nuolatiniu vizualinės–erdvinės darbinės atminties ir vykdomųjų funkcijų aktyvinimu dažnai žaidžiant. Taip pat, išreikštu PIN pasižymintiems asmenims nustatytas sumažėjęs funkcinis smegenų junglumas (angl. *brain connectivity*) kairiojoje parietalinės skilties srityje, priklausančioje dešiniajam frontoparietiniam tinklui (Sun et al., 2019), ir atspindintis sutrikusią tarppusrutulinę tinklų komunikaciją. Didesnis dešiniojo frontalinio pusrutulio aktyvumas taip pat nustatytas probleminių socialinių tinklų naudotojų imtyje (Tsilosani et al., 2023) ir IA grupėje (Yan et al., 2022); svarbu, kad šis dešinės pusės dominavimas IA grupėje sietas su prastesniais emocijų reguliavimo pasirinkimais.

Parietalinės srities alfa asimetrija PIN srityje iki šiol tirta nebuvo. Šio tyrimo metu nustatytas didesnis santykinis kairiojo pusrutulio aktyvumas parietalinėse srityse asmenims su aukštesniais įsitraukimo į internetines veiklas įverčiais hipotetiškai atitinka aptartus tyrimus, t.y. turint omenyje, kad parietalinė asimetrija neretai atspindi frontalinei sričiai priešingus dėsningumus (Baik et al., 2019; Blackhart et al., 2006; Metzen et al., 2022; Schiltz et al., 2018). Taip pat, dabartiniai rezultatai papildo Wang & Griskova-Bulanova (2018) pilotinio tyrimo su rekreaciniais interneto naudotojais rezultatus: autorės nenustatė sąsajų tarp interneto naudojimo įverčių ir frontalinės alfa asimetrijos; analogiškai tokių sąsajų frontalinėse srityse nenustatyta ir šiame tyrime su didesne tiriamųjų imtimi, tačiau reikšminga sąsaja išryškėjo parietalinėse srityse.

Pažymėtina, kad didesnis kairiojo pusrutulio aktyvumas parietalinėje srityje buvo susijęs su interneto naudojimo įverčiais tik atmerktų akių sąlygoje. Tikėtina, kad taip yra dėl skirtingų šių ramybės būsenų neurofiziologinių ypatybių: nors ir EO, ir EC dažnai laikomos ramybės būsenos bazinėmis sąlygomis, tyrimai rodo, kad jos nėra tapačios ir reikšmingai skiriasi sujaudinimo ir aktyvacijos lygiais (Barry, Clarke et al., 2007). EC sąlyga, kuriai būdinga mažesnė sensorinė apkrova ir gumburo–žievės ritmiškumas, atitinka žemesnio sužadinimo būseną ir gali būti mažiau jautri individualiems dėmesio ar motyvacijos skirtumams. Priešingai, EO sąlyga, net esant minimaliai vizualinei stimuliacijai, sukelia alfa desinchronizaciją ir platesnę žievinę aktyvaciją, įskaitant dėmesio kontrolei svarbių frontoparietalinių tinklų aktyvumą (Barry et al, 2007). Be to, su nesuvaržyta mentaline veikla (pvz., kaip kad savianalizė, aplinkos stebėsena, klajojimas mintyse) siejamos sritys, EO ir EC sąlygų metu įtraukiamos skirtingai: Yan et al. (2009) parodė, kad numatytojo rėžimo tinklo (DMN) sričių (ypač dalyvaujančių sensorinėje stebėsenoje ir stimulo svarbos (angl. *salience*) vertinime) funkcinis junglumas EO sąlygos metu dažnai yra didesnis nei EC atveju. Atitinkamai, Chang & Lee (2024) apžvalgoje apibendrinta, kad PIN siejasi ne su izoliuotų smegenų sričių pokyčiais, bet su plačiais tinklinio lygmens pokyčiais ir išryškina reikšmingus didelio masto smegenų tinklų, įskaitant DMN, sutrikimus, atspindinčius atlygio vertinimo, impulsyvumo, svarbos priskyrimo ir užuominų reaktyvumo poslinkius.

Be to, kaip neurofiziologinis rodiklis, alfa asimetrija laikoma atspindinanti tiek psichologinius bruožus, tiek pamatinius reguliacinius mechanizmus (Smith et al., 2017). Konkrečiai, parietalinė alfa asimetrija siejama su siekimo ir slopinimo sistemomis, ir didesnis kairiojo pusrutulio parietalinės srities aktyvumas atspindi intensyvesnę elgesio aktyvaciją (Schiltz et al., 2018); toks modelis gali būti būdingas asmenims, kompulsyviau įsitraukiantiems į internetines veiklas. Taip pat tiek frontalinių, tiek parietalinių sričių asimetrija siejama su dėmesio šališkumu (angl. *attentional bias*), nepriklausomai nuo nuotaikos ar nerimo sutrikimų subklinikinių simptomų (Grimshaw et al., 2014). Tai pagrindžia mintį, kad pusrutulių asimetrija galimai atspindi pamatinius informacijos apdorojimo „nuo apačios į viršų“ dėmesio kontrolės mechanizmus ir žymi dėmesio šališkumus, o ne vien psichologines problemas. Kaip teigiama Ophir et al. (2009), asmenys intensyviai įsitraukę į medijų daugiaveiką (angl. *multitaskers*) yra labiau pažeidžiami pašalinių dirgiklių trukdžiams, lengviau išsiblaško dėl kelių vienu metu naudojamų medijų srautų, prasčiau filtruoja trukdžius ir yra linkę į „nuo apačios į viršų“ dėmesio kontrolę, teikdami pirmenybę tiriamajam (angl. *exploratory*), o ne sutelktam „iš viršaus žemyn“ informacijos apdorojimui (lyginant su mažai daugiaveiką taikančiais asmenimis). Šiame kontekste padidėjęs reaktyvumas į išorės dirgiklius gali ryškiau atsispindėti EO sąlygos metu, jei laikomasi prielaidos, kad intensyvių interneto naudotojų už dėmesio kontrolę atsakingos sistemos yra labiau reaktyvios ir nukreiptos į išorę. Ši interpretacija (kartu su anksčiau publikuotais tyrimų rezultatais, indikuojančiais sumažėjusią bendrą alfa galią, atspindinčią padidėjusį žievės jaudrumą ir žemesnius percepcinius slenksčius (Foxe & Snyder, 2011), dera su teoriniais PIN modeliais, akcentuojančiais kompulsinį reaktyvumą į išorinius dirgiklius, sutrikusią dėmesio „iš viršaus žemyn“ reguliaciją bei atsako slopinimo deficitus (D’Hondt et al., 2015; Firth et al., 2019; Ioannidis et al., 2019).

Be to, šiame tyrime nenustatyta sąsajų tarp depresijos simptomų ir alfa asimetrijos. Nors alfa asimetrija plačiai tirta depresijos kontekste, dėl skirtingų rezultatų tarp skirtingų tyrimų alfa asimetrijos kryptingumas išlieka neaiškus (Marcu et al., 2023). Nors PIN ir depresijos simptomų įverčiai šioje imtyje teigiamai koreliavo (r_s = 0,285, p = 0,001), pradžioje stebėta neigiama depresijos simptomų ir parietalinės srities alfa asimetrijos įverčių koreliacija neatlaikė FDR korekcijos, ir tik PIN buvo reikšmingai susijęs su parietalinės srities alfa asimetrija. Vis dėlto, remiantis ankstesniais darbais (Mitchell & Pössel, 2012; Pössel et al., 2008; Reznik & Allen, 2018; Wang & Griskova-

Bulanova, 2018), dabartiniai rezultatai (rodantys, jog depresija siejasi su didesniu dešiniosios parietalinės srities aktyvumu, o PIN – su didesniu kairiosios parietalinės srities aktyvumu) gali indikuoti apie lateralizacijos krypties išsiskyrimą, atspindintį skirtingus nervinius procesus slypinčius po PIN ir depresijos simptomais, nepaisant jų persidengimo reguliariai internetu besinaudojančių asmenų imtyje.

Apibendrinant, šio eksperimento rezultatai praplečia PIN tyrimų lauką, identifikuodami parietalinės srities alfa asimetriją kaip galimą specifinį žymenį, atspindintį PIN reguliarių interneto naudotojų imtyje ir išryškindami EO ramybės būseną kaip jautresnę sąlygą aptikti su PIN susijusiems asimetrijos šablonams.

4.4.4. Ramybės būsena: Mikrobūsenos

EEG mikrobūsenų analizė dažnai taikoma vertinant pamatinių (didelio masto) smegenų tinklų būseną. Mikrobūsenų laikiniai parametrai (pvz., trukmė, indėlis, pasikartojimo dažnis) atspindi vidinių žievinių (angl. *intracortical*) generatorių veiklos sinchroniškumą ir jų polinkį aktyvuotis beveik nulinių fazių santykiu (t. y. vienu metu) (Khanna et al., 2015; Seeber & Michel, 2021; Tarailis et al., 2024). Mažesnės mikrobūsenų parametrų reikšmės gali rodyti stabilumo ar funkciniu požiūriu nesuderinamų tinklų koaktyvacijos stoką, taip pat informacijos srauto ir apdorojimo sutrikimus. Tuo tarpu aukštesnės parametrų vertės gali atspindėti ne tik stabilesnius ryšius ir informacijos dalijimąsi tarp tinklų centrų, bet ir hipervigilumą bei fizinį ir emocinį hiperaktyvumą (pvz., ADHD būklės atveju) (Férat, Arns et al., 2022) arba didesnį išlaikomą budrumą ir sustiprintą reakciją į stimulo svarbos apdorojimą (pvz., ribinio asmenybės sutrikimo atveju) (Deiber et al., 2024).

Vis dėlto mikrobūsenų analizė elgesio priklausomybių tyrimuose iki šiol taikyta retai (Ding et al., 2023; Li et al., 2022; Qi et al., 2023). Qi et al. (2023) nustatė sumažėjusią MS C trukmę ir indėlį PIN grupėje (palyginti su kontrole), be to, MS C trukmė buvo atvirkščiai susijusi su Go sąlygos reakcijos laikais PIN grupėje atliekant Go/NoGo užduotį. Taip pat, žemesnės MS D parametrų vertės (trukmės, pasirodymo dažnio ir indėlio) fiksuotos ir tarp nuolatinių medijų naudotojų (pvz., įsitraukusių į žinučių ir el. laiškų rašymą, socialinių tinklų, žaidimų naudojimą) (Zhang et al, 2024). Atitinkamai MS D pasirodymo dažnis turėjo neigiamas sąsajas su polinkiu į priklausomybę nuo mobiliojo telefono ir abstinencijos simptomais (Li et al., 2021). Tokius rezultatus pagrindžia elgesio ir fMRI tyrimų duomenys: smegenų veiklos bei funkcinio smegenų junglumo pokyčiai siejami su negebėjimu optimaliai paskirstyti su užduotimi susijusių dėmesio išteklių, suprastėjusiomis vykdomosiomis funkcijomis (Dong et al., 2012, 2015) ir gretutiniu depresijos, nerimo bei psichoaktyviųjų medžiagų vartojimo simptomų pasireiškimu (angl. *comorbidity*) (Cheng & Liu, 2020; Xie et al., 2023). Vis tik, minimi rezultatai nebuvo replikuoti šiame tyrime: MS C ar MS D parametrai nebuvo susiję su PIUQ-9 įverčiais reguliarių interneto naudotojų imtyje, kas leidžia manyti, jog šių mikrobūsenų pokyčiai gali būti ryškesni stipriai išreikštų PIN simptomų ar kliniškai diagnozuotais atvejais ir nėra aptinkami neklinikinėse ar subklinikinėse populiacijose.

Šio tyrimo metu buvo nustatytos teigiamos sąsajos tarp MS E indėlio bei pasirodymo dažnio tiek su bendrais PIUQ-9 įverčiais, tiek identifikuotos aukštesnės šių parametrų vertės aukšto interneto naudojimo grupėje lyginant su žemo interneto naudojimo grupe. Aukštesnės MS E parametrų reikšmes taip pat nustatytos asmenims, kurie nuolat naudojasi bet kokiomis medijomis (Zhang et al., 2024). Ši mikrobūsenų klasė siejama su interocepcinės ir emocinės informacijos apdorojimu (Pipinis et al., 2017; Tarailis et al., 2021; Tomescu et al., 2022; Tomescu, Van der Donck et al., 2024) ir tam tikromis kognityvinėmis funkcijomis (Jabès et al., 2021; Zanesco et al., 2021) ir, kaip manoma, yra generuojama smegenų sričių, persidengiančių su svarbos (SN, *angl. salience network*) ir cinguliniu–operkuliniu (angl. *cingulo-opercular network*) tinklais (Britz et al., 2010; Custo et al., 2017). Neseniai parodyta galima sąsaja tarp padidėjusios MS E veiklos ir tokių bruožų kaip emocinis nestabilumas bei impulsyvumas (Deiber et al., 2024), tačiau šiame tyrime reikšmingų sąsajų tarp MS E parametrų ir kurių nors vertintų psichologinių kintamųjų nenustatyta.

Vis tik, nustatytos reikšmingos sąsajos tarp MS D, MS C ir MS B parametrų ir nerimo bei obsesinių–kompulsinių simptomų. MS D aktyvumo sumažėjimas asmenims, turintiems nuotaikos ir nerimo sutrikimų buvo pademonstruotas Chivu et al. (2024) metaanalizėje, tuo tarpu gerai žinoma, jog PIN taip pat būdingi gretutinės depresijos ir nerimo simptomai (Burleigh et al., 2020; Lee et al., 2014; Zhou et al., 2011). Atitinkamai, ir šio tyrimo metu stebėtos reikšmingos neigiamos sąsajos tarp nerimo įverčių ir visų MS D parametrų: trukmės, indėlio ir pasirodymo dažnio. Nors PIUQ-9 įverčiai reikšmingai ir teigiamai koreliavo su visais vertintais psichologiniais kintamaisiais (nerimo, depresijos ir OKS simptomų įverčiais), specifinė MS E hiperaktyvumo sąsaja su įsitraukimu į internetines veiklas (bet ne su psichologiniais veiksniais) leidžia manyti, kad MS E gali būti neurofiziologinius procesus išimtinai PIN atveju atspindintis žymuo. Priešingai, MS C, MS B ir ypač MS D sąsajos gali atspindėti platesnius psichologinius bruožus sveikoje, neklinikinėje imtyje.

Šis tyrimas buvo pirmasis bandymas taikyti mikrobūsenų analizę neklinikinėje reguliarių interneto naudotojų imtyje, o gauti rezultatai leidžia teigti, kad EEG mikrobūsenos yra potencialiai jautrūs biomarkeriai, kuriuos galima naudoti ne tik neurologinėms ir psichologinėms būklėms diferencijuoti, bet ir galimai probleminiam interneto naudojimui identifikuoti.

Apibendrinimas

Šio darbo rezultatai atspinti galimą psichoneurofiziologinį modelį, susijusį su interneto naudojimo sunkumų raiškos laipsniu tarp sveikų, reguliariai internetu besinaudojančių asmenų.

Pirma, nustatyta sąsaja tarp aukštesnio interneto naudojimo sunkumų raiškos laipsnio ir didesnio psichologinio išsekimo atitinka ankstesnius tyrimus, rodančius, kad probleminis įsitraukimas į internetą gali stiprinti pažeidžiamumą emocijų reguliacijos sutrikimams (arba atvirkščiai, emocijų reguliacijos sutrikimai gali skatinti probleminį interneto naudojimą) (Fineberg et al., 2025; Kuss & Lopez-Fernandez, 2016). Pastebėta žemesnio interocepcinio įsisąmoninimo ir aukštesnio įsitraukimo į internetines veiklas sąsaja, ypač tarpininkaujant neurotiškumui, leidžia kelti prielaidą apie galimą atsiskyrimą nuo į kūną orientuotų savireguliacijos mechanizmų (Caplan, 2010; Jeronimus et al., 2016; Kayiş et al., 2016; Marciano et al., 2020; Mehling et al., 2012; Pastor et al., 2022; Tian et al., 2021). Ypač reikšminga sąsaja su interocepcinio įsisąmoninimo Nepaisymo aspektu, atspindinti sutrikusį dėmesio paskirstymą vidinėms būsenoms (Mehling et al., 2012) ir atitinka modelius, teigiančius, kad interneto naudojimas gali veikti kaip įveikos strategija, padedanti išvengti realaus gyvenimo veiklą trikdančio streso (Brand et al., 2019; Feher et al., 2023; Fineberg et al., 2025; Hussain & Griffiths, 2009; Mehroof & Griffiths, 2010). Toks streso ir sumažėjusio interocepcinio įsisąmoninimo sambūvis (angl. *co-occurrence*) gali atspindėti grįžtamąjį ryšį, kuriame emociškai reaktyvūs, ribotą kūnišką įžvalgą turintys asmenys kliaujasi skaitmeninėmis platformomis, taip stiprindami netinkamus interneto vartojimo įpročius.

Laikui bėgant toks įsitraukimas gali turėti įtakos neuroplastiškumo procesams ir lemti struktūrinius ir funkcinius smegenų pokyčius, ypač sistemose, atsakingose už dėmesį ir autoreferencinius mechanizmus. Šio tyrimo metu neklinikinėje imtyje stebėtos EEG parametrų variacijos gali reprezentuoti ankstyvas adaptacijas prie nuolatinės, itin stimuliuojančios, įtraukios, atlygį suteikiančios ir greito tempo skaitmeninės aplinkos ekspozicijos (Fineberg et al., 2025; Liu, 2005; Nicholas et al., 2009; Robbins & Clark, 2015). Elektrofiziologinių rezultatų visuma – N1 komponento moduliacija, parietalinės srities alfa asimetrija ir MC E vyravimas – apima vieningą dėmesio kontrolės ir savireguliacijos procesų disbalanso modelį, susijusį su interneto naudojimo sunkumų raiškos laipsniu. Rezultatai taip pat atitinka teorinių bei empirinių tyrimų duomenis, iliustruojančius, kad asmenys, pasižymintys dažna medijų daugiaveika, taip pat pasižymi didesniu išsiblaškymu, prastesniu nereikšmingų stimulų filtravimu ir polinkiu į nuo išorės stimulo priklausomą „nuo apačios į viršų“ dėmesio tipą (Firth et al., 2019; Ophir et al., 2009).

Konkrečiau, N1 komponentas atspindi ankstyvos stadijos klausos stimulo apdorojimą ir dėmesio nukreipimo procesus, paprastai sustiprėjančius, kai dėmesys nukreipiamas į su užduotimi susijusius stimulus (Fogarty et al., 2020b; Joos et al., 2014; Pires et al., 2014; Sokhadze et al., 2017; Tomé et al., 2015). Tai apima tiek „nuo apačios į viršų“ aukštyneigius jutiminius, tiek „iš viršaus žemyn“ žemyneigius predikcinius mechanizmus, dalyvaujant už dėmesio perkėlimą ir tikslo palaikymą atsakingoms smegenų sritims (pvz., ventrolateralinei prefrontalinei žievei, vlPFC) (Fogarty et al., 2020b; Joos et al., 2014). Asmenims, labiau linkusiems į probleminius interneto naudojimo modelius (ypač žaidimų srityje), N1 moduliacija gali atspindėti dėmesio filtracijos mechanizmų pokyčius, o ankstesnės N1 piko latencijos – hiperreaktyvumą į išorinės dirgiklius arba mažiau pastangų reikalaujantį dėmesio perjungimą, atspindintį aukštyneigės informacijos apdorojimo mechanizmų automatizaciją (Duven et al., 2015; Fogarty et al., 2020b; Joos et al., 2014), tikėtina, susiformavusią dėl ilgalaikės stimuliuojančios ir dirgikliais turtingos skaitmeninės aplinkos ekspozicijos.

Alfa dažnio smegenų aktyvumo rodikliai papildomai atspindi galimą dėmesio procesų disbalansą problemiškesnio įsitraukimo į internetines veiklas kontekste. Didesnis kairiojo pusrutulio parietalinės srities aktyvumas siejamas su į siekimą orientuoto (angl. *approach-related*) elgesio tendencijomis ir į išorę nukreiptu „nuo apačios į viršų“ dėmesiu (Schiltz et al., 2018). Mažesnė bendra alfa galia, atspindinti padidėjusį žievės jaudrumą ir žemesnius percepcinius slenksčius (Foxe & Snyder, 2011), sustiprina šią interpretaciją. Šie rezultatai, ypač atmerktų akių sąlygos metu, gali sufleruoti apie nuolatinį pasirengimą sąveikai su išoriniais stimulais neuroniniame lygmenyje ir patvirtina ankstesnius darbus, siejančius dėmesio disreguliaciją ir kompulsyvų reagavimą su PIN (D'Hondt et al., 2015; Firth et al., 2019; Ioannidis et al., 2019).

Be to, mikrobūsena E, pasižyminti centro-parietaline topografija ir siejama su svarbos tinklu (SN), yra susijusi tiek su emocijų, tiek su interocepcinės informacijos apdorojimu: anksčiau parodyta neigiama mikrobūsenos E laikinių parametrų sąsaja su somatiniu (kūno) įsisąmoninimu (Pipinis et al., 2017; Tarailis et al., 2021). Šio tyrimo rezultatai (didesnis MS E pasirodymo dažnis ir indėlis asmenims, turintiems aukštesnius probleminio interneto naudojimo įverčius) sufleruoja apie priešingą efektą – vyraujančias į išorę orientuotas kognityvines būsenas, dar kartą atspindinčias aukštyneigių „nuo apačios į viršų“ dėmesio mechanizmų ir stimulo svarbos valdomą informacijos apdorojimo dominavimą.

Nors aptarti rodikliai skiriasi laikinėmis ir erdvinėmis charakteristikomis, kartu jie atspindi platesnį neurokognityvinį poslinkį: nuo vidine (endogenine) kontrole grindžiamos, su interocepciniais siganalais suderintos „iš viršaus žemyn“ kontrolės link į nuo išorinių dirgiklių priklausomą, reaktyvų „iš apačios į viršų“ dėmesio apdorojimą. Šis poslinkis gali lemti/atspindėti pagrindinius PIN bruožus – psichologinį išsekimą, sumažėjusį kūno pojūčių įsisąmoninimą ir kompulsyvų įsitraukimą į skaitmeninį turinį – trikdydamas pusiausvyrą tarp vidinių ir išorinių dėmesio režimų.

IŠVADOS

1. Didesnis interneto naudojimo sunkumų raiškos laipsnis siejasi su stipriau išreikštu psichologiniu veiklą trikdančiu stresu (nerimo, depresijos, obsesijų–kompulsijų simptomai) neklinikinėje reguliariai internetu besinaudojančių asmenų imtyje.
2. Didesnis interneto naudojimo sunkumų raiškos laipsnis siejasi su silpnesniu interocepciniu įsisąmoninimu (Nesiblaškymo ir Pasitikėjimo aspektais); neurotiškumas sieja silpnesį kūno pojūčių įsisąmoninimą su probleminiais skaitmeninio elgesio modeliais.
3. Elgesiniai klausos lygių tikimybių Go/NoGo užduoties atlikimo rodikliai neatspindi interneto naudojimo sunkumų raiškos.
4. EEG SĮSP gauti klausos lygių tikimybių Go/NoGo užduotyje rodo specifines sąsajas su interneto naudojimu: neigiamos asociacijos taip N1 amplitudės ir Žaidimų dimensijos įverčių, Go-N1 latencijos ir DPIU įverčių ir teigiama asociacija tarp NoGo-P3 latencijos ir Informacijos paieškos dimensijos įverčių; vis dėlto SĮSP neišskiria skirtingų interneto naudojimo sunkumo lygių.
5. EEG parietalinė alfa asimetrija koreliuoja su interneto naudojimu, rodydama ryšį tarp didesnio kairiojo pusrutulio aktyvumo parietalinėje srityje ir aukštesnio interneto naudojimo lygio.
6. EEG mikrobūsenos E (MS E) parametrai (pasirodymo dažnis ir indėlis) koreliuoja su didesniu interneto naudojimu, rodydami ryšį tarp didesnio MS E aktyvumo ir aukštesnio interneto naudojimo lygio.

SUPPLEMENTARY MATERIAL 1

Table SM 1.1. Descriptive statistics for internet usage patterns and psychological measures across experiment subsamples.

Variable	Go/NoGo			Alternating resting-state (alpha asymmetry)			Eyes-closed resting-state (microstates)		
	Valid (n)	Mean	SD	Valid (n)	Mean	SD	Valid (n)	Mean	SD
Internet Usage Patterns (PIUQ-9, DPIU)									
PIUQ-9	133	19.85	5.32	129	19.39	5.2	156	19.65	5.29
DPIU_total score	133	25.97	18.8	-	-	-	-	-	-
Entertainment and Video Streaming	83	9.99	4.5	-	-	-	-	-	-
Social Media	84	9.55	4.33	-	-	-	-	-	-
Gaming	30	12.27	5.36	-	-	-	-	-	-
Messaging	33	13.3	5.26	-	-	-	-	-	-
Information Search	22	13.32	3.82	-	-	-	-	-	-
Psychological Characteristics									
BAI	132	31.71	7.64	128	31.78	7.39	155	31.70	7.51
BDI	129	10.72	8.95	125	10.37	8.77	152	10.41	8.73
CBOCI	132	19.49	11.67	132	19.59	11.72	155	19.10	11.24
CBOCI obsessions	132	11.99	6.93	128	11.84	6.73	155	11.66	6.66
CBOCI compulsions	133	7.54	5.91	129	7.8	6.12	156	7.49	5.79

"-" indicates variables not included in analysis for the given dataset. BAI—Beck Anxiety Inventory; BDI—Beck Depression Inventory; CBOCI—Clark–Beck Obsessive–Compulsive Inventory; DPIU—The Dimensions of Problematic Internet Use; and PIUQ-9—The Nine-Item Problematic Internet Use Questionnaire.

Table SM 1.2. Spearman's correlations between PIUQ-9 and psychological evaluation measures across experiment subsamples.

Variable	Spearman's rho	p-value	n
Go/NoGo task			
BAI	**0.366***	< .001	132
BDI	**0.333***	< .001	129
CBOCI	**0.421***	< .001	132
CBOCI obsessions	**0.357***	< .001	132
CBOCI compulsions	**0.376***	< .001	133
Alternating resting-state (alpha asymmetry)			
BAI	**0.316***	< .001	128
BDI	**0.285***	0.001	125
CBOCI	**0.406***	< .001	128
CBOCI obsessions	**0.355***	< .001	128
CBOCI compulsions	**0.349***	< .001	129
Eyes-closed resting-state (microstates)			
BAI	**0.286***	< .001	155
BDI	**0.26***	0.001	152
CBOCI	**0.362***	< .001	155
CBOCI obsessions	**0.295***	< .001	155
CBOCI compulsions	**0.312***	< .001	156

* The significance of the results survived FDR correction. BAI—Beck Anxiety Inventory; BDI—Beck Depression Inventory; CBOCI—Clark–Beck Obsessive–Compulsive Inventory; PIUQ-9—The Nine-Item Problematic Internet Use Questionnaire.

Table SM 1.3. Descriptive statistics for psychological measures between high and low internet use involvement groups across experiment subsamples.

Variable		Go/NoGo			Alternating resting-state (alpha asymmetry)			Eyes-closed resting-state (microstates)		
	Group	n	Mean	SD	n	Mean	SD	n	Mean	SD
PIUQ-9	High PIU	46	26.76	3	33	26.49	3.14	44	26.55	2.91
	Low PIU	45	13.83	1.95	36	13.72	2.07	43	13.77	2.07
BAI	High PIU	46	35.74	8.07	33	36.03	8.66	44	34.66	8.02
	Low PIU	44	28.59	6.35	35	29.06	5.64	42	29.14	6.42
BDI	High PIU	45	13.3	9.49	32	13.59	10.20	43	12.42	9.77
	Low PIU	44	6.97	6.08	35	7.66	5.94	42	7.41	5.84
CBOCI	High PIU	46	25.82	12.73	33	26.88	13.03	44	24.09	12.73
	Low PIU	45	13.83	8.88	36	14.97	9.09	43	14.44	8.56
CBOCI obsessions	High PIU	46	15.37	7.33	33	15.55	6.88	44	14.25	7.33
	Low PIU	45	9.54	5.62	36	9.72	5.56	43	9.58	5.36
CBOCI compulsions	High PIU	46	10.45	6.7	33	11.33	7.37	44	9.84	6.64
	Low PIU	45	4.4	4.22	36	5.36	4.51	43	4.95	4.28

BAI—Beck Anxiety Inventory; BDI—Beck Depression Inventory; CBOCI—Clark–Beck Obsessive–Compulsive Inventory; PIUQ-9—The Nine-Item Problematic Internet Use Questionnaire.

Table SM 1.4. Group differences between psychological evaluation measures across experiment subsamples.

Variable	U	*p*	Effect Size	SE Effect Size
Go/NoGo task				
PIUQ-9	1330	**<0.001 ***	1	0.135
BAI	997	**<0.001 ***	−0.54	0.136
BDI	891	**0.003 ***	−0.42	0.137
CBOCI	1040	**<0.001 ***	−0.57	0.135
CBOCI obsessions	975.5	**<0.001 ***	−0.47	0.135
CBOCI compulsions	1034	**<0.001 ***	−0.56	0.135
Alternating resting-state (alpha asymmetry)				
PIUQ-9	1188	**< .001***	1	0.139
BAI	860	**< .001***	0.49	0.14
BDI	748.5	**0.018***	0.34	0.141
CBOCI	923.5	**< .001***	0.56	0.139
CBOCI obsessions	882	**< .001***	0.49	0.139
CBOCI compulsions	893.5	**< .001***	0.5	0.139
Eyes-closed resting-state (microstates)				
PIUQ-9	1892	**< .001***	1	0.124
BAI	1323.5	**< .001***	0.43	0.125
BDI	1170	**0.019***	0.3	0.125
CBOCI	1384.5	**< .001***	0.47	0.124
CBOCI obsessions	1296.5	**0.003***	0.37	0.124
CBOCI compulsions	1366	**< .001***	0.44	0.124

* The significance of the results survived FDR correction. Mann–Whitney U test. BAI—Beck Anxiety Inventory; BDI—Beck Depression Inventory; CBOCI—Clark–Beck Obsessive–Compulsive Inventory; PIUQ-9—The Nine-Item Problematic Internet Use Questionnaire; SE effect size—standard error of effect size; and U—Mann–Whitney U test statistic.

SUPPLEMENTARY MATERIAL 2

Table SM 2.1. MAIA, Neo-Pi-R and PIUQ-9, DPIU edge weights obtained in the network analysis matrix.

Variable	Not-Worrying	Attention Regulation	Emotional Awareness	Self-Regulation	Body Listening	Trusting	Noticing	Not-Distracting	Neuroticism	Extraversion	Openness	Agreeableness	Conscientiousness	PIUQ9	DPIU_total
Interoceptive Awareness (MAIA)															
Not-Worrying	0	0.112	-0.117	0	0	0	0	0	-0.202	0	0	0	0	0	0
Attention Regulation	0.112	0	0	0.321	0.079	0.095	0.161	0	-0.041	0	0	0	0	0	0
Emotional Awareness	-0.117	0	0	0	0.445	0	0.152	0	0.018	0	0.034	0	0	0	0
Self-Regulation	0	0.321	0	0	0.282	0.175	0	0	-0.124	0	0.04	0	0	0	0
Body Listening	0	0.079	0.445	0.282	0	0	0.091	-0.025	0	0	0.061	0	0	0	0
Trusting	0	0.095	0	0.175	0	0	0	0	-0.239	0.03	0	0	0.063	-0.04	-0.011
Noticing	0	0.161	0.152	0	0.091	0	0	0	0	0	0	0	0	0	0
Not-Distracting	0	0	0	0	-0.025	0	0	0	0	0	0	0	0	-0.192	0
Personality Traits (Neo-Pi-R)															
Neuroticism	-0.202	-0.041	0.018	-0.124	0	-0.239	0	0	0	-0.029	0	0	-0.081	0.053	0.129
Extraversion	0	0	0	0	0	0.03	0	0	-0.029	0	0.267	0	0	0	0
Openness	0	0	0.034	0.04	0.061	0	0	0	0	0.267	0	0.033	0	0	0
Agreeableness	0	0	0	0	0	0	0	0	0	0	0.033	0	0	0	0
Conscientiousness	0	0	0	0	0	0.063	0	0	-0.081	0	0	0	0	0	-0.042

Variable	Not-Worrying	Attention Regulation	Emotional Awareness	Self-Regulation	Body Listening	Trusting	Noticing	Not-Distracting	Neuroticism	Extraversion	Openness	Agreeableness	Conscientiousness	PIUQ9	DPIU_total
Internet Usage Patterns (PIUQ-9, DPIU)															
PIUQ-9	0	0	0	0	0	-0.04	0	-0.192	0.053	0	0	0	0	0	0.421
DPIU_total	0	0	0	0	0	-0.011	0	0	0.129	0	0	0	-0.042	0.421	0

CBOCI = Clark-Beck Obsessive-Compulsive Inventory; DPIU = Dimensions of Problematic Internet Use; MAIA = Multidimensional Assessment of Interoceptive Awareness; NEO-PI-R = Revised NEO Personality Inventory; PIUQ-9 = Problematic Internet Use Questionnaire.

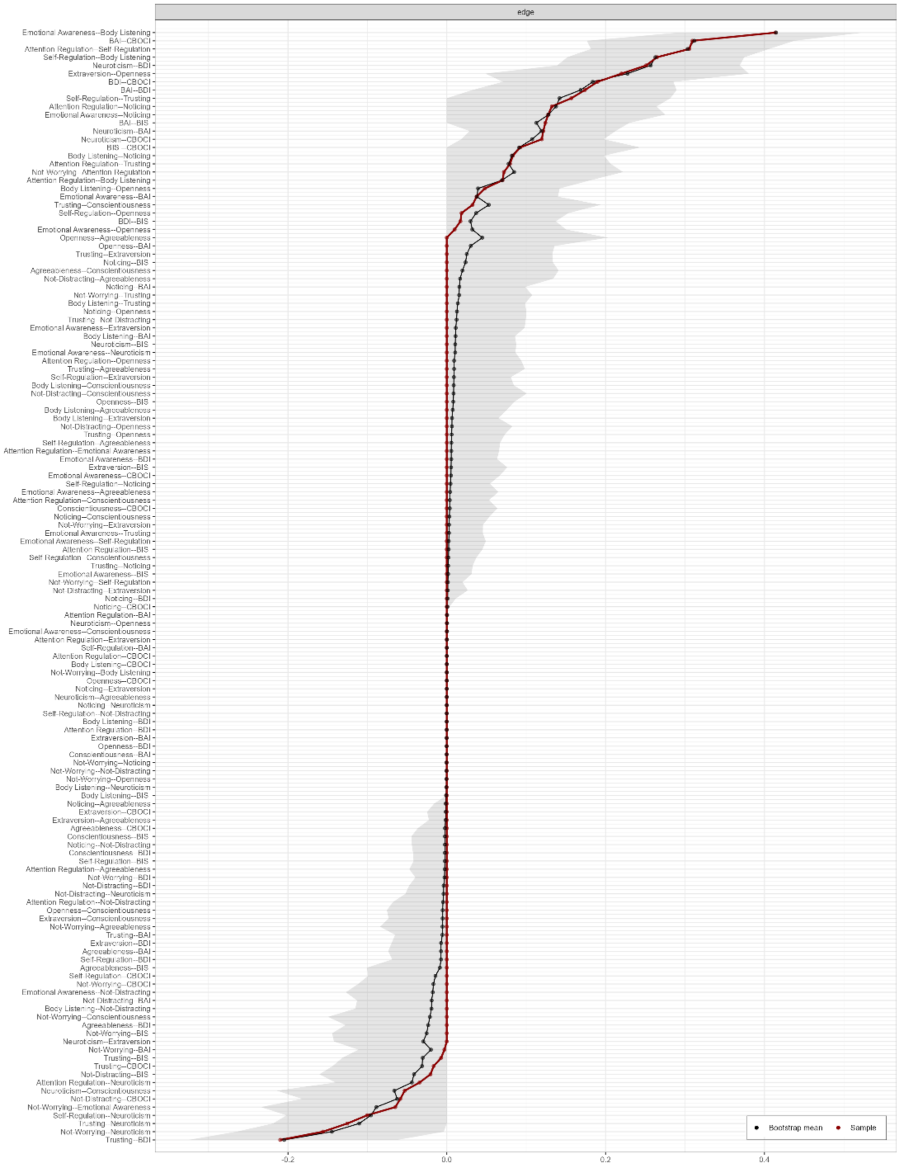


Figure SM 2.1. The accuracy and stability of the network for Interoceptive awareness, Personality traits, and Problematic Internet Use illustrated through bootstrapped confidence intervals (CIs) of estimated edge weights. In the figure, the x-axis represents the estimated edge-weight coefficients, while the y-axis lists each estimated edge weight in descending order from the highest to the lowest mean bootstrap edge-weight. The red line denotes the sample values, and the black line indicates the mean bootstrapped estimated edge-weights. Larger CIs, depicted by a wider shaded area around the mean bootstrapped estimated edge-weights (black line), imply a lower confidence in the accuracy of the edge-weight estimates between two specific nodes (Epskamp et al., 2018).

SUPPLEMENTARY MATERIAL 3

Table SM 3.1. Spearman's correlations between problematic internet use questionnaires (PIUQ-9 and DPIU) and behavioral responses.

Variable		Correct Go	Correct NoGo	Go RT
PIUQ-9	Spearman's rho	-0.045	0.044	0.082
	p-value	0.607	0.617	0.348
	n	133	133	133
Entertainment and Video Streaming	Spearman's rho	-0.009	0.255	0.112
	p-value	0.937	0.02	0.312
	n	83	83	83
Gaming	Spearman's rho	-0.101	0.101	**0.32***
	p-value	0.358	0.359	**0.003**
	n	84	84	84
Social Media	Spearman's rho	0.033	0.101	0.333
	p-value	0.861	0.596	0.072
	n	30	30	30
Messaging	Spearman's rho	0.018	0.212	0.004
	p-value	0.921	0.235	0.983
	n	33	33	33
Information Search	Spearman's rho	0.043	-0.451	0.063
	p-value	0.848	0.035	0.779
	n	22	22	22
DPIU_total	Spearman's rho	0.046	0.087	0.0007
	p-value	0.622	0.345	0.994
	n	119	119	119

* the significance of the results survived FDR correction. PIUQ-9 – The Nine-Item Problematic Internet Use Questionnaire, DPIU – The Dimensions of Problematic Internet Use, Go_RT – average Go Reaction Time.

Table SM 3.2. Descriptive statistics for behavioral responses between high and low internet use involvement groups.

Variable	Group	n	Mean	SD
Correct_Go	Low_PIU	35	73.34	2.84
	High_PIU	38	72.05	6.51
Correct_NoGo	Low_PIU	35	72.71	2.73
	High_PIU	38	72.95	2.43
GO_RT	Low_PIU	35	0.41	0.05
	High_PIU	38	0.42	0.07

GO_RT – average Go Reaction Time.

Table SM 3.3. Spearman's correlations between internet use questionnaires (PIUQ-9 and DPIU) and N1, N2, P2 and P3 amplitudes during Go trials.

Go trials amplitudes		PIUQ-9	Entertainment and Video Streaming	Social Media	Gaming	Messaging	Information Search	DPIU_total
Fz_N1	Spearman's rho	0.00015	0.114	0.17	-0.172	0.108	0.129	-0.11
	p-value	0.999	0.305	0.123	0.364	0.551	0.567	0.234
	n	133	83	84	30	33	22	119
Fz_N2	Spearman's rho	-0.084	-0.007	0.059	0.011	0.087	0.315	-0.044
	p-value	0.336	0.95	0.592	0.955	0.629	0.153	0.631
	n	133	83	84	30	33	22	119
Fz_P2	Spearman's rho	-0.069	0.036	-99.47	0.015	0.2	0.329	0.022
	p-value	0.428	0.748	0.993	0.939	0.264	0.135	0.812
	n	133	83	84	30	33	22	119
Fz_P3	Spearman's rho	-0.132	-0.13	-0.067	-0.125	-0.043	0.18	-0.145
	p-value	0.131	0.243	0.544	0.51	0.812	0.422	0.115
	n	133	83	84	30	33	22	119
FCz_N1	Spearman's rho	-0.075	0.058	0.09	-0.29	-0.055	-0.139	-0.177
	p-value	0.393	0.601	0.413	0.12	0.762	0.538	0.054
	n	133	83	84	30	33	22	119
FCz_N2	Spearman's rho	-0.075	-0.039	-0.065	-0.127	-0.069	0.109	0.001
	p-value	0.389	0.727	0.559	0.502	0.702	0.63	0.989
	n	133	83	84	30	33	22	119
FCz_P2	Spearman's rho	-0.039	0.047	-0.03	-0.067	0.178	0.176	0.015
	p-value	0.654	0.674	0.786	0.726	0.323	0.434	0.875
	n	133	83	84	30	33	22	119
FCz_P3	Spearman's rho	-0.069	-0.11	-0.112	-0.091	0.035	0.268	-0.033
	p-value	0.43	0.322	0.309	0.632	0.846	0.227	0.719
	n	133	83	84	30	33	22	119
Cz_N1	Spearman's rho	-0.147	-0.048	-0.03	**-0.467***	-0.209	-0.242	-0.182
	p-value	0.091	0.668	0.785	**0.009**	0.244	0.278	0.047

Go trials amplitudes		PIUQ-9	Entertainment and Video Streaming	Social Media	Gaming	Messaging	Information Search	DPIU_total
	n	133	83	84	30	33	22	119
Cz_N2	Spearman's rho	-0.029	-0.04	-0.186	-0.182	-0.047	0.023	-0.005
	p-value	0.737	0.718	0.091	0.337	0.794	0.919	0.961
	n	133	83	84	30	33	22	119
Cz_P2	Spearman's rho	-0.042	-0.057	-0.08	-0.245	0.081	0.13	-0.007
	p-value	0.627	0.611	0.471	0.191	0.654	0.564	0.938
	n	133	83	84	30	33	22	119
Cz_P3	Spearman's rho	-0.016	-0.055	-0.138	-0.115	0.189	0.261	0.008
	p-value	0.857	0.623	0.21	0.544	0.293	0.24	0.931
	n	133	83	84	30	33	22	119
CPz_N1	Spearman's rho	-0.132	-0.2	-0.133	-0.419	-0.126	-0.141	-0.219
	p-value	0.129	0.069	0.227	0.021	0.486	0.531	0.017
	n	133	83	84	30	33	22	119
CPz_N2	Spearman's rho	0.065	-0.041	-0.109	-0.216	0.078	0.048	0.005
	p-value	0.46	0.713	0.324	0.251	0.665	0.831	0.954
	n	133	83	84	30	33	22	119
CPz_P2	Spearman's rho	-0.064	-0.147	-0.085	-0.244	0.033	-0.05	-0.03
	p-value	0.462	0.185	0.442	0.195	0.855	0.827	0.744
	n	133	83	84	30	33	22	119
CPz_P3	Spearman's rho	0.069	0.048	-0.131	-0.113	0.246	0.216	0.104
	p-value	0.428	0.666	0.234	0.552	0.167	0.333	0.261
	n	133	83	84	30	33	22	119
Pz_N1	Spearman's rho	-0.176	-0.219	-0.181	-0.201	-0.047	0.121	-0.203
	p-value	0.043	0.047	0.099	0.287	0.795	0.592	0.026
	n	133	83	84	30	33	22	119
Pz_N2	Spearman's rho	0.066	-0.102	-0.113	-0.203	-0.013	0.041	-0.018
	p-value	0.453	0.359	0.307	0.282	0.944	0.855	0.849
	n	133	83	84	30	33	22	119

Go trials amplitudes		PIUQ-9	Entertainment and Video Streaming	Social Media	Gaming	Messaging	Information Search	DPIU_total
Pz_P2	Spearman's rho	-0.021	-0.069	-0.103	-0.121	-0.164	-0.051	-0.003
	p-value	0.807	0.538	0.352	0.524	0.361	0.821	0.974
	n	133	83	84	30	33	22	119
Pz_P3	Spearman's rho	0.121	0.063	-0.092	-0.045	0.143	-0.067	0.14
	p-value	0.166	0.572	0.407	0.814	0.427	0.768	0.128
	n	133	83	84	30	33	22	119

* the significance of the results survived FDR correction. *The variation in sample sizes across the subscales is attributed to the low overlap between specific dimensions, resulting in smaller sample sizes for certain subscales within the study.*

Table SM 3.4. Spearman's correlations between internet use questionnaires (PIUQ-9 and DPIU) and N1, N2, P2 and P3 latencies during Go trials

Go trials latencies		PIUQ-9	Entertainment and Video Streaming	Social Media	Gaming	Messaging	Information Search	DPIU_total
Fz_N1	Spearman's rho	-0.032	0.046	0.094	-0.016	-0.115	0.042	-0.068
	p-value	0.712	0.681	0.394	0.931	0.524	0.852	0.46
	n	133	83	84	30	33	22	119
Fz_N2	Spearman's rho	-0.101	-0.082	-0.026	-0.233	0.085	-0.048	0.007
	p-value	0.247	0.461	0.811	0.216	0.637	0.831	0.944
	n	133	83	84	30	33	22	119
Fz_P2	Spearman's rho	-0.095	-0.128	-0.107	0.146	-0.119	0.089	-0.064
	p-value	0.276	0.25	0.331	0.441	0.511	0.695	0.491
	n	133	83	84	30	33	22	119
Fz_P3	Spearman's rho	-0.198	-0.134	-0.196	-0.416	-0.177	-0.467	-0.14
	p-value	0.023	0.227	0.074	0.022	0.324	0.028	0.13
	n	133	83	84	30	33	22	119
FCz_N1	Spearman's rho	-0.088	-0.032	0.018	-0.144	-0.17	0.086	-0.162
	p-value	0.316	0.772	0.868	0.449	0.344	0.702	0.079

Go trials latencies		PIUQ-9	Entertainment and Video Streaming	Social Media	Gaming	Messaging	Information Search	DPIU_total
	n	133	83	84	30	33	22	119
FCz_N2	Spearman's rho	0.023	0.061	0.012	0.247	0.214	-0.062	-0.04
	p-value	0.792	0.584	0.911	0.187	0.233	0.782	0.663
	n	133	83	84	30	33	22	119
FCz_P2	Spearman's rho	-0.094	-0.003	-0.017	0.097	-0.023	0.065	-0.055
	p-value	0.284	0.981	0.877	0.61	0.898	0.775	0.554
	n	133	83	84	30	33	22	119
FCz_P3	Spearman's rho	-0.129	-0.142	-0.173	-0.072	0.134	0.013	-0.146
	p-value	0.138	0.2	0.116	0.707	0.458	0.953	0.113
	n	133	83	84	30	33	22	119
Cz_N1	Spearman's rho	-0.126	-0.178	-0.003	-0.127	-0.178	-0.006	-0.151
	p-value	0.149	0.108	0.979	0.504	0.321	0.98	0.101
	n	133	83	84	30	33	22	119
Cz_N2	Spearman's rho	0.037	0.125	0.135	0.101	0.16	0.01	0.064
	p-value	0.671	0.261	0.222	0.594	0.375	0.966	0.486
	n	133	83	84	30	33	22	119
Cz_P2	Spearman's rho	-0.022	-0.02	-0.051	-0.097	0.035	-0.209	-0.044
	p-value	0.799	0.859	0.645	0.609	0.848	0.351	0.633
	n	133	83	84	30	33	22	119
Cz_P3	Spearman's rho	0.039	-0.007	0.122	0.003	0.094	0.393	0.027
	p-value	0.653	0.948	0.27	0.986	0.602	0.071	0.77
	n	133	83	84	30	33	22	119
CPz_N1	Spearman's rho	-0.117	-0.139	-0.137	-0.001	-0.049	0.203	**-0.24***
	p-value	0.18	0.212	0.214	0.996	0.786	0.366	**0.009**
	n	133	83	84	30	33	22	119
CPz_N2	Spearman's rho	-0.102	-0.113	0.069	-0.027	0.109	0.046	-0.086
	p-value	0.241	0.308	0.531	0.887	0.544	0.84	0.351
	n	133	83	84	30	33	22	119

Go trials latencies		PIUQ-9	Entertainment and Video Streaming	Social Media	Gaming	Messaging	Information Search	DPIU_total
	Spearman's rho	-0.054	-0.132	-0.003	-0.035	0.037	0.115	-0.043
CPz_P2	p-value	0.534	0.234	0.976	0.852	0.838	0.61	0.643
	n	133	83	84	30	33	22	119
	Spearman's rho	0.001	0.058	0.165	0.151	0.077	0.13	0.093
CPz_P3	p-value	0.987	0.603	0.134	0.427	0.672	0.564	0.316
	n	133	83	84	30	33	22	119
	Spearman's rho	-0.057	-0.062	-0.102	-0.142	0.16	0.002	-0.155
Pz_N1	p-value	0.514	0.577	0.355	0.453	0.372	0.994	0.092
	n	133	83	84	30	33	22	119
	Spearman's rho	-0.171	-0.102	0.02	-0.1	-0.075	0.097	-0.117
Pz_N2	p-value	0.049	0.357	0.856	0.598	0.68	0.669	0.206
	n	133	83	84	30	33	22	119
	Spearman's rho	-0.019	-0.063	-0.004	-0.268	0.103	0.22	-0.096
Pz_P2	p-value	0.825	0.572	0.971	0.152	0.567	0.326	0.297
	n	133	83	84	30	33	22	119
	Spearman's rho	0.031	0.146	0.187	0.041	0.108	0.243	0.128
Pz_P3	p-value	0.725	0.188	0.089	0.829	0.548	0.276	0.167
	n	133	83	84	30	33	22	119

* the significance of the results survived FDR correction. The variation in sample sizes across the subscales is attributed to the low overlap between specific dimensions, resulting in smaller sample sizes for certain subscales within the study.

Table SM 3.5. Spearman's correlations between internet use questionnaires (PIUQ-9 and DPIU) and N1, N2, P2 and P3 amplitudes during NoGo trials

NoGo trials amplitudes		PIUQ-9	Entertainment and Video Streaming	Social Media	Gaming	Messaging	Information Search	DPIU_total
Fz_N1	Spearman's rho	-0.047	-0.058	0.147	-0.204	-0.153	0.073	-0.138
	p-value	0.59	0.602	0.183	0.28	0.394	0.746	0.135
	n	133	83	84	30	33	22	119
Fz_N2	Spearman's rho	0.02	0.037	0.04	0.129	0.011	-0.115	0.036
	p-value	0.819	0.737	0.718	0.496	0.952	0.612	0.697
	n	133	83	84	30	33	22	119
Fz_P2	Spearman's rho	-0.03	-0.042	0.043	0.083	-0.015	0.153	0.024
	p-value	0.734	0.709	0.701	0.663	0.934	0.498	0.793
	n	133	83	84	30	33	22	119
Fz_P3	Spearman's rho	0.015	0.018	-0.021	0.223	0.105	-0.036	0.05
	p-value	0.862	0.871	0.849	0.235	0.563	0.873	0.591
	n	133	83	84	30	33	22	119
FCz_N1	Spearman's rho	-0.071	-0.049	0.095	-0.324	-0.076	0.005	-0.174
	p-value	0.419	0.658	0.392	0.08	0.674	0.984	0.058
	n	133	83	84	30	33	22	119
FCz_N2	Spearman's rho	0.028	0.041	-0.022	0.21	0.03	0.11	0.108
	p-value	0.747	0.713	0.839	0.266	0.868	0.626	0.243
	n	133	83	84	30	33	22	119
FCz_P2	Spearman's rho	0.013	0.022	0.039	0.167	0.174	0.169	0.086
	p-value	0.886	0.846	0.727	0.378	0.332	0.451	0.354
	n	133	83	84	30	33	22	119
FCz_P3	Spearman's rho	0.019	-0.088	-0.163	0.039	0.128	0.096	0.107
	p-value	0.829	0.428	0.139	0.838	0.478	0.67	0.248
	n	133	83	84	30	33	22	119
Cz_N1	Spearman's rho	-0.066	-0.107	-0.042	**-0.486***	-0.164	-0.163	-0.169
	p-value	0.45	0.337	0.702	**0.006**	0.363	0.467	0.067

NoGo trials amplitudes		PIUQ-9	Entertainment and Video Streaming	Social Media	Gaming	Messaging	Information Search	DPIU_total
	n	133	83	84	30	33	22	119
Cz_N2	Spearman's rho	0.009	0.003	-0.131	0.052	0.156	0.304	0.138
	p-value	0.92	0.976	0.236	0.786	0.386	0.169	0.134
	n	133	83	84	30	33	22	119
Cz_P2	Spearman's rho	-0.01	-0.007	-0.002	-0.061	0.197	0.235	0.064
	p-value	0.912	0.947	0.984	0.749	0.271	0.292	0.49
	n	133	83	84	30	33	22	119
Cz_P3	Spearman's rho	0.047	-0.083	-0.207	-0.068	0.153	-0.045	0.136
	p-value	0.589	0.458	0.059	0.722	0.395	0.841	0.139
	n	133	83	84	30	33	22	119
CPz_N1	Spearman's rho	-0.025	-0.158	-0.117	**-0.549***	-0.08	-0.098	-0.124
	p-value	0.778	0.154	0.291	**0.002**	0.66	0.665	0.179
	n	133	83	84	30	33	22	119
CPz_N2	Spearman's rho	-0.044	-0.057	-0.186	-0.311	-0.042	0.134	0.029
	p-value	0.613	0.609	0.09	0.094	0.816	0.552	0.755
	n	133	83	84	30	33	22	119
CPz_P2	Spearman's rho	-0.025	-0.015	-0.172	-0.057	0.108	0.169	0.026
	p-value	0.774	0.895	0.119	0.766	0.551	0.451	0.779
	n	133	83	84	30	33	22	119
CPz_P3	Spearman's rho	0.053	-0.082	-0.221	-0.022	-87.89	0.176	0.067
	p-value	0.545	0.459	0.043	0.908	0.996	0.433	0.471
	n	133	83	84	30	33	22	119
Pz_N1	Spearman's rho	-0.021	-0.05	-0.078	-0.344	0.042	0.089	-0.089
	p-value	0.81	0.655	0.479	0.063	0.817	0.693	0.335
	n	133	83	84	30	33	22	119
Pz_N2	Spearman's rho	-0.067	-0.121	-0.189	-0.306	-0.176	0.121	-0.125
	p-value	0.445	0.275	0.085	0.101	0.326	0.592	0.177
	n	133	83	84	30	33	22	119

NoGo trials amplitudes		PIUQ-9	Entertainment and Video Streaming	Social Media	Gaming	Messaging	Information Search	DPIU_total
Pz_P2	Spearman's rho	-0.064	-0.058	-0.055	-0.053	0.013	0.219	-0.023
	p-value	0.465	0.604	0.622	0.779	0.942	0.328	0.803
	n	133	83	84	30	33	22	119
Pz_P3	Spearman's rho	-0.011	-0.082	**-0.223***	0.041	-0.127	0.085	-0.053
	p-value	0.899	0.459	0.041	0.831	0.483	0.708	0.567
	n	133	83	84	30	33	22	119

* the significance of the results survived FDR correction. The variation in sample sizes across the subscales is attributed to the low overlap between specific dimensions, resulting in smaller sample sizes for certain subscales within the study.

Table SM 3.6. Spearman's correlations between internet use questionnaires (PIUQ-9 and DPIU) and N1, N2, P2 and P3 latencies during NoGo trials.

NoGo trials latencies		PIUQ-9	Entertainment and Video Streaming	Social Media	Gaming	Messaging	Information Search	DPIU_total
Fz_N1	Spearman's rho	-0.023	0.124	-0.007	0.328	0.197	-0.111	-0.016
	p-value	0.789	0.265	0.952	0.076	0.272	0.622	0.865
	n	133	83	84	30	33	22	119
Fz_N2	Spearman's rho	-0.008	0.025	0.229	0.204	0.019	0.051	0.049
	p-value	0.923	0.823	0.036	0.281	0.918	0.821	0.599
	n	133	83	84	30	33	22	119
Fz_P2	Spearman's rho	0.042	0.122	0.074	0.365	0.156	-0.17	0.087
	p-value	0.63	0.273	0.504	0.047	0.386	0.45	0.349
	n	133	83	84	30	33	22	119
Fz_P3	Spearman's rho	0.024	-0.024	0.071	0.029	-0.007	**0.503***	-0.022
	p-value	0.783	0.828	0.519	0.878	0.967	**0.017**	0.813
	n	133	83	84	30	33	22	119
FCz_N1	Spearman's rho	-0.074	-0.011	-0.103	0.101	-0.167	0.064	-0.128

NoGo trials latencies		PIUQ-9	Entertainment and Video Streaming	Social Media	Gaming	Messaging	Information Search	DPIU_total
	p-value	0.397	0.923	0.352	0.595	0.352	0.778	0.165
	n	133	83	84	30	33	22	119
FCz_N2	Spearman's rho	-0.016	0.039	0.196	0.433	0.17	0.133	0.018
	p-value	0.858	0.723	0.074	0.017	0.344	0.555	0.843
	n	133	83	84	30	33	22	119
FCz_P2	Spearman's rho	0.025	0.123	0.11	0.378	0.206	-0.019	0.14
	p-value	0.779	0.267	0.319	0.04	0.25	0.933	0.128
	n	133	83	84	30	33	22	119
FCz_P3	Spearman's rho	-0.049	-0.062	0.047	0.03	0.002	**0.467***	-0.121
	p-value	0.578	0.578	0.669	0.876	0.993	**0.028**	0.188
	n	133	83	84	30	33	22	119
Cz_N1	Spearman's rho	-0.052	-0.067	-0.173	0.065	-0.091	0.474	-0.159
	p-value	0.549	0.546	0.117	0.733	0.614	0.026	0.084
	n	133	83	84	30	33	22	119
Cz_N2	Spearman's rho	-0.03	-0.009	0.115	0.258	0.2	0.405	-0.063
	p-value	0.729	0.938	0.296	0.168	0.264	0.061	0.495
	n	133	83	84	30	33	22	119
Cz_P2	Spearman's rho	-0.005	0.032	0.001	0.22	0.183	0.388	0.033
	p-value	0.954	0.774	0.993	0.244	0.308	0.074	0.719
	n	133	83	84	30	33	22	119
Cz_P3	Spearman's rho	-0.028	-0.029	0.144	0.094	0.059	**0.443***	-0.12
	p-value	0.75	0.795	0.192	0.623	0.745	**0.039**	0.195
	n	133	83	84	30	33	22	119
CPz_N1	Spearman's rho	0.042	-0.099	0.165	-0.056	0.01	0.333	-0.046
	p-value	0.632	0.372	0.133	0.768	0.958	0.13	0.622
	n	133	83	84	30	33	22	119
CPz_N2	Spearman's rho	-0.046	-0.099	0.09	-0.018	0.226	-0.018	-0.065
	p-value	0.601	0.373	0.414	0.924	0.206	0.935	0.483

NoGo trials latencies		PIUQ-9	Entertainment and Video Streaming	Social Media	Gaming	Messaging	Information Search	DPIU_total
	n	133	83	84	30	33	22	119
CPz_P2	Spearman's rho	-0.048	-0.025	-0.107	-0.023	0.096	0.165	-0.037
	p-value	0.586	0.821	0.334	0.904	0.595	0.462	0.693
	n	133	83	84	30	33	22	119
CPz_P3	Spearman's rho	0.099	-0.085	0.125	0.169	0.153	0.256	-0.038
	p-value	0.257	0.442	0.256	0.372	0.395	0.251	0.68
	n	133	83	84	30	33	22	119
Pz_N1	Spearman's rho	0.055	-0.039	0.14	-0.033	-0.168	-0.145	-0.048
	p-value	0.53	0.725	0.203	0.861	0.349	0.521	0.602
	n	133	83	84	30	33	22	119
Pz_N2	Spearman's rho	0.121	-0.025	0.073	-0.151	0.437	0.422	-0.007
	p-value	0.165	0.825	0.508	0.427	0.011	0.051	0.943
	n	133	83	84	30	33	22	119
Pz_P2	Spearman's rho	-0.025	-0.074	-0.114	-0.383	-0.172	-0.057	-0.16
	p-value	0.776	0.506	0.301	0.037	0.338	0.801	0.083
	n	133	83	84	30	33	22	119
Pz_P3	Spearman's rho	0.058	-0.021	0.175	-0.059	0.127	**0.466***	-0.023
	p-value	0.504	0.852	0.111	0.757	0.48	0.029	0.806
	n	133	83	84	30	33	22	119

* the significance of the results survived FDR correction. *The variation in sample sizes across the subscales is attributed to the low overlap between specific dimensions, resulting in smaller sample sizes for certain subscales within the study.*

Table SM 3.7. Descriptive statistics for the amplitudes and latencies of ERP components during Go and NoGo conditions within the high and low piu engagement groups.

Electrode	Group	Amplitudes				Latencies			
		N1	N2	P2	P3	N1	N2	P2	P3
Go									
Fz	Low	-2.51±1.43	-3.04±2.47	0.3±1.98	-0.91±2.1	125.81±13.89	284.6±46.61	188.78±14.62	381.22±65.29
	High	-2.27±1.46	-3.22±1.98	0.03±1.82	-1.37±1.99	126.75±9.2	274.94±38.7	188.64±21.7	353.39±73.12
FCz	Low	-2.34±1.38	-1.76±2.52	1.15±1.88	0.21±2.26	125.15±8.42	259.42±32.68	185.39±12.4	345.82±41.53
	High	-2.39±1.46	-2.05±2.05	1±1.89	0.27±3	124.64±11.8	263.97±30.38	185.57±19.03	334.06±42.93
Cz	Low	-1.43±1.05	-0.27±1.68	1.83±1.64	1.82±2.06	124.49±7.71	252.9±29.44	186.62±18.45	343.37±48.66
	High	-1.76±1.12	-0.43±1.7	1.53±1.49	2.12±2.92	121.56±13.37	261.17±39.55	189.53±20.04	354.47±54.06
CPz	Low	-0.68±0.8	0.65±1.69	2.09±1.41	3.24±1.9	112.58±21.36	243.43±45.59	187.97±25.89	364.4±66.74
	High	-1.05±0.9	0.76±1.5	1.65±1.34	3.8±2.59	109.13±17.5	237.52±37.99	188.07±27.55	368.22±57.75
Pz	Low	-0.31±0.97	0.7±1.82	1.92±1.43	3.96±2.18	102.2±24.94	226.52±37.57	174.41±27.66	357.7±63.39
	High	-0.8±0.92	0.71±1.63	1.57±1.28	4.36±2.24	97.21±20.41	210.67±27.91	171.49±29.47	362.36±52.72
NoGo									
Fz	Low	-2.61±1.43	-1.89±2.41	0.15±2.04	1.44±1.72	126.339±16.23	248.186±32.12	187.486±27.29	334.738±40.16
	High	-2.63±1.49	-1.51±1.7	0.28±1.99	1.75±2.14	130.461±15.35	251.735±36.91	193.128±29.77	344.213±43.05
FCz	Low	-2.5±1.44	-1.05±2.23	0.84±1.96	2.93±1.9	125.112±11.16	236.18±24.5	186.11±18.12	331.61±38.33
	High	-2.59±1.5	-0.65±1.72	1.29±1.96	3.37±3.11	126.5±11.94	245.43±37.32	192.45±26.68	334.42±40.3
Cz	Low	-1.65±1.13	0.08±1.35	1.47±1.45	3.31±1.63	123.86±7.65	232.98±27.82	181.47±12.38	327±43.2
	High	-1.76±1.16	0.16±1.38	1.49±1.33	3.78±2.67	123.09±7.37	234.04±34.22	183.22±17.11	327.68±41.81
CPz	Low	-0.74±0.89	0.69±1.04	1.8±1.03	2.92±1.4	115.9±15.72	230.61±25.99	185.81±23.6	318.58±44.85
	High	-0.87±0.86	0.52±1.43	1.7±1.26	3.06±1.78	116.43±15.38	238.58±40.27	189.01±30.55	341.87±61.08
Pz	Low	-0.47±0.66	0.3±1.33	1.81±1.09	2.23±1.44	92.4±21.43	237.15±52.44	182.09±32.75	339.89±65.49
	High	-0.63±1.01	0.03±1.61	1.65±1.48	2.03±1.38	103.12±31.18	245.17±42.82	183.16±34.64	352.51±59.65

Amplitudes are reported in microvolts (μV) and latencies are reported in milliseconds (ms); means ± SDs provided.

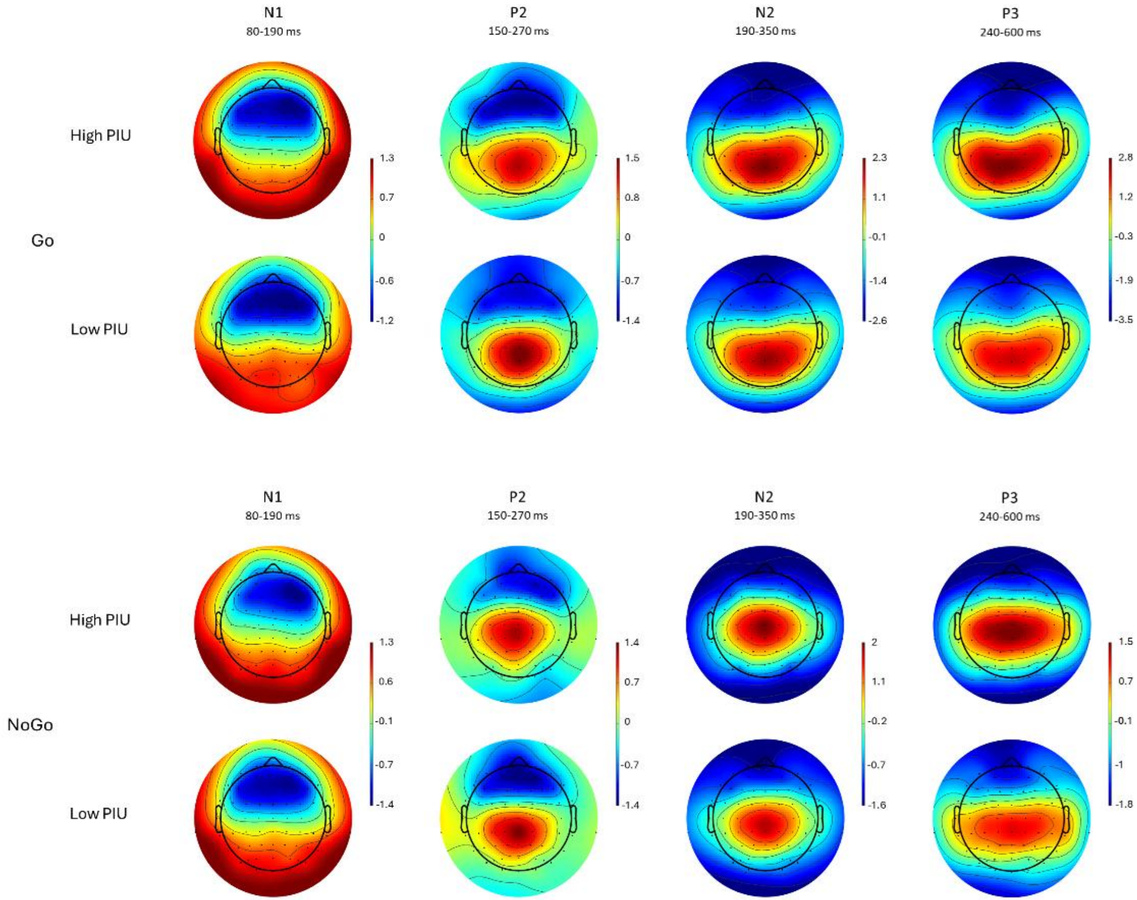


Figure SM 3.1. Topographical representation of the N1 (first column), P2 (second column), N2 (third column), and P3 (fourth column) waves in response to Go (upper rows) and NoGo (lower rows) stimuli between High PIU and Low PIU groups. No significant differences were observed between groups at any of the electrode sites. Scale in microvolts (μV).

SUPPLEMENTARY MATERIAL 4

Table SM 4.1. Spearman's correlations between the scores of the Problematic Internet Use Questionnaire (PIUQ-9), psychological measures, and averaged absolute alpha power within frontal and parietal regions during eyes open and eyes closed conditions.

Variable		PIUQ-9	BAI	BDI	CBOCI	CBOCI obsessions	CBOCI compulsions
EO frontal	Spearman's rho	**-0.248***	-0.129	-0.118	-0.067	-0.108	-0.016
	p-value	**0.005**	0.15	0.193	0.452	0.227	0.857
	n	128	127	124	127	127	128
EO parietal	Spearman's rho	**-0.209***	-0.095	-0.107	-0.042	-0.098	0.042
	p-value	**0.018**	0.288	0.235	0.637	0.275	0.639
	n	128	127	124	127	127	128
EC frontal	Spearman's rho	**-0.241***	0.03	-0.004	-0.023	-0.092	0.067
	p-value	**0.006**	0.735	0.966	0.8	0.303	0.448
	n	129	128	125	128	128	129
EC parietal	Spearman's rho	**-0.183***	0.027	-0.006	-0.023	-0.083	0.064
	p-value	**0.038**	0.763	0.943	0.801	0.351	0.474
	n	129	128	125	128	128	129

* the significance of the results survived FDR correction. PIUQ-9 – The Nine-Item Problematic Internet Use Questionnaire, BAI – The Beck Anxiety Inventory, BDI-II – Beck's Depression Inventory, CBOCI – The Clark-Beck Obsessive-Compulsive Inventory.

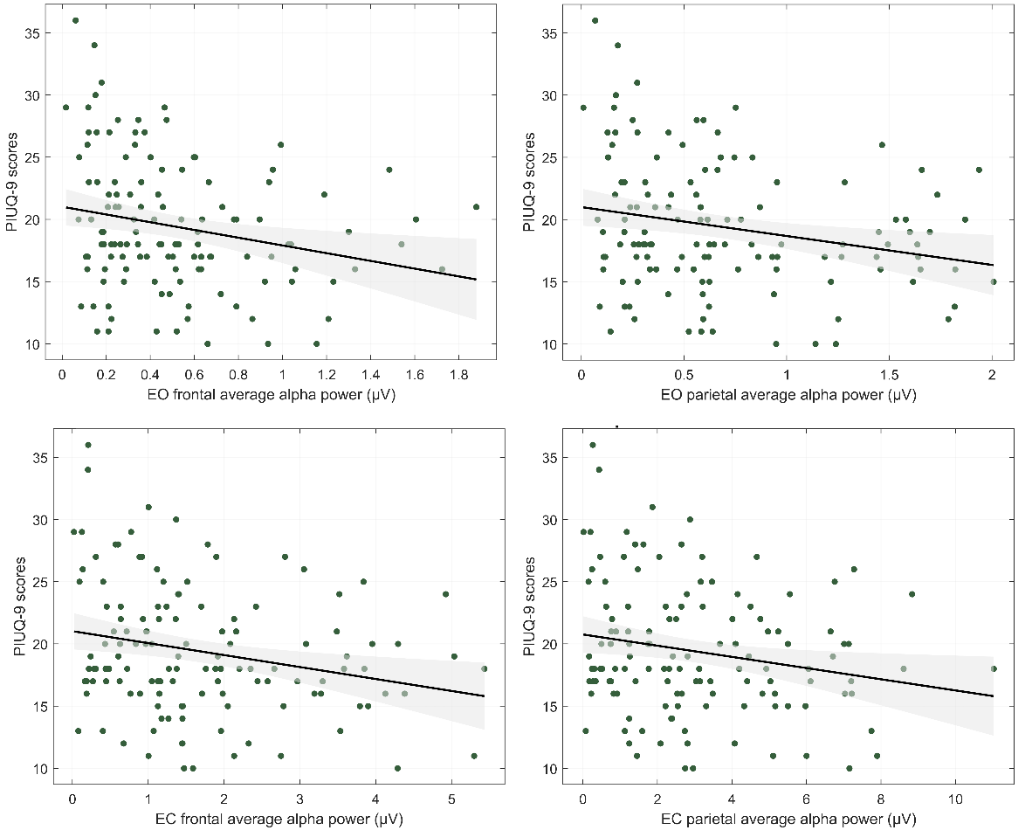


Figure SM 4.1. Correlation plots of internet use severity (measured by PIUQ-9 scores, y axis) with average absolute alpha power (µV) (x axis) in frontal and parietal regions. EO – Eyes Open condition, EC – Eyes Closed condition. Shaded areas represent the 95% confidence interval of the regression estimates.

Table SM 4.2. Descriptive statistics for alpha frequency and alpha asymmetry scores between high and low PIU groups.

Variable	Group	n	Mean	SD
Alpha frequency (µV)				
EO_frontal	High PIU	33	0.39	0.33
	Low PIU	36	0.61	0.4
EO_parietal	High PIU	33	0.54	0.47
	Low PIU	36	0.81	0.57
EC_frontal	High PIU	33	1.32	1.18
	Low PIU	36	2.04	1.31
EC_parietal	High PIU	33	2.51	2.21
	Low PIU	36	3.52	2.24
Alpha asymmetry scores				
Eyes Open				
F3/F4	High PIU	33	-0.01	0.25
	Low PIU	35	-0.06	0.24
F7/F8	High PIU	33	-0.13	0.69
	Low PIU	35	-0.04	0.38
P3/P4	High PIU	33	0.28	0.46
	Low PIU	34	0.02	0.29
P7/P8	High PIU	32	0.29	0.51
	Low PIU	33	0.04	0.35
Eyes closed				
F3/F4	High PIU	33	-0.08	0.22
	Low PIU	36	-0.05	0.16
F7/F8	High PIU	33	-0.14	0.63
	Low PIU	36	-0.02	0.28
P3/P4	High PIU	32	0.41	0.55
	Low PIU	36	0.30	0.49
P7/P8	High PIU	32	0.49	0.70
	Low PIU	33	0.27	0.40

BAI – Beck Anxiety Inventory; BDI – Beck Depression Inventory; CBOCI – Clark–Beck Obsessive–Compulsive Inventory; PIUQ-9 – The Nine-Item Problematic Internet Use Questionnaire.

SUPPLEMENTARY MATERIAL 5

Table SM 5.1. Descriptive statistics for microstates spatiotemporal parameters between High and Low PIU involvement groups.

Variable	Group	n	Duration (ms)	Occurrence rate	Coverage (%)
MS A	High PIU	44	52.05 ± 3.69	2.96 ± 0.56	18.12 ± 4.35
	Low PIU	43	51.8 ± 3.8	2.91 ± 0.69	17.82 ± 5.14
MS B	High PIU	44	53.86 ± 4.14	3.24 ± 0.57	20.9 ± 5.06
	Low PIU	43	54.32 ± 4.29	3.27 ± 0.57	21.49 ± 5.45
MS C	High PIU	44	69.18 ± 11.43	4.33 ± 0.37	38.88 ± 9.76
	Low PIU	43	69.85 ± 9.2	4.35 ± 0.39	39.83 ± 8.37
MS D	High PIU	44	45.83 ± 2.87	1.87 ± 0.58	9.74 ± 3.5
	Low PIU	43	47.04 ± 3.37	2.15 ± 0.51	11.57 ± 3.39
MS E	High PIU	44	47.61 ± 4.17	2.23 ± 0.76	12.36 ± 5.31
	Low PIU	43	45.79 ± 3.11	1.78 ± 0.61	9.29 ± 3.76

Means ± SDs provided

Table SM 5.2. Spearman's correlations between internet use (PIUQ-9) and microstates' spatiotemporal parameters.

Microstates		Duration (ms)	Occurrence rate	Coverage (%)
MS A	Spearman's rho	0.007	-0.01	2.38×10^{-4}
	p-value	0.936	0.898	0.998
	n	156	156	156
MS B	Spearman's rho	-0.018	0.008	0.009
	p-value	0.822	0.92	0.91
	n	156	156	156
MS C	Spearman's rho	-0.087	-0.04	-0.078
	p-value	0.281	0.617	0.331
	n	156	156	156
MS D	Spearman's rho	-0.171	-0.149	-0.183
	p-value	0.033	0.063	0.022
	n	156	156	156
MS E	Spearman's rho	0.175	**0.235***	**0.241***
	p-value	0.029	**0.003**	**0.002**
	n	156	156	156

* the significance of the results survived FDR correction.

Table SM 5.3. Spearman's correlations between psychological measures and microstates spatiotemporal parameters.

Microstates		BAI	BDI	CBOCI	CBOCI_obsessions	CBOCI_compulsions
Duration (ms)						
MS A	Spearman's rho	0.034	0.039	-0.02	-0.012	0.009
	p-value	0.672	0.635	0.806	0.885	0.912
	n	155	152	155	155	156
MS B	Spearman's rho	-0.162	-0.086	-0.059	-0.05	-0.024
	p-value	0.043	0.292	0.469	0.536	0.764
	n	155	152	155	155	156
MS C	Spearman's rho	0.167	0.17	0.026	-0.015	0.087
	p-value	0.038	0.036	0.751	0.856	0.279
	n	155	152	155	155	156
MS D	Spearman's rho	**-0.263***	-0.183	**-0.215***	-0.185	-0.199
	p-value	**< .001**	0.024	**0.007**	0.021	0.013
	n	155	152	155	155	156
MS E	Spearman's rho	-0.016	0.04	0.031	0.074	-0.036
	p-value	0.842	0.626	0.698	0.36	0.658
	n	155	152	155	155	156
Occurrence rate						
MS A	Spearman's rho	-0.033	-0.071	-0.034	-0.016	-0.054
	p-value	0.687	0.386	0.673	0.841	0.506
	n	155	152	155	155	156
MS B	Spearman's rho	**-0.216***	-0.173	-0.044	-0.021	-0.065
	p-value	**0.007**	0.033	0.585	0.798	0.417
	n	155	152	155	155	156
MS C	Spearman's rho	0.038	0.042	0.024	0.065	-0.044
	p-value	0.639	0.611	0.771	0.422	0.584
	n	155	152	155	155	156
MS D	Spearman's rho	**-0.205***	-0.2	-0.148	-0.098	-0.184

Microstates		BAI	BDI	CBOCI	CBOCI_obsessions	CBOCI_compulsions
	p-value	**0.01**	0.014	0.067	0.224	0.021
	n	155	152	155	155	156
	Spearman's rho	0.07	0.026	0.074	0.124	-0.023
MS E	p-value	0.386	0.753	0.362	0.125	0.772
	n	155	152	155	155	156
Coverage (%)						
	Spearman's rho	0.009	-0.019	-0.024	-0.009	-0.027
MS A	p-value	0.908	0.819	0.762	0.915	0.737
	n	155	152	155	155	156
	Spearman's rho	**-0.198***	-0.146	-0.041	-0.025	-0.039
MS B	p-value	**0.014**	0.072	0.61	0.755	0.631
	n	155	152	155	155	156
	Spearman's rho	**0.189***	0.163	0.063	0.024	0.104
MS C	p-value	**0.019**	0.045	0.44	0.768	0.196
	n	155	152	155	155	156
	Spearman's rho	**-0.237***	-0.197	-0.193	-0.148	-0.206
MS D	p-value	**0.003**	0.015	0.016	0.066	0.01
	n	155	152	155	155	156
	Spearman's rho	0.059	0.03	0.072	0.116	-0.017
MS E	p-value	0.466	0.712	0.376	0.152	0.837
	n	155	152	155	155	156

* the significance of the results survived FDR correction. *BAI—Beck Anxiety Inventory; BDI—Beck Depression Inventory; CBOCI—Clark–Beck Obsessive–Compulsive Inventory.*

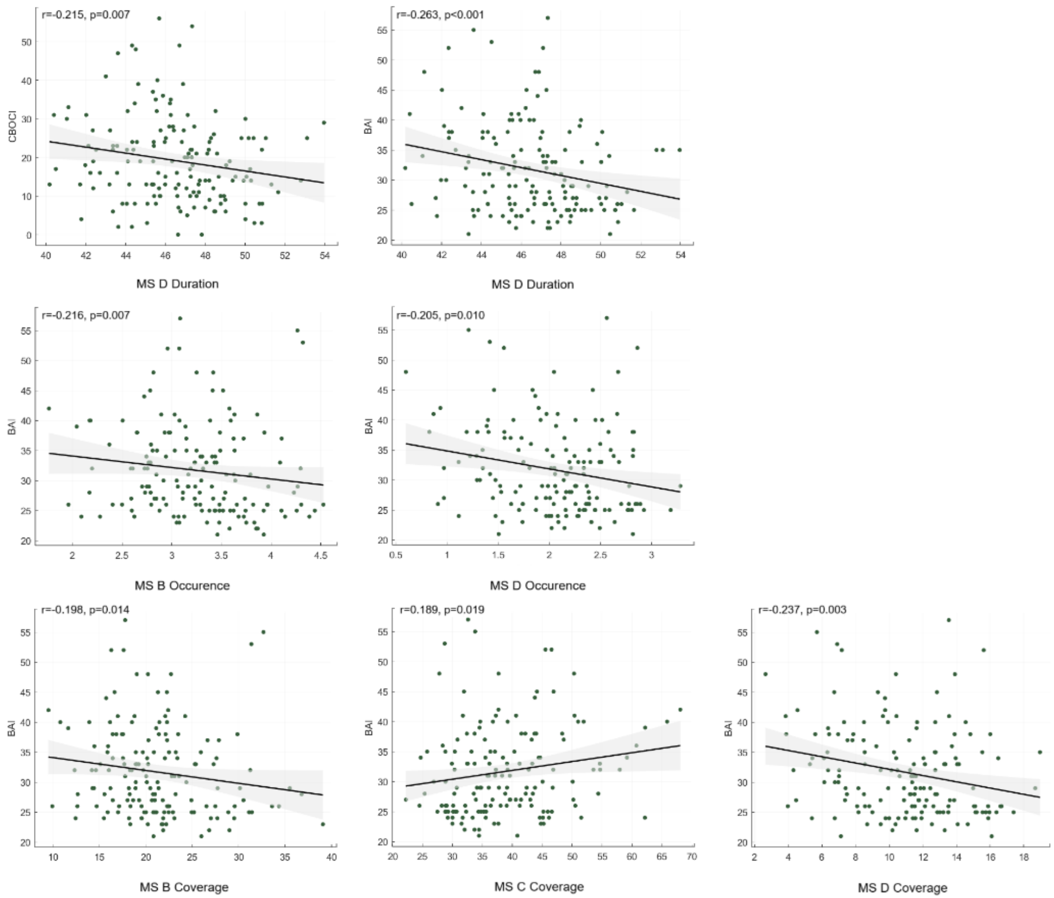


Figure SM 5.1. Correlations plots of psychological variables with microstates parameters that reached significance (y axis – questionnaires scores, x axis – microstate parameters: duration (ms), occurrence rate, coverage (%)). BAI – Beck Anxiety Inventory; CBOCI – Clark–Beck Obsessive–Compulsive Inventory. Shaded areas represent the 95% confidence interval of the regression estimates.

Notes

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